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

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September 2018

Abstract

Whereas attitudes towards risk 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 risk attitudes change with variation in insecurity and uncertainty brought on by unprecedented changes in local-area violent crime. Exploiting the fact that the timing, virulence and spatial distribution of changes in violent crime were unanticipated, we establish there is a rise in risk aversion spread across the entire local population as local-area violent crime increases.

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We are grateful to Ben Crost, Gabriela Farfan, Erica Field, Elizabeth Frankenberg, Robert Garlick, Maria Genoni, Amar Hamoudi, Nick Ingwersen, Craig McIntosh, Hani Mansour, Owen Ozier, Marcos Rangel, Luis Rubalcava, Manisha Shah, Hitoshi Shigeoka, Graciela Teruel, Xiao Yu Wang, Richard Zeckhauser, three anonymous referees and participants at the 2015 NEUDC Conference, 2015 LACEA Annual Meeting, 2015 SEA Annual Meeting, 2015 NBER National Security Working Group, and 2017 Pac-Dev Conference for comments. Financial support from the National Institutes on Aging (R01AG030668), the National Institute of Child Health and Human Development (R01HD047522) are gratefully acknowledged.

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 over the life course 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, 2018; 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 or with other, contemporaneous changes in their lives. For example, relatively more risk averse individuals likely engage in behaviors that mitigate exposure to uncertainty in the environment, resulting in sorting of individuals by exposure, which contaminates 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 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 assign a causal interpretation to these estimates are tested exploiting the panel dimension of the survey.

To explore whether changes in the level of violence impacted 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. 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 gambles with different payoffs.[1] Key

[1] The literature generally considers such empirical measures of risk aversion as capturing underlying risk preferences. In economic theory, risk preferences are summarized by measures derived from utility-based models of behavior under uncertainty. These models make several

for our study, the first follow-up (MxFLS2) took place during a time, 2005-2006, of relatively stable levels of violent crime and the second follow-up (MxFLS3) was conducted after the major escalation in violence, 2009-2012.[2] In order to measure how attitudes towards risk vary as the level of local area violent crime changes over time, individual level information from MxFLS is combined with municipality- and month-specific homicide data collected by the National Institute of Statistics and Geography (INEGI). 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 information about risk attitudes was collected 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 that links 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. Specifically, 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, taking into

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strong assumptions such as the form of the utility function, whether gamble amounts are integrated with personal wealth, whether savings are allowed and whether background risk is accounted for (Arrow, 1970; Pratt, 1964; Gollier, 2000). We take a more agnostic approach and, to avoid confusion, we do not interpret our empirical measures of risk aversion as capturing underlying preferences, but rather as measuring attitudes towards risk more generally.

[2] 94% of the MxFLS3 interviews occurred before 2011.

account all individual-specific characteristics that are fixed. This is a significant advance over the existing literature relating exposure to violence with individual risk attitudes.

A key challenge in this literature is that behavioral responses to a locale's level of safety, such as residential sorting, may be correlated with individual characteristics resulting in a spurious correlation between exposure to violence and risk attitudes. 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, these potential confounds significantly impact conclusions when using a cross-section based approach. To establish this issue we compare results from an analysis using only data from before the surge in violence (i.e. MxFLS2), an analysis only using data from after the plausibly exogenous escalation in violence (i.e. MxFLS3), and an analysis that combines the two survey waves and include individual fixed effects. When we solely use MxFLS2 and exploit only historical variation in violence levels, we find exposure to violence is associated with decreased risk aversion, while we cannot establish any relationship when we exploit MxFLS3 and focus on current levels of violence caused by a plausibly exogenous event.[3]

[3]These results match the conclusions from the two prominent studies in this field, Voors et al. (2012) and Callen et al. (2014), which, as in our study, examine the impact of an indirect measure of violence exposure on risk aversion, but only have access to 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, fearful recollections increase risk tolerance under uncertainty but marginally decrease risk tolerance in the presence of certainty.

However, after taking into account unobserved fixed respondent-level heterogeneity by exploiting the longitudinal data and including individual fixed effects in our models, we uncover 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 estimates are likely to be biased, even when variation in violence is plausible exogenous, without also taking into account unobserved individual heterogeneity.

The next section provides a description of the increase in violence observed in Mexico since 2008. Section 3 places our work in the literature and describes potential pathways that link exposure to violence with risk attitudes. The data, and particularly, the risk measures that are used as our primary outcome of interest, are discussed in Section 4. The empirical strategy is described in section 5 and results in section 6. Potential mechanisms are explored in section 7, additional threats to identification and robustness checks are described in section 8 and section 9 concludes.

II. Background

Since early 2008, there has been a dramatic increase in violent crime in Mexico. The monthly homicide rate (per 10,000 inhabitants) from 2000 until 2011, in Figure 1, establishes the homicide rate was stable for almost a decade prior to 2007. The subsequent rise in homicides in 2008 has been attributed to a change in policy of the Government of Mexico when, soon after his inauguration in December 2006, President Felipe Calderón declared a war on drugs. The subsequent increase in homicides has been directly linked to the rise in violence due to encounters between the government and drug cartels and battles among the splintered cartels.

Specifically, in contrast with previous administrations, Calderón mobilized the army to directly confront Organized Crime Groups (OCGs). As his troops successfully displaced the leaders of some of the OCGs, the cartels split into smaller cells and viciously fought among themselves for territorial control while also fighting government forces. Overall, the number of cartels operating in Mexico grew from six in 2006 to sixteen by 2011. Moreover, not only did violence escalate in areas traditionally under the control of OCGs but violence spread across the country reaching into areas that had not been of strategic value to OCGs and had, until that time, not been exposed to the violence of the cartels (Guerrero-Gutiérrez, 2011). Thus, while, in aggregate, violence in Mexico has risen consistently over time, there is tremendous variation in changes in homicide rates across municipalities over time. This is illustrated in Figure 2 which maps municipality-level homicide rates per 10,000 inhabitants in 2002, 2005, and 2009. In 2002 and 2005, before Calderón took office, violence was heavily concentrated along a small number of primary drug trade routes. By 2009, the patterns are completely different: not only had homicide rates considerably increased but violence covered a much broader swath of Mexico.

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 (such as extortion, kidnapping, car theft), there are several channels through which this new environment created by the Mexican drug war potentially affected people's levels of risk aversion.

For example, the emotional strain generated by living in a dangerous environment may trigger depression, anxiety, or post-traumatic stress disorder (Mollica et al., 1988; Vinck et al., 2007; Yehuda, 2002), and these types of mental health issues have been linked to risk attitudes (Campos-Vasquez and Cuilty, 2014; Raghunathan and Pham, 1999). Recent work by Moya (2018) has provided evidence of the salience of this channel as it relates to directly experienced violence. Specifically, Moya (2018) shows that household-level episodes of victimization in Colombia triggered increased risk aversion and suggests an important pathway for this relationship was the development of anxiety disorders.

Alternatively, and potentially more relevant for our study, while the trauma of direct victimization may generate serious mental health issues, the indirect experience of living in an insecure environment may manifest more generally into fear. What makes fear as a reaction to local violence and insecurity particularly pertinent to this study is that a large literature exists exploring how that emotional response impacts risk attitudes. Notably, the preponderance of evidence indicates that increased fear leads to less optimism about the future and more risk averse attitudes and behaviors (Cohn et al., 2015; Heilman et al., 2010; Lerner and Keltner, 2001; Lerner and Keltner, 2000; Nguyen and Noussair, 2014).

Another potential pathway is financial. Studies on the impact of the Mexican drug war have found that exposure to violence resulted in worse economic outcomes (Dell, 2015; Robles et al., 2013; Velásquez, 2015). Relying on different identification strategies, these studies find that the rise in crime resulted in reduced labor market participation and lower income. 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 that require more personal interactions such as street vendors, small business owners and domestic service providers (Velásquez, 2015). To the extent that greater income or wealth results in reduced risk aversion, (Barsky et al., 1997; Guiso and Paiella, 2008), exposure to violence and the concomitant reduced income would increase levels of risk aversion.

Lastly, living in a violent environment has the potential to adversely affect physical health through various channels including direct victimization, the stress of indirect exposure, reduced access to healthcare, and/or restricted health inputs. Recent studies document that during the Mexican drug war, elevated violence is linked to significant increases in blood pressure and heart disease mortality (Brown et al., 2017; Lee and Bruckner, 2017). Moreover, evidence suggests that negative physical health shocks can increase individual risk aversion (Decker and Schmitz, 2015).

Whereas there are multiple potential pathways linking violent environments and attitudes towards risk, there is a paucity of empirical evidence establishing a causal pathway. Voors et al. (2012) and Callen et al. (2014) made important contributions to this literature. Voors et al. (2012) examine the impact of a civil war in Burundi on social risk, and intertemporal choices. From 1993 to 2003, the civil war between the two main ethnic groups in Burundi resulted in intense violence. Using measures from experimental games collected in 2009, the authors study the cumulative effect of a decade's worth of violence on risk attitudes, amongst other preferences. They report 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) explore the impact on risk attitudes of violence in Afghanistan. While the country had been racked by violence for nearly thirty years, the authors focus on local violence that occurred over a slightly less than 8 years period prior to their collection of risk attitudes at the end of 2010. They report that, in contrast with Voors et al., there is no direct impact of exposure to violence on the risk attitudes of individuals. However, they do report that when a random subsample of respondents were asked to recall an experience that caused them fear or anxiety in the past year, the recalls influenced attitudes towards risk and certainty among those who had been exposed to violence. This 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. Moya (2018) provides evidence on this question and documents that more recent and intense traumatic experiences lead to increased risk aversion

In an innovative study of 14 to 31 year olds in Busia District, Kenya, Jakiela and Ozier (2016) exploit the unexpected violence after the 2007 Kenyan election in conjunction with the timing of survey interviews some of which were before the violence and others after it ended. They find higher rates of risk aversion among individuals interviewed after the post-election violence subsided. As they note, it is difficult to rule out the possibility that this may also reflect the effects of other contemporaneous changes in the socio-economic and political environmental.

The reasons for the incongruent results in the literature are not clear. It is possible that estimates that rely on cross-section variation are contaminated by unobserved individual-specific heterogeneity and that highly aggregated measures of violence fail to separate exposure to violence from other changes in the environment. Our data and methods are designed to directly address these challenges.

IV. Data

Data are drawn from two sources. First, the Mexican Family Life Survey (MxFLS), a rich longitudinal survey, is representative of the Mexican population at the national level as well as for urban and rural sectors within each region at the time of the 2002 baseline. The survey covers 150 municipalities that are spread across the country and are representative of the change in violent crime seen at the national level (Appendix Table 1). Second, the National Institute of Statistics and Geography (INEGI) provides information on all officially-reported intentional homicides at the municipality and month level. 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.

MxFLS collects information on a wide range of socioeconomic and demographic indicators on individuals across three rounds. The baseline gathered information on a sample of over 35,000 individuals living in over 8,400 households in 16 states. The first follow-up (MxFLS2) was conducted in 2005/2006, when violence was relatively stable, and the second follow-up (MxFLS3) was conducted in 2009/2012, 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.

Although MxFLS has achieved high rates of survey retention with 89% of baseline respondents being re-contacted in both MxFLS2 and MxFLS3 (Rubalcava and Teruel, 2013), it is important to establish that attrition is not correlated with the change in the conflict environment. This is investigated in section VI and we 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. MxFLS2 and MxFLS3 included a set of hypothetical questions of this sort that had been carefully pretested and validated. The instrument was designed to be easy for the respondent to understand and answers to these hypothetical questions were compare with parallel questions in an experimental setting in Mexico in which respondents were paid based on their answers. There was very close correspondence in the answers (Hamoudi, 2007).[4] We rely on the hypothetical questions in MxFLS to construct our measures of risk aversion.

In Panel A of Table 1, 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).[5] 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

[4] Other studies have reported that answers to hypotheticals and questions with real payouts are not the same. There are many potential reasons for these discrepancies. A key advantage of our design is that we compare change over time for the same individual. To the extent any biases in hypothetical responses are fixed, the change will not biased. For the difference in elicitation methods between hypothetical and real stakes to cause bias in our estimates, it would need to be the case that exposure to violence changes the way people react to hypothetical questions versus real stakes questions in a way unrelated to the true change in their risk attitudes.

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

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 in the first column to the right of the hypothetical question diagram, 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 improving the respondent's comprehension. Panel B of Table 1 provides the choices in MxFLS3. One innovation in MxFLS3 is the inclusion of a question at the beginning of the instrument to assure the respondent understands the choices. 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 and the choice was offered a second time. About two-thirds of respondents that were asked a second time switched to choosing the gamble. If the respondent again chose the dominated sure amount, we infer the respondent is very risk averse, or "gamble averse," preferring a sure amount to a gamble that would pay at least as much. In order to probe further, respondents who chose the dominated sure amount were offered a follow-up choice in which both alternatives in the gamble were strictly greater than the sure amount. Even in this case, 7.4% of the respondents 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 in the first column to the right of the hypothetical question diagram [6]

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. 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

[6] A well-understood potential concern with using information from survey questions is that the sequence, structure, and prompts used in a question may lead to unintended and non-random measurement error in the information that is collected. With regard to how this relates to the risk attitudes questions in the MxFLS and our analysis specifically, for bias to occur, the pattern of the measurement error from the survey design would have to take a very specific form. For example, if changes in the risk attitude questions from MxFLS2 to MxFLS3 led to new frames, anchors, order effects, or other unintended prompts, the fixed change this would have on individual responses would be captured by the simple inclusion of year of interview fixed effects as the unintended stimuli are common within a survey year (wave). Thus, for unintended measurement error related to question design to bias our results it would have to be that individuals experiencing more violence prior to the interview are for some reason impacted by these prompts in a systematically different way than those experiencing less violence.

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. In MxFLS2 we classify as "most risk averse" those with a risk aversion index equal to 5, 6 or 7. For the MxFLS3 we classify as "most risk averse" those with a risk aversion index equal to 5. To put these choices in perspective, if we assume the utility function of individuals in our sample takes the form of constant relative risk aversion and calculate Arrow-Pratt coefficients of relative risk aversion, the choice of "most risk averse" is equivalent to a risk coefficient of (4.103, ∞) in MxFLS2 and (3.77, ∞) in MxFLS3.[7]

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

[7] In order to account for the gamble averse individuals in MxFLS3, their risk coefficient is set to be the same as our most risk averse group in MxFLS3. Also, since the least risk averse group will have -∞ as its lower bound, we follow Cameron and Shah (2015) and set its risk coefficient to an arbitrarily small number and the results are not sensitive to this choice. Lastly, given that a negative value cannot be raised to a power less than 1, the option of -100 for (risk index 1) is also set to an arbitrary small number, and the results are not sensitive to this choice. The distribution of our sample by Arrow-Pratt coefficients of relative risk aversion is provided in the final column of Table 1, as well as, Panel A of Appendix Table A2. In addition, Panels B, C, D, E of Appendix Table A2 provide the distribution of our sample separately for municipalities that experienced no, low (bottom quartile), moderate (below median), and high (top quartile) increases in the homicide rate, respectively.

seems like the most natural group for these individuals, in section VIII 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 VIII we also confirm the robustness of our results to several different classifications of "most risk averse", as well as, continuous versions of our risk measure.[8]

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[8]To further explore the relevance of our risk measure to true risk attitudes, Appendix Table A3 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. In our sample, men are typically the household's breadwinner and thus we focus on risky economic behaviors for men. In particular, for men, our indicator of risky behavior equals 1 if the respondent is self-employed in MxFLS3 or has migrated between MxFLS2 and MxFLS3 for at least a month. For women, the rich reproductive health information collected in the MxFLS allows us to explore changes in risky sexual activity. Thus, for women, our indicator of risky behavior equals 1 if the respondent reports having more than 1 sexual partner in MxFLS3 or reports not using any type of contraception during sex. We then regress our risky behavior indicator on whether the respondent was measured as "most risk averse" in MxFLS2. We additionally control for municipality fixed effects and household/individual characteristics measured in MxFLS2. The results for this analysis, found in columns 1 and 2 of Table A3, show

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 local area changes in the conflict environment contributes to this change.

The MxFLS survey responses are matched at the municipality-level with the homicide dataset collected by INEGI, taking into account the timing of each interview. The homicide rate is used to capture the overall crime environment created by the drug war. Researchers have shown that the INEGI intentional homicide data matches the temporal and geographic

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that being "most risk averse" in MxFLS2 is negatively and significantly related to risky behaviors in MxFLS3. In addition, since not all women answer the reproductive health instrument, we also provide the results looking only at men in columns 3 and 4 of Table A3 and again find evidence that risk averse individuals are less likely to be making riskier decisions.

[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 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 A4 provides descriptive statistics for our analytical sample.

[11] Appendix Table A5 provides the risk attitudes index transition matrix.

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).[12]

V. Identification strategy

The main empirical strategy used for this analysis can be summarized in the following regression framework:

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

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],

[12] Using information from MxFLS2 and MxFLS3, we estimate the effect of the municipal homicide rate experienced by an individual over the last 12 on their personal reports of victimization in a model with individual, municipality, date of interview fixed effects, and time-variant controls at the individuals and household level. The results found in Appendix Table A6 show that respondents exposed to increased local violence report more assaults in the last year and are more likely to report any instances of being personally assaulted in the last year.

[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,

θ_i captures individual fixed effects, γ_t captures date of interview fixed effects, which include year and month of interview fixed effects, and λ_m represents fixed effects for the municipality of current residence.[14]

In Online Appendix B we discuss our analysis of migration as a behavioral response to local violence in Mexico and report that individuals living in rural areas are more likely to move out of their municipality in response to increased crime than individuals living in urban areas. In addition, unmarried individuals are more likely to move in response to local violence. If individual risk attitudes are correlated with these drivers of violence-related migration (or with other, unobserved factors) failure to take endogenous migration responses into account will yield biased estimates. To account for this potential problem, homicide exposure in (1) is assigned based on the individual's place of residence in MxFLS2, which is before the escalation in violence occurred. By assigning exposure in this way we shield our estimates from potential bias induced by endogenous migration.

VI. Results

VI.1. Using Cross-Sectional Data

Before moving to the main results from the full specification described in equation 1, it is useful to present results that are comparable to the wider literature that uses cross-sectional variation in

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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.

violence exposure to identify the effects on risk. This analysis is conducted by estimating equation 1 separately for MxFLS2 and MxFLS3 without individual fixed effects.[15] The results of these cross-sectional regressions are found in columns 1 for the MxFLS2 data and column 2 for the MxFLS3 data of Table 2.

Column 1 of Table 2, 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. Using this approach we find that violent crime is associated with significantly increased risk tolerance, similar to the conclusions of Voors et al. (2012).

An alternative to using variation in violence that comes from a long-standing conflict or persistent environment of insecurity, 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 2 of Table 2, and indicate that no significant relationship

[15]Municipal fixed effects are also excluded in the cross-sectional analysis, as within-municipality violence variation is limited in the cross-section. These models also more closely reflect those used in Voors et al. (2012) and Callen et al. (2014), as neither study included geographic fixed effects at the same level as the violence measure when exploring the direct relationship between local violence and risk attitudes.

exists between risk attitudes and exposure to local violent crime, which is similar to the comparable results in Callen et al. (2014).[16]

The main concern with both of these cross-sectional analyses is that the estimates may be biased by unobserved individual heterogeneity related to both risk attitudes and local violence that is driven by residential sorting, within-municipality differences in the date of survey, and non-random attrition. For example, the result in column 1 may be a function of less risk averse individuals being more likely to reside in places with higher levels of persistent violence. If we then add some amount of quasi-random variation into the location of violence this can help break that strong connection and potentially lead to a neutralization of this confounding relationship, as seen in column 2. Only using the MxFLS3 cross-section though, still suffers from potential bias generated by unobserved individual heterogeneity. In particular, to the extent that some aspect of the level of violence during the escalation is related to historical levels of violence, and thus historical residential sorting column 2 would still provide biased results. Alternatively, if the unobserved characteristics of the type of individual, within a municipality, that agrees to complete the survey when local violence is particularly elevated versus re-scheduling to a different time are related to risk attitudes, this would confound the results in column 2. Lastly, if

[16]Callen et al. (2014), whose violence is measured at a local level with no temporal variation is unable to use local level fixed effects, but as an alternative includes province level fixed effects. If we similarly include higher than municipality level geographic fixed effects, such as state of residence fixed effects, into the model used in column 2 there is no discernable statistical or economic difference in our coefficient.

there is any degree of non-random attrition correlated with risk attitudes and local violence exposure a cross-section analysis will not be internally valid.

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, controls for any of this 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 1.

VI.1. Using Longitudinal Data

The results of estimating (1) with our longitudinal sample are in Table 2, columns 3 (with individual fixed effects) and 4 (with individual and municipality fixed effects). The estimates in both columns provide evidence that individual heterogeneity is 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, 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 explore whether these effects vary across population sub-groups. 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 estimated fully interacted versions of equation 1. The results of this heterogeneity analysis are found in Table 3.

The first difference we examine is between women and men. In Mexico, relative to women, men are much more likely to be in the paid labor force and thus may be more exposed to extortions, kidnappings and business thefts. An additional difference in exposure by gender is that women face higher 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 3, column 2. We find that the relationship between local violent crime exposure and risk aversion does not differ significantly by gender.

Similarly, the differences in occupations, potential exposures, and personal responsibilities amongst individuals of different ages within our sample may have an association with how sensitive the respondent's risk attitudes are to increased local violence. As such, we explore the whether there is any heterogeneity in the main treatment effect by age in column 3 of Table 3, but find no such relationship.

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. This potential heterogeneity is tested in column 4 of Table 3. The results provide no evidence of a difference in the impact of violence on risk attitudes by urban/rural status.

A fourth piece of heterogeneity we explore is 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.

We use two indicators of low SES. First, we define an indicator variable for individuals in the bottom quartile of education level and fully interact our main regression with this indicator. We find no differential effect on this sub-group (column 5 of Table 3). Second, 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 6 of Table 3. The estimates suggest that, unlike the rest of the respondents, the risk attitudes of individuals living in households in the lowest quartile of PCE are not as 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). Alternatively, 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.

The last source of heterogeneity based on MxFLS2 characteristics that we explore is intended to provide preliminary clues about the mechanisms 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.

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 7 of Table 3 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.

VII. Mechanisms

While our initial heterogeneity analysis allowed us to begin exploring the mechanisms behind the relationship between exposure to violence in Mexico and risk aversion, in this section we more formally examine these pathways. In particular we focus on characteristics that, as discussed in Section III, prior literature has identified as having a significant relationship to risk attitudes and are likely affected by living in a violent environment including economic wellbeing, mental health, physical health, and fear.

First, we explore to what extent these potential mechanisms were impacted by the increased violence in Mexico. Specifically, we employ the same model as in our primary analysis, equation 1, but rather than our indicator of risk aversion, we use a measure for each potential mechanism as the dependent variable. The results of these analyses are found in Table 4. In columns 1 and 2 we use whether an individual is employed or whether an individual's household is in the bottom quartile of household PCE as a measure of economic wellbeing and find that they have no significant relationship with local violence exposure.[17]

We turn next to health, broadly-defined. We begin with an index constructed from questions in MxFLS that are approximately equivalent to the Short Form 36 (SF-36) Survey Instrument as the dependent variable in equation 1. As shown in column 3 of Table 4, we find no evidence that increases in local violence exposure in Mexico during our sample period is linked with significant increases in this index; nor is there a link with specific items including anxiety and sadness.[18]

Previous evidence in Brown et al. (2017) suggests living in Mexico during the escalation of violence has had a toll on physical health. To explore this relationship in our sample, we estimate equation 1 using systolic blood pressure (SBP) as the dependent variable.[19] Our results,

[17]While no labor market effect is detected from exposure to violence on the overall sample in columns 1 and 2 of Table 4, we can replicate the decline in the earnings and employment of the self-employed found in Velásquez (2015). Despite this relationship, as seen in column 7 of Table 3, the self-employed are not experiencing any particularly elevated risk aversion response to local violence exposure.

[18]The lack of an overall relationship between local violence exposure and mental health does not indicate that certain subgroups did not suffer deleterious effects on their mental health. In fact, Brown (2018) provides evidence that women who were pregnant during the Mexican drug war report poorer emotional wellbeing.

[19]Systolic blood pressure is measured using an Omron upper arm cuff. In both the baseline and MxFLS3 the same field protocols were used, but in MxFLS2 blood pressure was measured

provided in column 4 of Table 4, suggest that exposure to elevated crime is estimated to increase SBP by 0.38 mm Hg.

Lastly, we explore the relationship between living in a more violent community and feelings of fear and insecurity. In particular we use an indicator for the individual reporting fear of being assaulted at night, as well as, an indicator for the individual reporting they feel less safe than 5 years ago as two alternative dependent variables in equation 1. These results are found in columns 5 and 6 of Table 4, and provide strong evidence that increased local violence led to significantly elevated feelings of fear and insecurity.

The results in Table 4 suggest that from our original list of potential mechanisms, the channels most relevant to our context are fear and physical health. Moreover, both of these pathways, negative physical health shocks and increased fear, have previously been shown to be correlated with increased risk aversion (Cohn et al., 2015; Decker and Schmitz, 2015; Heilman et al., 2010; Lerner and Keltner, 2001; Lerner and Keltner, 2000; Nguyen and Noussair, 2014).

We proceed by testing if that type of relationship between these potential mechanisms and risk aversion exists amongst our sample. To provide this information we again use equation 1 but this time replace our primary independent variable of interest, the measure of local violence exposure, with the potential mechanism. The results of this analysis are found in Appendix Table A7 and show a strong, significant positive relationship between increased feelings of fear and

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manually with a different procedure and accuracy to only units of ten mmHg. Since the blood pressure protocol was identical in MxFLS1 and MxFLS3 and due to concerns with measurement error in MxFLS2, in this study the MxFLS1 values for blood pressure are assigned to all pre-MxFLS3 observations.

increased risk aversion, but no relationship between worsened physical health and risk aversion. Thus, overall, from exploring the relevant mechanisms behind our main findings, feelings of fear and insecurity appear to be the mostly likely candidates.

Having provided suggestive evidence that the most likely channel by which violence during the Mexican Drug War impacts risk aversion is fear/insecurity, we next explore whether this heterogeneous relationship exists in the data. Specifically, we run separate regressions for each potential mediator in which we fully interact our main model, equation 1, with a measure for each of the mechanisms.[20] The goal of this analysis is to see if a mechanism is predictive of which respondents have risk attitudes that are the most sensitive to the increase in violent crime. The results of this heterogeneity analysis are reported in Table 5. Consistent with the results in Table 4 and Appendix Table A7, the relationship between local violence and risk aversion is strongest for those individuals who report increased fear/insecurity and the relationship does not vary with any of the other potential mediators in the table.

Lastly, as a complement to our heterogeneity analysis, we use formal mediation techniques to provide suggestive evidence regarding how much of the direct effect we describe in column 4 of Table 2 is mediated by our potential mechanisms. We adopt the mediation procedure outlined in Acharya et al. (2016) and compare estimates of the average controlled direct effect (ACDE) with our main result to provide a sense of how much of the effect of violence on risk aversion can be explained by different sets of mediators. The method has been used in the violence and risk aversion literature by Moya (2018).

[20] The non-interacted direct effect of each mechanism variable is also included in the model.

The specifications and results are described in Online Appendix C. To summarize, if measures of economic wellbeing, mental health, physical health (SBP), or the combination of mental and physical health are used as the mediators, the ACDE is qualitatively and quantitatively indistinguishable from our main result from column 4 of Table 2. On the other hand, when we use reported feelings of fear of being assaulted and reported feelings of being less safe than 5 years ago, the ACDE is no longer statistically different than 0 and the magnitude is only 12% of the original treatment effect estimated in the main analysis.

While the heterogeneity results of Table 5 and the mediation analysis in Online Appendix C provide consistent suggestive evidence that the primary channel through which exposure to local violence is acting on risk attitudes is through increased feelings of fear, this interpretation requires important assumptions. The specific assumptions and evidence regarding whether they are likely to hold in this case are described in detail in Online Appendix C. In short, we show that our conclusion that fear is the primary mechanism for the relationship between local violence exposure and risk attitudes is not caused by a composition difference in the types of respondents who experience increased fear when violence is elevated and that if there is an alternative unobserved mediator driving fear, it is not working through or strongly associated with any of the other observed characteristics specific to individuals reporting more fear in MxFLS3. In addition, given the literature on the consequences of conflict and the previous research on the determinants of risk preferences we have attempted to test all plausible alternative mechanisms and found no similar relationship. This implies that if an unobserved mechanism not related to feelings of fear and insecurity is actually driving the relationship between violence exposure and risk attitudes it would have to additionally be unrelated to economic wellbeing, mental health, and physical health.

VIII. Threats to Identification

The main threat to identification that remains in our analysis 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.

To investigate this concern we exploit the information available in MxFLS1 on potential drivers of risk attitudes such as economic wellbeing, mental health, and self-reported feelings of safety to provide supporting evidence.[21] In particular we explore if respondents that would later be exposed to elevated levels of violence were already on differential trends in these important mechanisms. Specifically, we estimate within-individual models analogous to equation 1 and find no correlation between changes in these characteristics between MxFLS1 and MxFLS2 (i.e. pre-escalation of violence) and the subsequent changes in homicide rate that actually occurred between 2005 and 2009. These results, which are found in Appendix Table A8, suggest that individuals living in municipalities that would subsequently be exposed to larger increases in violence were not already on a downward trend in economic wellbeing, mental health, or fear/insecurity.[22]

[21] Due to a change in protocol in the collection of systolic blood pressure in MxFLS2, this analysis cannot be performed for our measure of physical health.

[22] More generally, Brown (2018) and Velásquez (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

While these two pieces of evidence suggest that there are not linear unobserved trends that are correlated with the homicide rate, they would not be able to detect a non-linear 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.

In Online Appendix D we explore one potential event that occurred between the MxFLS2 and MxFLS3 survey waves that plausibly fits this description: the 2008 Great Recession. Results from specifications that include controls for economic activity, as well as, estimates that exclude individuals living in the regions most impacted by the Great Recession provide qualitatively and quantitatively equivalent results to the main analysis and lead us to conclude that our findings are not an artifact of this event.

Another potential threat to the validity of our results is the choices we made with regard to the creation of our main dependent variable. In Online Appendix D we explore multiple alternatives to the assignment of "gamble averse" respondents, use continuous measures of risk attitudes instead of binary, and experiment with 5 alternative constructions of our binary risk aversion measure. In each case the conclusions from our main analysis are confirmed.

Finally, selective attrition is a potential source of contamination in any analysis of longitudinal survey data and may be especially important in the context of a major environmental shock. In Online Appendix D we develop and estimate a test to detect the presence of attrition

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violence. 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 A9.

that is correlated with local violence exposure. We find that attrition is neither correlated with the change in violence for our overall sample nor for any specific subgroups of our sample.

IX. Conclusion

This research examines 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 major empirical challenges 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. While the direction and magnitude of this finding is incongruent with the seminal work by Voors et al. (2012) and Callen et al. (2014), it is in line with recent work by Jakiela and Ozier, (2016), who provide evidence that exposure to politically motivated violence in Kenya reduced risk tolerance.[23,24]

Moreover, our results do not seem to be driven by the respondents that have suffered a shock to economic wellbeing, mental health, or physical health due to the escalation of violence, but rather it is those who report increased fear and insecurity that are the most likely to become more risk averse. The importance of this potential mechanism is consistent with a larger previous literature that has shown fear induces more risk aversion (Cohn et al., 2015; Heilman et al., 2010; Lerner and Keltner, 2001; Lerner and Keltner, 2000; Nguyen and Noussair, 2014).

While these findings increase our understanding of the ways risk attitudes evolve in response to changes in the environment, they also provide evidence of another 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 another pathway

[23]While Callen et al. (2014) find no overall effect of conflict exposure on risk attitudes, they show that respondents that have experienced violence and are primed to have a fearful recollection do exhibit different behavior. The elicited fearful memory leads to increased risk tolerance under uncertainty and marginally less risk tolerance in the presence of certainty.

[24]Though not directly comparable due to differences in the type of exposure examined, our result is also consistent with Moya's (2018) finding that individuals who themselves or a household member experienced direct victimization are more risk averse.

through which growth and development can be impacted by violent conflict and insecurity is elevated risk aversion and, thereby, reduced wealth accumulation over the long-term.

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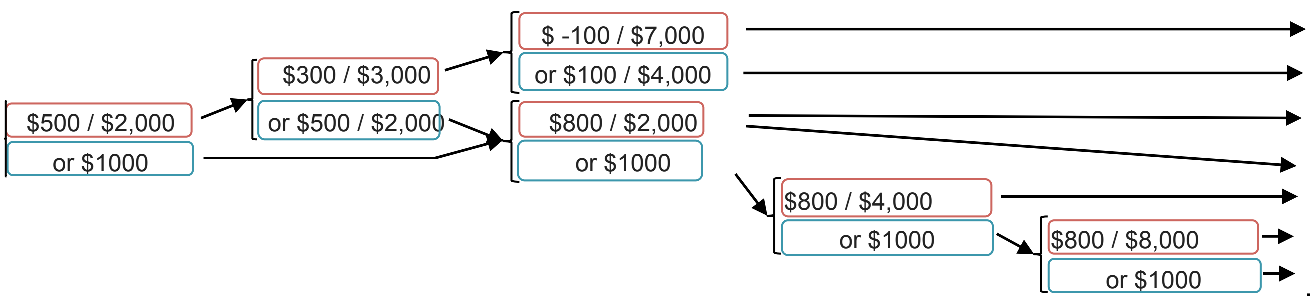
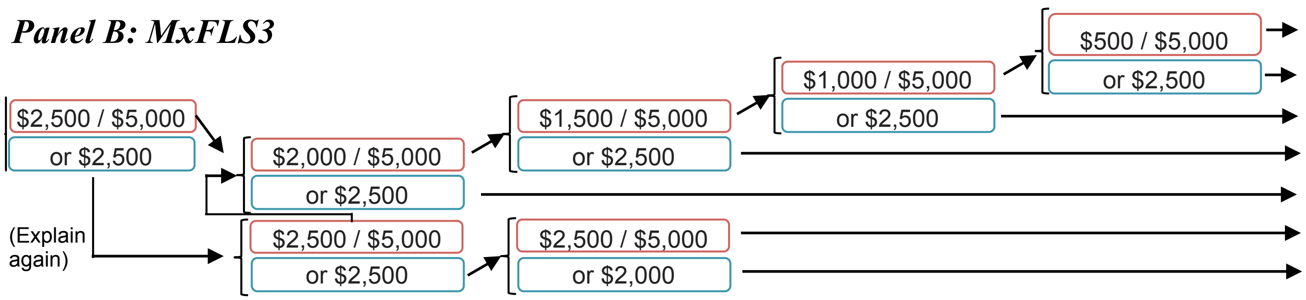
Table 1: Risk Aversion Measurement in MxFLS2 and MxFLS3

Panel A: MxFLS2



Index number	Relative Risk Aversion Coefficient	% of sample
1	(-∞, .62)	33.0%
2	(.62, .88)	4.9%
3	(.88, 1)	8.3%
4	(1, 3.77)	36.3%
5	(3.77, 4.075)	7.3%
6	(4.075, 4.103)	1.8%
7	(4.103, ∞)	8.4%

Panel B: MxFLS3



Index number	Relative Risk Aversion Coefficient	% of sample
1	(-∞, .23)	22.9%
2	(.23, .66)	4.7%
3	(.66, 1.52)	11.1%
4	(1.52, 3.77)	17.2%
5	(3.77, ∞)	30.9%
6	(3.77, ∞)	5.8%
7	(3.77, ∞)	7.4%

Notes: 11,348 respondents in each panel. In MxFLS2, risk aversion increases with index number. In MxFLS3, risk aversion increases with index to 5 and gamble averse respondents are assigned index of 6 or 7.

Table 2: Impact of violent crime on risk aversion

	Most risk averse = 100			
	Only MxFLS2	Only MxFLS3	MxFLS2 & MxFLS3	MxFLS2 & MxFLS3
	(1)	(2)	(3)	(4)
Homicide rate	-2.203***	0.373	1.472***	1.525***
	[0.772]	[0.329]	[0.465]	[0.481]
Mean dep. variable	17.51	44.14	30.82	30.82
Observations	11,348	11,348	22,696	22,696
Number of individuals	-	-	11,348	11,348
Individual Fixed Effects	NO	NO	YES	YES
Municipality Fixed Effects	NO	NO	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, household characteristics, and date of interview fixed effects.

Table 3: Heterogeneous 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)	(6)	(7)
Homicide rate	1.525***	1.519***	1.663**	1.482***	1.609***	1.828***	1.462***
	[0.481]	[0.492]	[0.796]	[0.556]	[0.501]	[0.501]	[0.482]
Homicide Rate*I(Male=1)		0.030					
		[0.528]					
Homicide Rate*I(Age in MxFLS2)			-0.003				
			[0.015]				
Homicide Rate*I(Live in Rural Locality in MxFLS2=1)				-0.095			
				[0.922]			
Homicide Rate*I(Bottom Quartile of Years of Education in MxFLS2=1)					-0.135		
					[0.485]		
Homicide Rate*I(Bottom Quartile of PCE in MxFLS2=1)						-0.935	
						[1.122]	
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	0.04	0.07	0.02	0.41	0.20
Mean dep. variable	30.82	30.82	30.82	30.82	30.83	30.82	30.81
Observations	22,696	22,696	22,696	22,696	22,694	22,494	22,628
Number of Individuals	11,348	11,348	11,348	11,348	11,347	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, municipality, and individual fixed effects, as well as, the interaction of each of these controls with the relevant subgroup.

Table 4: Impact of violent crime on potential mediators

	Employed= 100	Bottom Quartile of PCE =100	Quartic Root of Emotional Wellbeing Index	Systolic Blood Pressure	Feel less safe than 5 years ago = 100	Feel scared of being attacked during the night = 100
	(1)	(2)	(3)	(4)	(5)	(6)
Homicide rate	0.042	0.113	-0.010	0.378*	2.96***	1.40***
	[0.234]	[0.352]	[0.009]	[0.209]	[0.584]	[0.404]
Mean dep. variable	54.71	24.67	1.09	126.4	30.05	20.93
Observations	23,292	22,946	23,390	17,056	23,170	23,170
Number of individuals	11,646	11,473	11,695	8,528	11,585	11,585
Individual Fixed Effects	YES	YES	YES	YES	YES	YES
Municipality Fixed Effects	YES	YES	YES	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, household characteristics, and date of interview fixed effects.

Table 5: Heterogeneous impact of violent crime on risk aversion by potential mediators measured in MxFLS2 and MxFLS3

	Most risk averse = 100						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Homicide rate	1.525***	1.452***	1.453**	1.348*	2.602	0.447	1.044*
	[0.481]	[0.531]	[0.581]	[0.743]	[2.485]	[0.696]	[0.591]
Homicide Rate*I(Employed)		0.126					
		[0.581]					
Homicide Rate*I(Bottom Quartile of Change in PCE)			0.533				
			[0.650]				
Homicide Rate*I(Quartic Root of Emotional Wellbeing Score)				-0.023			
				[0.493]			
Homicide Rate*I(Systolic Blood Pressure)					-0.010		
					[0.019]		
Homicide Rate*I(Feel Less Safe Than 5 Years Ago)						2.170**	
						[1.041]	
Homicide Rate*I(Scared of Being Attacked at Night)							1.630*
							[0.948]
P-value for F-Test (Homicide Rate + Homicide Rate Interaction=0):		0.01	0.00	0.01	0.30	0.00	0.00
Mean dep. variable	30.82	30.81	30.83	30.81	30.76	30.82	30.82
Observations	22,696	22,558	22,212	22,658	16,512	22,540	22,540
Number of Individuals	11,348	11,279	11,106	11,329	8,256	11,270	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, municipality, and individual fixed effects, as well as, the interaction of each of these controls with the relevant subgroup.