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Risk Aversion, Time Preferences and the Effects of Crime and Violence

Research Master Thesis in Economics

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We investigate the relationship between crime, violence and individual preferences. Specifically, risk and time preferences. We use information of a lottery experiment for a representative sample of the Mexican population to elicit risk attitudes and a set of questions to elicit time preferences. The channels of impact explored are the level of depression, fear and expectations which could be caused by crime and violence. We document an effect of crime which causes people to be more likely to be risk averse and patient. The relevant variables associated to mental states are average depression for risk aversion and severe depression for time preferences. These channels however do not explain the direction of the effect of violence. We find that expectations about the future have a similar effect as the effect of crime on risk and time preferences. The results can have implications for possible economic recovery after trauma.

1. Introduction

Analyzing the effects of crime and violence on economic performance has drawn a lot of attention from economists of diverse backgrounds. While there are some macro-level oriented studies which focus on estimating the costs of this behavior, not much research has been done at the micro-level. Crime and violence are associated to loss of assets, temporary drops of income, distress sales and other adverse economic shocks. However, these are not the only channels through which crime can have an impact on individual welfare. The focus of this study will be to assess the impact of crime and violence on individual preferences. Specifically, we will study risk attitudes and intertemporal decision making after being victim of a crime.

The relationship between individual preferences and economic success is of great relevance to this matter of study. If preferences are one of the determinants of economic success, then a shock to these preferences will be another channel through which violence and crime can impact welfare. People who suffer from violence, theft and insecurity might incur in behavior that will prevent them from a fast economic recovery. If an individual is very impatient (i.e. discounts the future at very high rates), she might be reluctant to invest in her own future or her family's (e.g. education, technology). If an individual is very risk averse, she might not be willing to invest in projects which imply risky returns. Therefore, understanding how preferences are determined and what their role is in determining economic outcomes, can shed light on why some people may remain poor (Tanaka, Camerer, & Nguyen, 2010). Recent literature in experimental and development economics has been studying this last issue in countries like Vietnam, Burundi, Afghanistan and Colombia.

In order to motivate our analysis of the study of individual preferences, and its economic relevance, we analyzed first their possible relationship with saving behavior[1]. With our data we can observe how the decision to save and the amount saved are related to time preference and risk aversion parameters. More risk averse people and more patient people are more likely to save part of their income.

As a consequence, in order to have a better prediction individual behavior we need to explore its possible determinants. The evidence from current literature presents mixed results on the direction of the effect of violence. Existing studies present evidence for a reduction as well as for an increase in the level of risk aversion due to an episode of violence. The evidence for the duration of these effects is also mixed. Some studies on other types of trauma (e.g. natural disasters) claim it to have a short-term effect (Eckel, El-Gamal, & Wilson, 2009) while others claim it can have a long term effect (Cameron, 2011).Though their methodologies differ, psychological tools are used to explain the channel through which trauma could have an impact on preferences.

In order to contribute to the ongoing debate, we will take advantage of an extensive survey from Mexico (Mexican Life and Family Survey) which allows us to use data on individual preferences

[1] Appendix A contains more details on the analysis of savings.

and criminal incidence. This research will differ from previous studies since it does not focus on episodes of widespread violence and civil conflict, but rather on more general violent delinquency. Therefore, the results can have implications not only in countries with civil conflicts (e.g. Burundi, Afghanistan) but also in countries with high criminality rates.

Our study will also contribute to the literature by describing the attitudes of the Mexican population towards risk and intertemporal choice. While there are a few studies which separately use these two variables with the Mexican population, to our knowledge this is the first one to integrate them together and thoroughly describe them. As will be shown later, the Mexican population has a tendency to be risk-seeking and has a high degree of impatience. We also analyze some of the demographic and socioeconomic factors that could be related to them, such as age, gender and level of education. For the risk aversion variable, we find no significant explanatory power of such covariates. For the time preference results we find them to be significant.

One of the channels through which violence and crime can impact risk and time preferences can be related to the psychological consequences of these shocks. It can generate conditions such as depression, post-traumatic stress disorder (PSTD), substance abuse, hypertension and a wide range of health and psychological reactions. One of the main contributions of this stream of literature is the "Risk as feelings" hypothesis by Loewenstein, Weber, Hsee, & Welch (2001). According to this theory, risk behavior can be not only a cognitive exercise but feelings can sometimes play a predominant role at the time of the decision. For this study we will use information gathered in the survey regarding depression, fear of crime and expectations and compare our results to those of previous research.

Results indicate that crime incidence and victimization are correlated with a higher degree of risk aversion and a low level of impatience. Propensity score matching estimates show that being involved in a criminal event increases the likelihood of being risk averse by approximately 3 percentage points and it also increases the degree of patience. The duration of these effects is significant for more than four years. The results for the psychological variables of fear are not significant. Those of depression are significant in explaining risk aversion and time preferences but do not seem to be the channel through which crime has an impact on behavior. Therefore, we find that the mechanism through which crime and violence impacts preferences cannot be explained by these psychological states.

Section two summarizes the relevant literature on risk and time preferences and the literature related to violent trauma. Section three describes the situation in Mexico and motivates the main hypotheses. Section four presents descriptive statistics of the sample at hand and the way the variables of risk and time preferences are constructed. This section also contains an analysis on the way that these variables are correlated. Section five contains the results of the effect of violence on risk and time preferences. Section six shows the relationship between these and psychological variables. Finally, the last section concludes and provides recommendations for future research.

2. Conceptual Framework

This study is related to the literature on violence and individual preferences. In order to have a better understanding of the relevance of risk aversion and time preferences, we will briefly summarize the literature on these topics. Two important elements are worth mentioning. The first one is that the literature on the measurement of risk aversion and time preferences has developed greatly in the last few years. It has gone from estimating parameters of Expected Utility Theory (EUT) to estimating models of Prospect Theory (PT) and ambiguity aversion among others. I will briefly mention an overview on the development of the literature in this area in subsections 2.1 and 2.2.

The second element is to note that research has also been directed at finding which factors can explain variation in these preference parameters. Especially useful for this thesis will be the relationship between traumatic events (in this case caused by violence) and individual decision making. The literature has also explored other factors that influence behavior. For example, a recent study by Renneboog & Spaenjers (2011), who look at differences in economic attitudes according to the religious background of individuals. In a similar way, some experiments have been made to find the relationship between measures of impatience and risk in adolescents' field behavior regarding eating and smoking (Sutter, Kocher, Trautmann, & Rützler, 2010). And also related to this second element, another stream of the literature has gone into psychological factors to explain the underlying changes in the preferences of individual decision makers (Slovic, Finucane, Peters, & MacGregor, 2004). This will be further explained in subsection 2.3.

First, I consider the implications and results of models that estimate risk aversion parameters, loss aversion, time preferences and uncertainty aversion to put in context the current study. Second, I discuss the relevant literature that has studied the effects of violence on individual preferences. This literature will include some background principles of the psychological factors that are linked to consequences of traumatic events.

2.1 Risk aversion

A. Theory and laboratory experimental literature

The existing literature on risk aversion dates back to von Neumann and Morgenstern's Theory of Games and Economic Behavior (1954). Later the seminal work of Arrow (1971) and Pratt (1964) provided the foundations for measuring risk attitudes based on the curvature of the utility function. Expected utility theory assumes linearity in probabilities which would imply linearity of indifference curves. This theory states that the decision maker chooses between risky or uncertain prospects by comparing their expected utility values[2]. One of the first identified challenges to EUT is the well known example of The Allais Paradox (Allais, 1953), where a clear violation on one of the assumptions of EUT is shown to appear. In order to explain anomalies in the expected utility

[2] For information on the detailed axioms behind EUT the reader is advised to consult chapter 6 of the book:*Microeconomic Theory* of Mas-Colell, Whinston and Green (1995)

framework, Kahneman & Tversky (1979), introduced Prospect Theory (PT). According to this theory a decision maker's preference is composed of a utility function, a reference point and a pair of probability weighting functions. They introduce the idea of "loss aversion" by pointing out that the outcomes below the reference point have transformed probabilities which are identified as losses (and valued differently). The weighting functions are a way of transforming the initial probabilities that are used in EUT. They claim that the utility function has a kink at zero; therefore it has different slopes on the gains and losses domains. Many experimental studies have surged since then, confirming the theory that people do in fact display risk aversion and it is reflected in the curvature of the utility function.

Several modifications to EUT have been proposed in the literature that would account for observed heterogeneity in the utility curvature. Moffatt (2005), for example, proposes a random coefficient model of heterogeneity between subjects. He uses data from risky choice experiments and tests EUT vs. RDEUT (rank dependent expected utility theory). Furthermore, he introduces two types of errors that could influence decision making. He concludes that his model predicts better the choices made by individuals than EUT. Another study which allows different "types" of people is a mixture model proposed by Harrison & Rutström (2008). They model the probability of picking a certain option as a mixture of either EUT or PT. They jointly estimate the parameters of each theory. Their evidence suggests support for each theory and identifies for which demographics one theory performs better than the other.

About the methodologies used for the elicitation of risk attitudes, an important contribution from experimental economics is the risk preference Multiple Price List (MPL) methodology (Binswanger, 1980; Holt & Laury, 2002). This method became increasingly popular in laboratory experiments as well as in experiments performed in the field. In these types of experiments, subjects make a series of choices involving a safe option and a risky binary gamble with variable outcomes. When subjects proceed through the task, the probability of the high outcome increases until it becomes one. In some experiments, subjects are allowed to switch more than once giving rise to inconsistencies. Other experiments limit the actions of the individuals and only allow for one switch. This facilitates the task of the experimenter because the switching point carries information regarding risk aversion. Andersen, Harrison, Lau, & Rutström (2006) examine MPL methods in detail and find that enforcing a single switching point does not change the results.

B. Experimental and Survey literature

Binswanger & Sillers, (1983) summarize risk experiments done among peasants in multiple countries (India, El Salvador, Thailand and the Philippines). They find evidence that farmers in developing countries are mainly risk averse but they find no evidence supporting the idea that neither wealth nor income have a significant effect. Binswanger appears to be the first experimental economist to identify risk attitudes using the MPL with real payoffs.

Henrich & Mcelreath (2002) conduct two binary choice experiments with the Mapuche in Chile and the Sangu in Tanzania. They want to study whether risk aversion can be associated with slower adoption of new technologies by farmers. They find that these two groups are actually "risk-preferring" decision makers. What seems to predict these preferences is a control variable for cultural group. Age, gender and wealth are not significant for predicting risk preferences in any group. These results are in the same direction as those of Holt & Laury (2002) who also found that age, gender, income and wealth failed to predict any significant proportion of the variation in risk preferences across their high stakes sample. In their study the only variable that is able to predict preferences was a dummy for being "Hispanic". This group seemed to be significantly less risk averse than the rest of the population.

The approach by Tanaka, Camerer, & Nguyen (2010) was to gather preference measures experimentally and correlate those measures with demographic and economic variables such as income, ethnicity, literacy rate and education among others. They perform their experiments in Vietnam. They find that people living in poor villages are averse to loss. They also find that household income is correlated with patience (lower interest rate) but not with risk preferences. They also find a present bias. Because their study is a cross-sectional analysis, it is difficult to infer causality between economic preferences and economic circumstances.

In a more recent study, von Gaudecker, van Soest, & Wengström (2011) estimate explicitly parameters for the utility curvature, loss aversion and preferences for different timing of uncertainty resolution. They do so following tasks similar to those of Holt & Laury (2002) and introducing different timing for uncertainty resolution. Their novel aspect is the joint estimation of individual-specific parameters to measure the curvature and the strength of the utility kink in a structural model. Another important aspect of their study is that the experiment was performed as part of a Dutch survey[3]. Having survey data allowed them to have background socioeconomic information on each household (even though they found that these explain overall heterogeneity very little).

As von Gaudecker et al. (2011), a lot of studies have gone into implementing experiments outside laboratories in universities. Instead, researchers are going out to the field and integrating their experimental methods with survey methodologies. It is worth mentioning that these experiments do not always involve real payments, and thus there is ongoing debate about the validity of hypothetical results. Nevertheless, there is some evidence that using survey questions in order to elicit risk attitudes can be representative of what a real-stakes experiments would implement (Dohmen et al., 2011).

For this current thesis and as will be explained in Section 4, the use of survey data is justified by a pilot exercise that involved real-stakes in a subsample of the population surveyed. The correlation between risk attitudes between the real-stakes experiment and the hypothetical questions

[3] They implemented the experiment in the CentER panel, a Dutch household survey administered via the Internet. http://www.centerdata.nl/en/centerpanel

supports the use of the survey (Hamoudi, 2006). The survey includes information on crime and victimization, emotional distress, demographic and socioeconomic information. Because of the way that the risk aversion questions were elicited in the survey, it will not be possible to parametrically estimate parameters of utility curvature, loss aversion or time preference precisely. Only a degree of riskiness will be estimated with a categorical variable like the study by Donkers & van Soest, (1999). This is elicited with lottery questions but differs from the typical Multiple Price List explained above.

2.2 Time preferences

A novel feature of the literature of the past decade has been the inclusion of time preferences in the analysis of decision making under uncertainty. Andersen, Harrison, Morten, & Rutstrom (2008) find that joint elicitation provides estimates of discount rates that are significantly lower than those found in other studies. Anderhub et al. (2001) find that there is correlation between risk attitudes and discount factors, with risk-averse agents discounting the future more heavily. They perform their experiments in a classroom setting. Their results suggest that discounting is partially due to the uncertainty encapsulated in future payoffs. The estimation of the curvature of the utility function and computation of time preference parameters jointly is now an active topic of research (Ventura, 2003). If risk and time-preferences are correlated, omitting one of the preference factors might lead to a wrong attribution of behavioral effects to the included one.

The work by Andreoni & Sprenger (2010) shows how risk and time are intertwined. In their study, intertemporal decision making involves a combination of certainty and uncertainty. Their findings indicate that certain and uncertain consumption are evaluated differently. They justify a bias for the present by a preference for certainty when it is available. Therefore, what is seen as impatience might be that certain present consumption is disproportionately favored over future uncertain consumption.

We might also be interested in how demographic and economic variables help explain time preferences. For example, age and gender are normally presented along with the results of the models. Older people might have a more stable financial situation and hence can take more risks. Hence, with aging the remaining lifetime shortens and this means a shorter planning horizon and stronger discounting might be observed (van Praag & Booij, 2003). But on the other hand, older people tend to be more cautious and therefore take fewer risks. Tu (2005) presents a short summary on the relationship of these variables and time preference. Some of the literature finds also that older people tend to be more patient (Donkers & van Soest, 1999). Others find a U-shaped relationship between the discount rate and age, implying that people at young age and at very old age discount heavier than people in the middle of the distribution. Kirby et al. (2002) found lower discount rates at the age of 20 and increasing discount rates afterwards. The typical results for gender in the literature are that men discount at higher rates than females on average (Donkers & van Soest, 1999). However, this is not always the case and some other studies find no significant effect of gender on time preferences (Harrison, Lau & Williams, 2002).

2.3 Violence and individual preferences

The literature on the effect of trauma on risk preferences presents mixed results. In this subsection we present a few of the existing experimental studies, their methodology and main conclusions. Some of these studies focus on trauma related to natural disasters and others will refer directly to violence. While some studies find that after a traumatic episode, risk aversion decreases (Callen, Long, Isaqzedeh, & Sprenger, 2012; Eckel et al., 2009; Voors et al., 2012) others find that it actually increases (Moya, 2012; Cameron & Sha, 2010). The literature also presents mixed results with regards to the duration of the effect. Cameron and Sha (2010) claim that the effects of trauma might be long-lasting while Eckel et al. (2009) find that effects disappear after one year. Moya (2012) observes that the effect of being involved in a violent attack lasts approximately 4 years.

Each of the papers related to violence presents a different methodology where they try to solve for "selection into violence" which might give an incorrect interpretation of the effects (some people might be more risk seeking and therefore take less care and be more likely to suffer from violence).

Much of the current literature is aiming to link results from lottery experiments that elicit risk attitudes (and in some cases time preferences) to the existing literature in psychology. The claim is that the mechanism through which crime and violence has an effect on preferences is through the induction of a certain emotional state. The "Risk-as-feelings hypothesis" suggests that feelings play a predominant role in risky decision making and these point towards different effects according to different feelings (Loewenstein et al., 2001). According to the appraisal-theory framework of Lerner & Keltner (2001), fear and anger have opposite effects on risk perception. People who were fearful expressed pessimistic risk estimates and risk averse choices, whereas angry people presented optimistic risk estimates and risk-seeking choices.

Some of the above studies find explanations for the relationship between preferences and violent and traumatic events with these theories. The idea is that violence can cause disorders like post-traumatic stress disorder (PTSD), depression, generalized anxiety, substance abuse and a range of other health conditions. This would suggest that it is reasonable to expect shifts in risk attitudes especially if a large part of the population experiences for example, PTSD. The fear and depression would then be reflected in individuals who are more risk averse. The results by Voors et al. (2012) would fit more a population who as a result of violence is angry and reflects riskier behavior (if indeed psychology was the driving mechanism for behavioral change). However, the social variable that they use is altruism and not emotional states.

Callen et al. (2012) use a couple of questions based on the psychological literature to recall fearful and joyful events. Moya (2012) uses the Symptom Checklist 90 (SCL-90-R) which is a questionnaire to measure incidence of emotional distress. Voors et al. (2012) use a modified version of a social value orientation experiment devised by Liebrand (1984) to measure the degree of altruism and relate this to risk and time attitudes.

Callen et al. (2012) made a recent study which explores the effect of the exposure to trauma on risk preferences. They claim that trauma can have complex and lasting effects on mental and physical health, which in turn translates into a change in preferences regarding risky behavior. They perform an experiment in Afghanistan which is a nation exposed to widespread violent trauma for already 30 years. The type of violence experienced by subjects is caused by indirect fire, explosions, suicide attacks or direct fire among others. They have data on successful attacks and failed attacks; therefore they use this variation to make the comparison on the effects of trauma. The methodology which they introduce is designed to elicit risk preferences and to test predictions of EUT and other behavioral models designed to accommodate certainty effects (cumulative prospect theory, disappointment aversion, u-v preferences).Their procedure is based on the uncertainty equivalents introduced by Andreoni & Sprenger (2010). In order to test which of these theories actually best predicts behavior, they calculate a Certainty premium which is the distance between the value of utility under certainty and utility under uncertainty. Cumulative prospect theory predicts this difference to be negative, while DA and u-v preferences predict a positive difference greater than zero. They find support for DA and u-v preferences against EUT and CPT. Together with the results from their priming psychological experiment they find that the combination of traumatic exposure and fearful recollections increases risk tolerance under uncertainty and increases measured Certainty Premia*.*

Voors et al. (2012) use a series of field experiments in rural Burundi to examine the impact of exposure to conflict on social, risk and time preferences. They collected data on violent episodes in a set of communities and on a range of household and community variables. They find that individuals who have suffered violence themselves, or belong to a community that has been attacked, display more altruistic behavior, are more risk seeking and act less patiently. To measure risk preferences they used a type of lottery where they allowed for one switching point in order to measure the degree of risk aversion. To measure time preferences they presented subjects with choices for delayed payments and elicited an interest rate. In order to solve for concerns of "selection into violence" they use as instrument for violence distance to Bujumbura (a nearby town). They show a significant correlation between altruistic behavior and conflict intensity. They also find a positive correlation between conflict intensity and risk seeking behavior. Their model also suggests that exposure to conflict increases discount rates. They claim that their results might help explain why some countries who suffer from civil wars or other types of trauma experience growth afterwards. This might be due to the pro-social behavior of individuals which they document with their altruism variable.

Moya (2012) motivate his research by recent findings from neuroscience and social psychology which suggest that the incidence of emotional distress that prevails after episodes of victimization can induce changes in the risk attitudes of victims. He studies displaced individuals in Colombia due to Guerrilla attacks. The way they perform their experiments is by sorting the villages that were displaced and where there was indiscriminate violence. Therefore, the decision to migrate or be displaced is exogenous to household characteristics and preferences. To overcome the lack of pre-war information on risk preferences, the displaced individuals were matched with a control group of similar people in towns that were also likely to have a violent attack but did not have one. To elicit risk preferences he used the “Choose lottery” approach with 3 different tasks over gains, losses and ambiguity domains. His results indicate that victimization and forced displacement induce a considerable shift towards more risk averse behavior in the regions included in the sample. The results also indicate that emotional trauma could be driving the higher levels of risk aversion. Phobic anxiety and psychotic behavior are found to be associated with higher levels of risk aversion. This is in line with results from neuroscience and social psychology which finds that fearful and anxious individuals consider ambiguous situations threatening, prefer low reward low risk options, and generally display higher levels of risk aversion. He finds that these changes are not permanent but that it may take several years in order for victims to recover. Moreover, these behavioral changes can reinforce negative welfare consequences and present an obstacle for economic recovery.

The studies so far measure preferences in different ways, and come to different conclusions as of the directions of the effect of violence. This issue will lead to our main hypotheses which are explained in the next section.

In order to contribute to the current literature on this topic, we want to test whether violence in our sample has an effect on individual preferences, the direction of such effect and its duration. With the available data and measurements we investigate the degree of risk aversion and time preferences of the sample. Then, we relate these measurements to the effect of violence and some possible channels through which these affect our variables of interest. Given that these studies make use of psychological theories to explain their results, we will also compare our results to them.

3. Crime, Violence and Individual Preferences

Crime and violence in Mexico have always been an important issue. As many other developing countries, Mexico has long suffered from weak institutions, poverty and great inequality which foster a climate of insecurity. More recently, the conflict with drug cartels is bringing more violent types of crime which have the increasing effect of terrorizing the population. Even though the data was collected in 2005 (and the drug related violence had not fully exploded), we will observe an effect on individual decision making. We would expect that in the next wave of the survey, more violent crimes will show up in the data.

Changes in economic behavior are of great relevance. These could lead to a cycle of costly recoveries, low investment decisions, interruption of schooling and migration (Moya, 2012; Conroy, 2007). Therefore, it is worthwhile studying how behavior can change due to these shocks and what might be the underlying causes for it. It is intuitive that security in country will induce certain types of behavior. The level of trust in law enforcement in Mexico is very low and it is reflected in the number of people who report crime to the police. Only around 22% of these crimes are reported officially in our sample. The main reasons for not reporting them are: fear that criminals will return, low trust in police, lack of effectiveness. The lack of enforcement might induce people to live in constant fear and to take more precaution in their daily lives. The MxFLS data provides information which is useful for this analysis. It contains data on individual victimization with detailed information on the date and type of incident. More details and descriptive statistics will be presented in Section 5.

The impact of crime and violence will be analyzed. Specifically, how this issue can be relevant from the perspective of individual decision making. First, we will describe our two variables of interest, risk aversion and time preferences in detail. Then, a description of the crime and violence measurements will be presented along with variables related to security perception. Afterwards, the results will follow relating to the possible effects on our variables of risk and time preferences.

The sample at hand consists of approximately 18,783 people. The number of individuals who have reported an incident related to victimization and crime are 1,376. Most of these incidents are armed robberies that sometimes include violence such as gunshot, body lesions, stabbings or even death. There are also other types of incidents such as kidnappings and rape. The average cost of recovery from the reported incident is of $6781.85[4]. Some people have been involved in more than one incident; the average number of incidents for the sample is 1.32. The time that has elapsed since the last incident is shown in Figure 1. This variable will be used when we study the duration of the effect of violence and crime on risk aversion and time preferences.

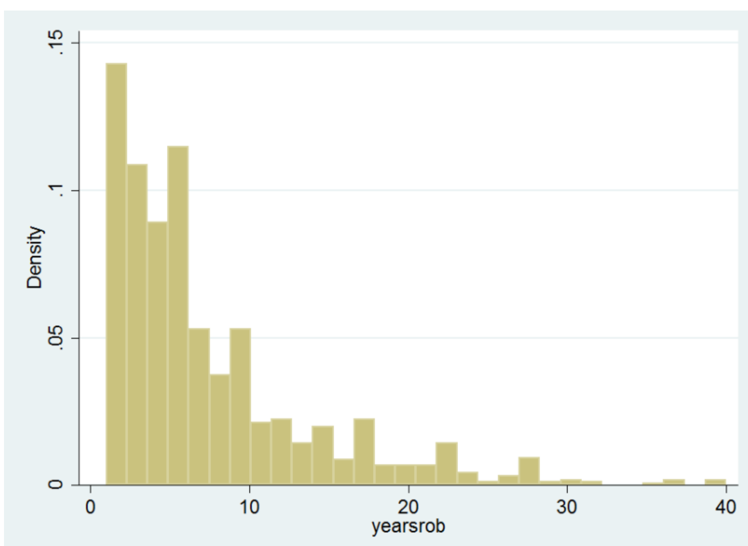

Figure 1. Years since the crime

[4] All money amounts will be presented in the local currency: Mexican pesos.

Since much of the literature has pointed towards psychological explanations for the change in risk attitudes and time preferences due to violence, we will also use questions from the survey related to fear and perceptions of insecurity in Mexico. The questions are the following:

- Are you afraid of being robbed during the day/night?
- What is the outlook on crime and violence in Mexico in the next 3 years?

In addition to these questions, we make use of a module in the survey which was designed and tested by researchers of the Mexican Institute of Psychiatry to diagnose depressive syndrome among the Mexican population. This questionnaire will be used to make a comparison with the results of previous studies regarding psychological trauma and its relationship to individual preferences.

It might be the case that people who have suffered a traumatic event have changed their attitudes towards risk or time preferences. Therefore, to investigate the possible effects that crime and violence may have in altering people's attitudes towards risk and time preferences, we motivate four hypotheses.

According to Voors et al.(2012), the civil war that occurred in Burundi has a clear impact, people became more risk-seeking as a consequence and presented higher discount rates. They record an increase in altruistic attitude that can possibly explain a mechanism through which the community cares about each other's welfare. For this study, we consider this will not be the case. The situation in Mexico was not at the level of a civil war with widespread violence but rather regular crime and violence. The possible mechanism through which crime might have an influence on preferences will be motivated by a few psychological factors. These factors have been used in studies before by Callen et al. (2012) and Moya (2012). If we consider that after being victimized people will be fearful, we will expect people to be more risk averse (Lerner & Keltner, 2001). If the climate of insecurity does not improve and people continue living in fear, we would expect the effect to be long lasting. Since this is the case for Mexico, where violent crimes have increased in the past decade, we will expect the effect to be long lasting.

The effect on time preferences is not straightforward. If people suffer from a violent crime, they might decide to better postpone consumption for the future. This is because they might be afraid of losing their goods or cash due to a robbery in the present. Therefore we would expect a positive correlation between people who suffered an attack and their level of patience.

In summary, we motivate the following hypotheses:

H_1 : People who have suffered directly from violence are more risk averse.

H_2: People who are afraid of being robbed are more risk averse.

H_3 : People who have experienced violence will be more patient.

H_4 : The duration of the violence effect is long lasting.

The survey does not collect information on risk and time preferences before and after the incident and because of this issue it will be difficult to establish a causal relationship. The claim might be the following. There might be unobserved heterogeneity which makes people more likely to be victimized. For example, they can behave in a "riskier" manner by taking less precaution by going into the wrong neighborhoods, taking strolls in the middle of the night, being more aggressive, etc. Therefore, if we would find that people who are victimized are less risk averse, the above claim might question the results due to a selection bias. Selection bias would cause our estimates to be biased if these individual characteristics that make them more prone to being victimized are correlated with their risk attitudes. Hence, if the above claim is true, we would observe a downward bias in the estimates for risk aversion. As will be shown, the results point towards a positive relationship between risk and victimization (in the presence of bias, estimates would actually indicate a "lower bound" on the true effect).

4. The Data and description of variables

The data for this study comes from the Mexican Family Life Survey (MxFLS).[5] The MxFLS is a longitudinal database which collects information on socioeconomic indicators, demographics and health indicators on a representative sample of the Mexican population. The first wave of study was conducted in 2002, the second wave in 2005 and the third wave is in progress. The survey provides detailed information on family members of around 8,500 households with approximately 35,000 individual interviews in 150 communities throughout the country. Not all household individuals have answered all sections of the survey (because in some sections only people above 15 years old were asked to participate; there is one section with information regarding the characteristics of those under 15 years).

For the purpose of this study, only the second wave will be used since it contains questions regarding risk preferences and expectations which were not included in the first wave. The risk aversion module was answered by a total of 20,607 people. On average there were between two and three people in the household who answered the risk module. The module for the time preference questions was answered by 20,607 people. As will be explained in Subsection 3.1, my sample will consist of approximately 18,783 people (due to the risk preference results). Section A of the third book contains all the information regarding income, education, violence and victimization among others. The modules we are interested in (risk and time preferences) are contained in the third book section B along with other questionnaires related to health, mood states and savings behavior.

[5] www.ennvih-mxfls.org

Table 1 contains the descriptive statistics of the sample. Around 56 percent of the sample is women, the mean of respondents' age is 38 years and sixty percent of the sample lives in a couple. The dummy of living in a couple includes a person who is married or lives in a partnership (couple=1). Being single, separated, widowed, divorced is classified as couple=0. The variable *educat* ranges from 1 to 5 and it stands for the level of education. The category with most people in them is category 2 (primary school) with 36.65 percent. The average household size is 2.5 members. Only 5,768 people report any income, this is about 65% of the working people from the sample.

The data is especially suited for this analysis because it contains rich information on preferences as well as on safety perceptions and actual incidental crime and violence. In this section, the variables of interest are risk aversion and time preference. First, I will present a description of both in detail. Thereafter, I will present a brief discussion on the relationship between them.

Table 1. Descriptive Statistics

Variable	**Obs**	**Mean**	**Min**	**Max**
Female	18780	0.558946	0	1
Age groups				
15-24	18783	0.2894	0	1
25-44	18783	0.37124	0	1
45-64	18783	0.240058	0	1
>65	18783	0.099345	0	1
Couple	18781	0.604867	0	1
Household size (*hhsize*)	18783	2.506469	1	18
Education category (*educat*)				
primary	18742	0.366503	0	1
secondary	18742	0.273397	0	1
high school	18742	0.150411	0	1
university	18742	0.105165	0	1
Annual labor income (*yincome2*)	5768	44949.97	1	3801988
Worked last week (wlw)	18783	.4681361	0	1

4.1 Risk aversion

A set of questions was designed to elicit risk attitudes from respondents who were above 15 years old. The questionnaire was performed face to face by an interviewer. In each question, the respondent was presented with a pair of hypothetical lotteries and asked which one he would prefer. It starts off with a lottery offering a certain payment of $1,000 pesos (which is about 17 times the daily minimum wage) and a 50/50 gamble over different amounts. The first decision led to an unfolding tree of increasingly fine tradeoffs. Figure 1 (from Hamoudi, 2006) shows the detailed procedure of elicitation and classification.

According to their degree of risk aversion they were classified into five categories. A person will be thought of risk averse if she prefers the certain amount over the gamble at least twice (and her degree of risk aversion will be based upon this choice). She will be very risk averse if she always prefers the certain gamble. Category 1 is the most risk averse and category 5 is labeled as the least risk averse or risk seeking. In category 5, people always preferred the gamble with most variance.

There is an additional category (category 6) which should never be reached since it is weakly dominated by category 5. Nevertheless, approximately less than 5% reached this point. There are also some people who did not seem to understand the exercise and together with people from category 6, they are excluded from the sample. This leaves a sample of 18,783 people. From the original sample, 8,793 people claim to have worked recently while 9,990 claims they are housewives/husbands, went to school, searched for a job, and are retired or sick. Only 5,768 report any information about their annual income (65 percent of the working sample).

Experimental measures of individual preferences are often regarded to be more reliable than survey data. Therefore, in order to validate the use of the hypothetical lottery, a separate project was designed to obtain experimental measures with real stakes. A subset of 600 households of the 2005 wave was invited to participate in the MxFLS-Preferences Project (MxFLS-PP)[6] and data on risk aversion and expectations was gathered. They did not use the traditional multiple price list (MPL) format which is typically used in experimental studies (for example see Andersen, Harrison, Lau, & Rutström, (2006), for a discussion on MPL methods). Instead, in the MxFLS-PP they designed a method through various experiments where they measure the risk attitudes of a subsample. The ranking in terms of risk aversion elicited by this project and the one elicited by the hypothetical task were very highly correlated (Hamoudi, 2006). Consequently, there is confidence to use the MxFLS with the advantage that it gives more information on a larger set of households and individuals which we can exploit.

Figure 2 below shows the distribution of outcomes of risk aversion for the representative Mexican population. Category 1 is the most risk averse. We see that the majority of people fall into the categories 4 and 5 which are the not risk averse. The mean level of risk aversion is 3.92. This is somewhat similar to what Henrich & Mcelreath (2002) find in their experiment with small-scale farmers of the Mapuche in Chile and Sangu of Tanzania. They find that their subjects are generally *risk preferring*. The distribution within categories does not vary much when we allow income to vary.

The questionnaire displays a gradual increase of the expected value of the risky lottery. Therefore, people that take longer to make the "switch" to the risky lottery are considered more risk averse. Nevertheless, there are some people that never make the choice for the safe lottery. These people will be classified as not risk averse.

[6] MxFLS-PP's principal investigators are professors Duncan Thomas (UCLA), Joseph Hotz (UCLA), Catherine Eckel (Virginia Tech), Graciela Teruel (Universidad Iberoamericana, Mexico), Luis Rubalcava (CIDE, Mexico), and Susan Parker (CIDE, Mexico).

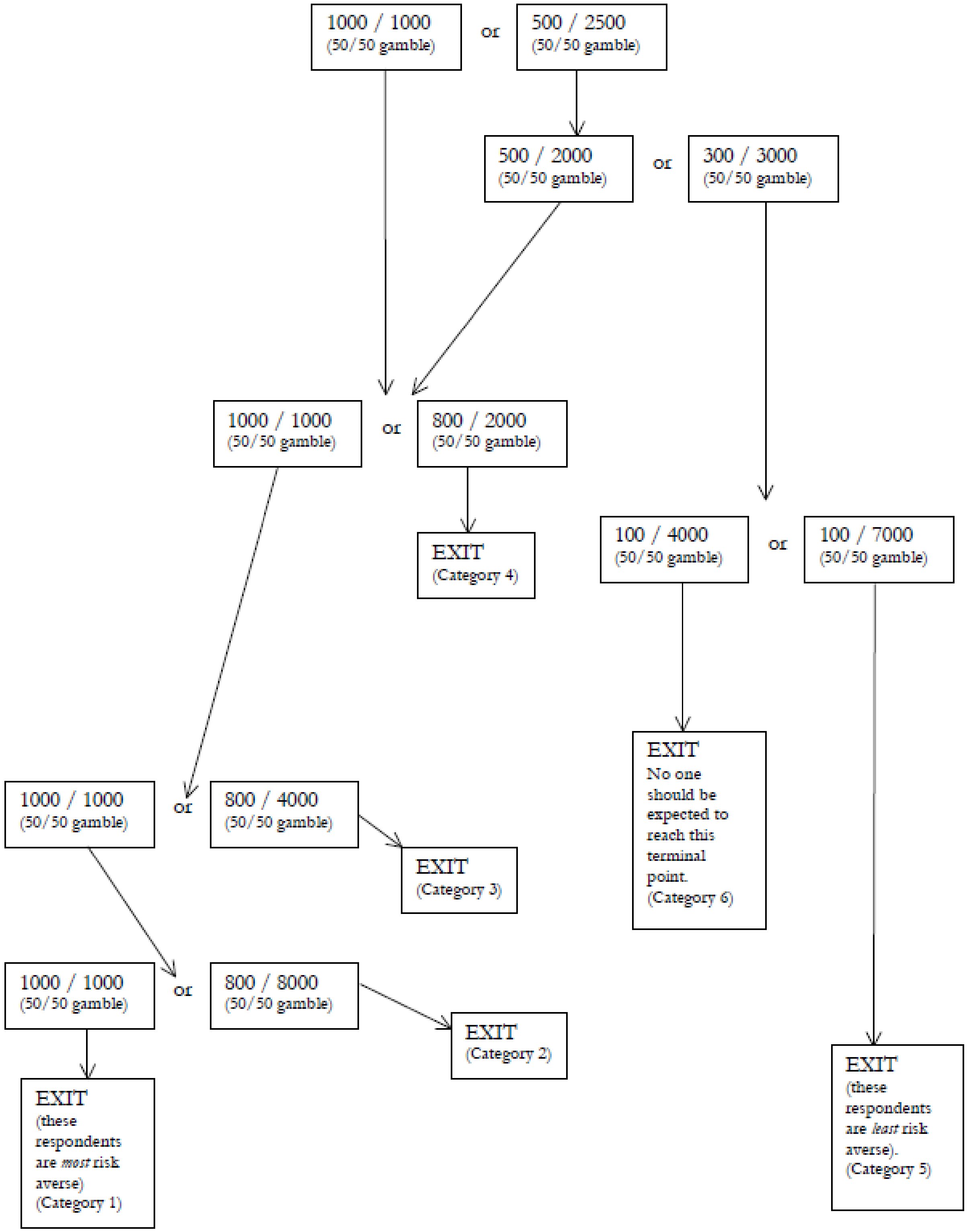

Figure 2. Elicitation of Risk attitudes (source: Hamoudi, 2006)

In order to build a risk aversion indicator, the five categories are used in the following way. The sample will be split into the people who never took the safe lottery and the rest. The majority of people fall in the categories that never pick the safe lottery (see Figure 2). Therefore to see a dramatic change in attitudes, we will be interested in a switch away from these two categories. The risk averse people will be those who choose the safe option in the lottery at least once. These people are the ones who fall into categories 1, 2 and 3. The reason for performing this clustering is that between these three categories, the information on risk aversion attitudes is not significantly different (they are people who require a very high expected value in order to switch from the safe lottery). People who fall into categories 4 and 5 are those who never choose the safe lottery (could be considered as risk-seeking). Hamoudi (2010) divides the categories into the same blocks. He argues that for his analyses of the effect of risk aversion on family partition, the coefficient estimates of the first three groups are very similar, therefore by grouping them together he could improve the power of his model.

With our variables of interest, we perform robustness checks for different specifications of the variable risk aversion and find that our results will be sensitive to this specification[7]. The dummy for risk aversion will be *riskav* and it will take a value of 1 if individual is risk averse and zero otherwise. For the following analyses on risk aversion, the dummy *riskav* will be used instead of the five risk categories described above. The mean value of this variable is 20 percent being risk averse.

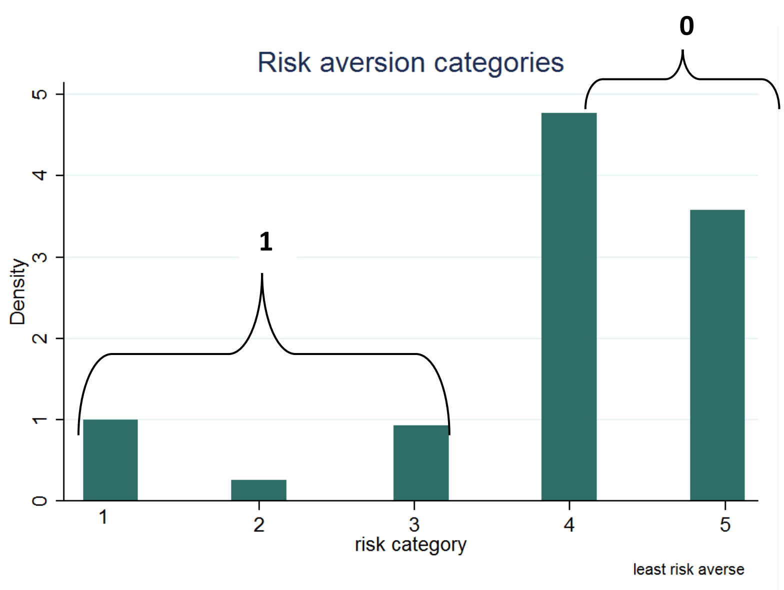

Figure 3

[7] The robustness checks were performed using ordered probit analysis with five categories of risk aversion. The results are not significant in that case.

In order to estimate the likelihood of an individual of falling into either category of risk, a probit will be modeled. This is because probit analysis is well suited to model problems of binary choice[8].

$$y^* = x'\beta + \epsilon,$$

$$y = \begin{cases} 1 \text{ if } y^* > 0 \\ 0 \text{ if } y^* \leq 0 \end{cases}$$

$\epsilon \sim N(0,1)$, ϵ *and* x are independent.

Where y^* is the latent variable and y is the observed category where the individual falls as a result of the lottery questionnaire. The variables that we control for in the vector *x* are: gender, age, civil status and level of education in Model (1). We then use maximum likelihood estimation to estimate the parameters. The results are presented in Table 2 with clustered standard errors by family.

The estimate of female is the only variable which is significant, at 10 percent level in Model (1). Women seem to be more risk averse than men, on average. This is a common finding in the literature on risk aversion (see Eckel & Grossman (2008) for a review of the results from experimental measures on risk aversion). Age has a positive sign implying that older people are associated with more risk aversion, this result has also been shown before by Dohmen et al., (2011). This effect however is not significant in our sample.

We would expect a negative coefficient for education. Better educated people may be more aware of risk and therefore be more risk-aware. The different levels of education are not significant and depending on the specification of the model, the coefficients have different signs. The direction of the effect is the same as the study by van Praag & Booij (2003). Nevertheless, they find their estimates to be significant. Being married or in living with a couple is never significant in all specifications.

In specification (2) the variable income is included. This variable represents the logarithm of the annual labor income reported by the subject. In specification (2), income is positive if it is reported and zero otherwise, this would classify people who have no income the same as people who have income and do not report it. A dummy variable (*wlw)* is included which is equal to one if the subject worked the week before the survey and zero otherwise. Neither income nor the dummy wlw are significant.

[8] See Wooldridge (2002) for a detailed description on models of latent dependent variables and binary choice.

Table 2
Probit estimates for Risk averse (*riskav*)

EQUATION	VARIABLES	(1) Riskav	(2) Riskav
Risk aversion	female	0.038*	0.035
		(0.020)	(0.023)
	logage	0.033	0.034
		(0.029)	(0.029)
	couple	0.015	0.016
		(0.024)	(0.024)
	primary	-0.045	-0.045
		(0.038)	(0.038)
	secondary	-0.039	-0.039
		(0.044)	(0.044)
	high school	-0.003	-0.003
		(0.049)	(0.049)
	university	-0.007	-0.008
		(0.051)	(0.052)
	logincome		0.002
			(0.003)
	wlw		-0.020
			(0.030)
	Constant	-0.939***	-0.939***
		(0.118)	(0.118)
	Observations	18,736	18,736

Note: Clustered standard errors in parentheses (by family) . *** p<0.01, ** p<0.05, * p<0.1

The literature on income and risk aversion is quite diverse. Some empirical evidence suggests that wealthier households invest in riskier productive activities and earn higher returns (in line with expected utility theory). However, experimental evidence in developing countries gives mixed results. Binswanger (1980) for example, finds no significant association between risk aversion and wealth, while Yesuf (2004) finds negative correlations (Tanaka et al., 2010). It can be seen from Table 2 that most of our explanatory variables are not significant. Covariates such as the ones mentioned above can barely capture the heterogeneity in risk preferences. This has also been found by von Gaudecker et al.(2011).

4.2 Time preferences

In order to measure the degree of patience that a person has towards future income, a set of questions from the MxFLS was used. Just as with the questionnaire for risk aversion, the questions here are hypothetical. The responses were also analyzed together in the MxFLS-PP involving real payments in a subsample of the actual MxFLS. The questionnaire is composed of two sections. One section involves a one month delay in payment and another one offers a three year delay. The first question of the first treatment was the following:

- *Imagine you win a lottery of $1,000. Would you rather receive $1,000 now or $1,000 in one month?*

After the first question, an unfolding set of questions which increased the amount of money to be received in the future were presented to each subject. This was done with the purpose of discovering how much money a person would be willing to accept in order to postpone receiving a certain amount for one month.

With this information, a rate of time preference can be constructed to understand what these options imply. For example, for the question whether to receive $1,000 now or $1,500 in one month:

$$r = \frac{1{,}500 - 1{,}000}{1{,}000} = .5 \Rightarrow 50\%$$

This implies a monthly return of 50 percent for his “investment”.

The implied interest rates for the one month questions are: 0, 10, 20, 50 and 100 percent. The set of questions unfolds as is shown in Figure 4.

For the second treatment the same questions were repeated but with a longer time span and a larger starting amount, instead of $1,000 the offer increases to $10,000. Stakes increase in a similar way. But the implied interest rates change. If we transform them into monthly interest rates they would be: .5, 1.1, 1.9, and 3.9 percent.

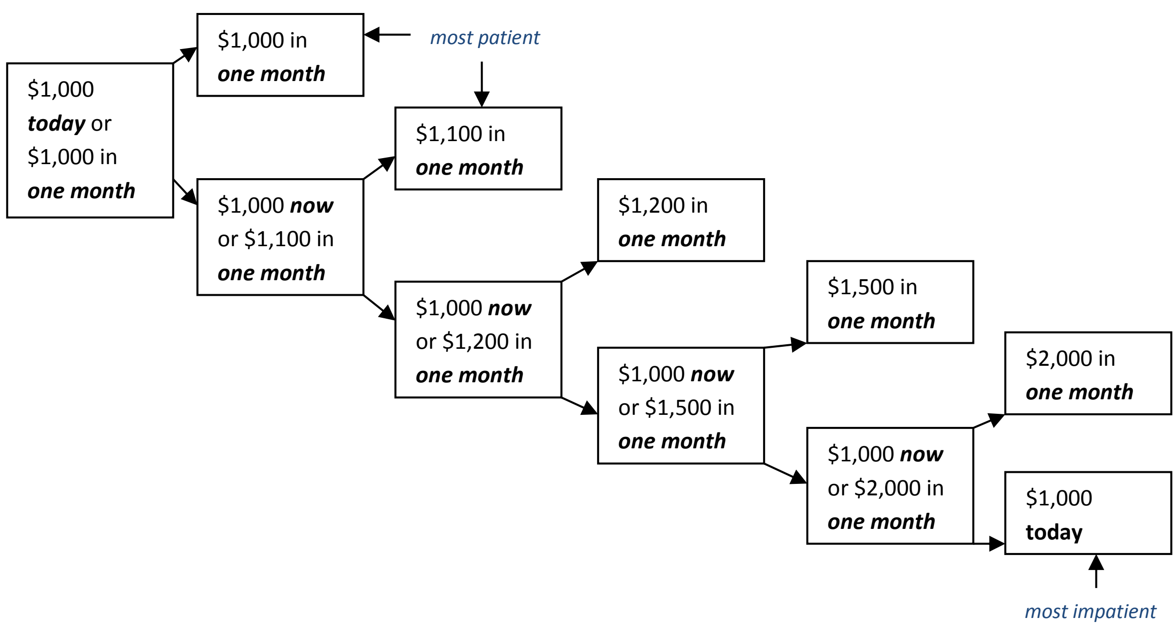

Figure 4. Elicitation of Time Preferences

There is one more question which is asked in both treatments and is as follows. To the people who would accept a zero percent interest rate on their money, they ask one more question. They ask what the choice would be if they were asked to receive $1,200 pesos now or $1,000 in the future. This would be equivalent to offering a negative interest rate. The percentage of people who arrived at this point is 3.1 percent of the whole sample. For the rest of the analysis, these people will be included with set of people who choose a zero percent interest rate (most patient).

As we can see in Figure 5, the numbers above the bars are the respective effective monthly interest rates. The distribution among the different levels of patience is the same for both types of interest rates, even though the one for 3 years is much lower. This could be a strong argument in favor of hyperbolic discounting[9]. Hyperbolic discounting would mean that the per-period discount rate falls over time.

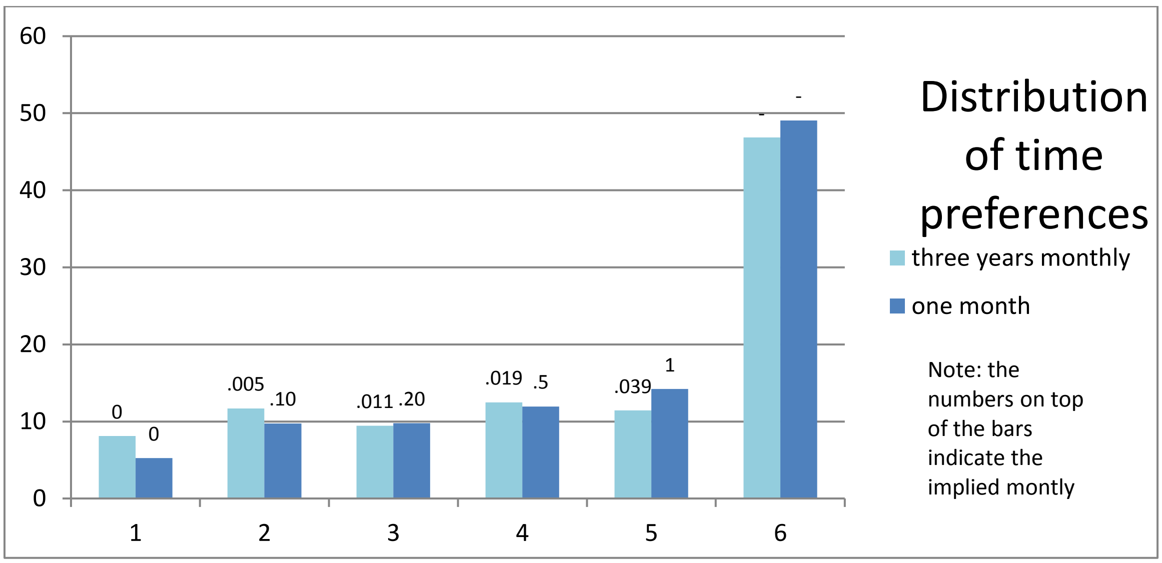

Figure 5. Distribution of Time Preferences

Based on these questionnaires I present the following results which show the difference between men and women's time preferences. They represent the proportion of male or females that fall into each category of implied interest rates. As we can see from Table 3, men are more impatient than women on average. Almost half of the sample is very impatient, preferring always the $1,000 amount in the current period. This is in line with what other studies have found when they estimate the discount rate of delay of gains (Kirby & Marakovic, 1996).

[9] See Frederick, Loewenstein, & O'Donoghue (2002) for an overview on intertemporal choices.

Table 3. Gender differences in Time Preferences

One month Proportions	Female	Male	Dif	Three years Proportions	Female	Male	Dif
$1,000 today				*$10,000 today*			
(most impatient)	0.464	0.474	-0.010	*(most impatient)*	0.492	0.490	0.002
100%	0.107	0.124	-0.017	*3.9%*	0.130	0.158	-0.028
50%	0.121	0.130	-0.009	*1.9%*	0.117	0.123	-0.006
20%	0.101	0.086	0.016	*1.1%*	0.104	0.090	0.014
10%	0.125	0.107	0.018	*.5%*	0.106	0.087	0.019
*zeror**	0.082	0.079	0.003	*zeror2**	0.052	0.053	-0.001
(most patient)				*(most patient)*			
Total	1	1		*Total*	1	1	

**picks zero interest rate*

Model (1) shows the results for the one month questions and Model (2) the results for the three year questions. The dependent variable is the degree of patience that an individual has, classified according to his preferred implied interest rate. It ranges from 1 (most impatient), to 6 (most patient). Table 4 shows that in fact women are more patient than men and the effect is significant for both models. In order to analyze the age effect in time preferences, we categorize age groups in the following way:

- agegroup=1 if $(age \geq 15 \,\&\, age < 25)$
- agegroup =2 if $(age \geq 25 \,\&\, age < 45)$
- agegroup =3 if $(age \geq 45 \,\&\, age < 65)$
- agegroup =4 if $(age \geq 65)$

Next, in order to see which variables correlate with time preferences at the individual level, Table 4 presents the estimates for a bivariate ordered probit regression.[10] This model postulates the bivariate relationship between individuals' time preferences in the short and long term. We also estimated separately the two models and found that coefficients are very similar. As expected we see a very high correlation between these two models since it is the same people who answer both exercises and have the same unobserved heterogeneity. The null hypothesis of zero correlation of the error terms ($\rho = 0$) is rejected.

[10] See (Sajaia, 2008)"Bioprobit: Stata module for bivariate ordered probit regression"

Table 4. Bivariate Ordered Probit estimates for Time Preferences

VARIABLES	(1) timepref	s.e.	(2) timepref3	s.e
female	0.046***	(0.015)	0.026*	(0.015)
couple	0.004	(0.020)	-0.015	(0.020)
Age				
agegroup2	-0.142***	(0.023)	-0.137***	(0.023)
agegroup3	-0.267***	(0.028)	-0.298***	(0.028)
agegroup4	-0.353***	(0.039)	-0.411***	(0.039)
Education				
primary	-0.072**	(0.032)	-0.089***	(0.033)
secundary	-0.090**	(0.036)	-0.194***	(0.037)
high school	-0.014	(0.040)	-0.122***	(0.041)
university	0.026	(0.041)	-0.121***	(0.042)
Constant	0.982***	(0.013)		
cut1	-0.227***	(0.040)	-0.271***	(0.041)
cut2	0.075*	(0.040)	0.091**	(0.041)
cut3	0.412***	(0.040)	0.424***	(0.041)
cut4	0.703***	(0.040)	0.763***	(0.041)
cut5	1.189***	(0.040)	1.314***	(0.042)
rho	0.754	(0.0056)		
Observations	18,728		18,728	

Note: Clustered standard errors in parentheses (by family)
*** p<0.01, ** p<0.05, * p<0.1

Age has a negative sign in all categories which means that as people get older they get more impatient. This is in contrast with other studies which show that older people tend to be more patient, for example the study by Tanaka et al. (2010). The estimate for education has a negative sign and is significant for the first levels (primary and secondary) in Model (1). People who have studied only primary and secondary school therefore are correlated with more impatience. More education might be seen as a long-term investment; therefore people who decide not to invest in higher education might have lower planning horizons. For Model (2) education it is always significant and negative. Living in a couple or married is never significant. The study made by van Praag & Booij (2003), shows how singles have a wider time horizon.

In order to compare both estimates we performed a T-test to test for the equality of the slopes of each explanatory variable. We reject equality of the slopes for all variables. This suggests that there are different effects of explanatory variables depending on the time horizon.

4.3 Time and risk preferences

Table 5 shows the correlation between time preferences and risk aversion. The first part of the table presents the correlation for one month questions. The second part belongs to the three year questions. The interpretation for the sign of the correlation is the following: the variable time preference goes from 1 being most impatient to 6 most patient, and the dummy for risk is equal to one if a person is risk averse. Hence, the negative sign implies that a more patient person is less risk averse.

As for the size of the correlation, for the case of one month, the correlation is not significant. On the other hand the correlation for the three year question is significant. However, for both cases, the correlation is rather small. For the analyses in the following section, risk and time were modeled together with a bivariate ordered probit, but given that the correlation between them is small we will present the results for separate models only.[11]

Table 5. Correlation between time preferences and risk aversion

Correlation	riskav
timepref	-0.0038
timepref3	-0.0297***

5. The Model and Results

The measurement used for violence is a dummy variable for having suffered a robbery, kidnapping or rape. The majority of reported cases are armed robberies. In total 1,376 people from the sample suffered a traumatic event like the ones mentioned above. Variable *vli04a* is an indicator of how the individual expects crime and violence to evolve in the next 3 years in the whole country. It can take the values of 1-5, the first two indicate it will become much worse (unsafe), the third one states that it will stay the same, and 4 and 5 indicate that it will become much safer. Variable *vli01* asks people whether they feel insecure when they go out during the day; it ranges from 1-4 with 1 being very scared and 4 not scared at all. The reason for taking into consideration these perception variables is to test for the possible correlation of risk and fear of crime and not only crime itself. This is in line with previous studies that combine psychological effects with economic effects of suffering from a traumatic event (Callen et al., 2012).

5.1 The Model

Two different econometric models will be estimated. In order to address possible "selection into violence" concerns, we perform treatment evaluation with propensity score matching and probit analysis. Both models require different assumptions that will be mentioned below. Ideally, we would like to know the individual outcome with and without the treatment. Since this is not possible, the matching approach might be a possible solution to this problem. The basic idea is to find in a large group of "non-participants" (in this case people who were not victims), people with similar pre-treatment characteristics to those of the victims. Matched sampling attempts to

[11] The estimated correlation coefficient ρ is close to zero in both cases and only significant for the three year questions.

choose controls such that the treated participants will be similar to untreated ones with respect to background variables (Rosenbaum & Rubin, 1983). This approach is typically used in program evaluations and health economics to estimate the impact of a certain program or treatment.

The reason for first estimating a propensity score matching methodology is that in order to estimate the effect of being robbed (treatment) on risk aversion (outcome), we can try to identify a control group that best matches the people of the treatment group. We want to find those people who were also likely to be robbed but were not. In the first estimation, the control group will be consisting of those people who have not been robbed at all. The treatment group will be the people who have been robbed at least once. Later, different specifications will be estimated in order to refine our results.

The control variables used to build the propensity score are: gender, age, level of education, state and town size (measured as the number of inhabitants). The reason for not including the psychological variables as matching covariates is that these might not be independent of the treatment. An important assumption for this model to hold is the conditional independence assumption (CIA) which states that conditional on a group of control variables, the treatment is independent of the outcome$(Y_{1i}, Y_{0i}|X_i \perp D_i)$. The control variables should not be altered by the treatment variable. For this we will make a reasonable assumption which is that people did not move to a different state or to a town of different size due to the incident (because even if some people moved, it is unlikely that this happened in a significant number of cases).

The average treatment effect on the treated (ATET) will be estimated using nearest neighbor propensity score matching. The ATET is computed in the following way:

$$(1)\quad E(Y_{1i}|D_i = 1) - E(Y_{0i}|D_i = 1)$$

$$D_i = assault1 \begin{cases} 1\ if\ robbed \\ 0\ if\ not\ robbed \end{cases}$$

$$X_i = control\ variables$$

The first term can be computed easily since it is observed, but the counterfactual needs to be estimated. For this estimation we use the command in stata *nnmatch* which uses as a weighting function the nearest neighbor matching (Abadie, Drukker, Herr, & Imbens, 2004). The way it works is by calculating first the propensity $P(X_i) = P(D_i = 1|X_i)$, usually with a probit or logit. Then it applies the weighting function to calculate the counterfactual for every match:

$$\widehat{\mu_0}(X_i) = \sum_{j|D=0} w_{ij} Y_j$$

Finally, computes the second part of (1):

$$E(Y_{0i}|D_i = 1) = \frac{1}{N} \sum_{i|D_i=1} \hat{\mu}\,(X_i)$$

5.2 Results

5.2.1 Risk aversion and Victimization

Some preliminary results are shown in Table 11 in the Appendix where the means of risk aversion are separated by those who have been victimized and those who have not. These preliminary results show a significant difference in their means of risk aversion. People who have been victimized are more risk averse on average.

The results for the ATET estimations are shown in Table 6. The estimates are computed for the nearest neighbor and for comparison also the five nearest neighbors were taken into account in a separate model. The effect of being robbed on risk aversion is positive and significant for both cases. According to these results, being robbed will increase the likelihood of being risk averse by approximately 3 percentage points. In the following subsections robustness tests are included with different specifications of the model (e.g. the effect of being robbed in different time periods on those people being robbed once).

Table 6. Average Treatment Effect on the Treated

Risk Aversion	**(1)**	**(2)**
	riskav	riskav
ATET	0.030**	0.026**
	(0.013)	(0.013)
Observations	18,732	18,732

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

In order to see not only the possible effects of individual victimization, but also the variables of perception and fear, the second econometric model is estimated. A binary probit with the dependent variable being the dummy for risk aversion (riskav) is estimated. As explanatory variables, we include the variable *vli04a* and *vli01* which are the perception variable and the fear variable respectively. In the second model we control for income by adding the variables *wlw* and *logincome*.

Table 7 shows the results for the probit estimations. The variable for crime (*assault1*) is positive and significant as expected. Therefore, we can confirm hypothesis H_1. These results are as expected different from the study by Voors et al. (2012) where they find risk-seeking behavior after the Burundi massacre. The variable which reflects people's expectations for security in the next 3 years is positive and significant for those who expect that it will be much safer in the future. It seems that people who are more optimistic about the future behave in a more risk averse manner. Fear has the expected sign, people who are more afraid are more risk averse, but it is not significant. Given that fear is not significant we cannot confirm hypothesis H_2. Callen et al. (2012), find that the interaction between fearful recollections and exposure to violence increases risk tolerance and the preference for certainty. We performed separately regressions with fear and assault1 interacted, but found no significant effect in the interactions. Neither the variable for income nor the dummy for having worked last week appear to be significant.

The marginal effect of being robbed is computed from the probit model in order to compare the size of the victimization effect with the ATET. We find that the marginal effect estimated from the probit model is 0.037[12] and significant at 1 percent level. This means that being robbed increases the likelihood of being risk averse by 3.7 percent. This is of similar size to the effect of victimization that we found using the ATET (0.030). In the Appendix B we present results also for the raw difference of the means of aversion between people who were victims and people who were not. According to these estimates, the difference is 0.037 and it is significant. Therefore, we can conclude a positive effect of being a victim on the likelihood of being considered risk averse as we defined in Section 3.

Table 7. Probit estimates for Risk Aversion and Victimization

Risk Aversion	(1)		(2)	
	riskav	se	riskav	se
female	0.045**	(0.020)	0.042*	(0.023)
logage	0.032	(0.027)	0.033	(0.027)
education				
primary	-0.047	(0.038)	-0.047	(0.038)
secondary	-0.044	(0.044)	-0.045	(0.044)
high school	-0.015	(0.050)	-0.015	(0.050)
university	-0.026	(0.052)	-0.027	(0.052)
assault1	0.132***	(0.040)	0.133***	(0.040)
2.vli04a	0.045	(0.029)	0.045	(0.029)
3.vli04a	0.018	(0.031)	0.018	(0.031)
4.vli04a	-0.133***	(0.042)	-0.132***	(0.042)
5.vli04a	0.293***	(0.094)	0.292***	(0.094)
vli01	0.003	(0.013)	0.003	(0.013)
wlw			-0.019	(0.030)
logincome			0.002	(0.003)
Constant	-0.957***	(0.128)	-0.959***	(0.129)
Observations	18,720		18,720	

Note: Clustered standard errors by family in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.2.2 Duration

In order to test for H4, the duration of the effect, a variable for the date of the incident is used. To estimate the duration, we estimated both models from the previous subsection using "time since the incident dummies". The regression results for the probit and ATET can be found in the Appendix B, Tables 13 and 14 respectively.

The effect is significant and positive for criminal events that happened 4 or more years ago. This might be because the change in individual behavior only takes place once the effect has been fully internalized by the subject. This would indicate a slow process of adjustment in risk attitudes due to the traumatic event and this is why the effect is only significant after several years. It will be

[12] The results of the marginal effect of assault1 on risk aversion are shown in Table 12 of the Appendix B.

interesting to see which psychological effects might be underlying this change in behavior. It might be the case that people in the short term have different responses to this type of trauma than in the long term. In Section 6 we will relate our results to the psychological variables available and compare them to those results of previous studies.

5.2.3 Robustness

In order to check for robustness of these results, we performed the analysis on people who have been robbed only once and checked for the effect of being robbed in different time periods. The sample that has been only robbed once consists of 1376 people. This is illustrative since we can assume these people have the same likelihood of being robbed (since they have actually been robbed once). We also find similar results under this specification. The results indicate that there is a positive and significant effect when people have been victimized 4 or more years ago.

Since we have information on the times that a person has been victimized, we use this to make a simple mean comparison between groups. Looking at these differences, we see that people who have been robbed more than once have a higher mean of risk aversion than those who have been robbed only once. The mean risk aversion of those people having been robbed once on average is 0.231, and the mean risk aversion of those robbed more than once is 0.270.[13] However, this difference is not statistically significant. To our knowledge there is no study yet which analyzes the impact of having suffered from crime more than once on preferences.

5.3 Time preference and victimization

To test for hypothesis H_3, the effect of crime and violence on time preferences, we estimate a bivariate ordered probit. The dependent variables are both of our time preference measurements. Table 7 presents the results of two bivariate ordered probits for time preferences including the variables for violence and perception of crime. Models (1) and (3) show the results for the one month rates and Models (2) and (4) the results for the three year rates.

The variable *assault1* has a positive coefficient. Being involved in a robbery is correlated with more patience. Most of our explanatory variables are significant, except the dummy for being in a couple and having higher education. In this case the variable for fear *vli01* (fear) is significant. Its negative coefficient indicates that people who are less afraid are also more likely to be more impatient, this result goes in the same direction as *assault1*. The rationale for this result might be that people who have suffered a loss (in a traumatic event) are more willing to postpone consumption for later because of the fear of present losses. People might not want to hold money now if they fear it can be stolen. Therefore we confirm our hypothesis H_3 claiming that people do become more patient as a result of a criminal event.

[13] Table 15 of Appendix B

The variable of expectations of the future (*vli04*) security in Mexico has a negative coefficient, which means that people who are more positive about security in the future are also more likely to be impatient. It seems that the level of insecurity fosters a climate of patience among the Mexican population. This is supported by our three variables related to crime and violence. This can have important economic implications in the micro as well as the macro level. This study is just a first attempt at looking at the possible consequences of insecurity on individual preferences. Better indicators of insecurity and fear measurements could shed more light into the precise mechanism of crime. Our results contrast those of Voors et al. (2012) and Callen et al. (2012).

Some studies on the effects of background mood on time preferences suggest different effects. The literature on mood is not conclusive in the sense that recent studies still find opposing results. Some studies claim that people who are in a positive mood exhibit higher discount rates(Drichoutis & Nayga, 2010), while others claim positive mood replenishes will power and increases forward looking behavior and self control (Hermalin & Isen, 2007). While we do not have direct comparable information on positive or negative mood, we can just say positive expectations of the future make people likely to be more impatient. In the next section we analyze further the possible psychological factors by introducing an index of depression.

Table 7. Bivariate Ordered Probit of Time Preferences and Victimization

	(1)		(2)		(3)		(4)	
Time Preferences	timepref	Std. Err.	timepref3	Std. Err.	timepref	Std. Err.	timepref3	Std. Err.
female	0.047***	(0.016)	0.025	(0.016)	0.077***	(0.018)	0.049***	(0.018)
couple	0.001	(0.020)	-0.016	(0.020)	0.004	(0.020)	-0.014	(0.020)
Age group								
agegp2	-0.159***	(0.023)	-0.148***	(0.023)	-0.175***	(0.024)	-0.161***	(0.024)
agegp3	-0.288***	(0.028)	-0.309***	(0.029)	-0.305***	(0.028)	-0.323***	(0.029)
agegp4	-0.368***	(0.039)	-0.420***	(0.039)	-0.369***	(0.039)	-0.420***	(0.039)
Education								
primary	-0.087***	(0.032)	-0.096***	(0.033)	-0.087***	(0.032)	-0.097***	(0.033)
secondary	-0.121***	(0.036)	-0.211***	(0.037)	-0.122***	(0.036)	-0.212***	(0.037)
high school	-0.058	(0.040)	-0.147***	(0.041)	-0.057	(0.040)	-0.146***	(0.041)
university	-0.029	(0.041)	-0.152***	(0.042)	-0.030	(0.042)	-0.153***	(0.042)
assault1	0.315***	(0.032)	0.178***	(0.032)	0.310***	(0.032)	0.174***	(0.032)
vli04a	-0.026***	(0.009)	-0.010	(0.009)	-0.026***	(0.009)	-0.009	(0.009)
vli01	-0.030***	(0.011)	-0.025**	(0.011)	-0.030***	(0.011)	-0.025**	(0.011)
wlw					0.101***	(0.024)	0.079***	(0.024)
logincome					-0.006**	(0.002)	-0.004*	(0.002)
athrho	0.981***	(0.013)			0.981***	(0.013)		
cut1	-0.411***	(0.060)	-0.391***	(0.060)	-0.373***	(0.061)	-0.359***	(0.061)
cut2	-0.108*	(0.060)	-0.028	(0.060)	-0.069	(0.061)	0.003	(0.061)
cut3	0.232***	(0.060)	0.306***	(0.060)	0.270***	(0.061)	0.337***	(0.061)
cut4	0.524***	(0.060)	0.646***	(0.060)	0.563***	(0.061)	0.678***	(0.062)
cut5	1.013***	(0.059)	1.197***	(0.061)	1.052***	(0.060)	1.229***	-0.061
rho	0.753539	(0.0056)			0.753348	(.0056)		
Observations	18,710		18,710		18,710		18,710	

Note: Clustered standard errors in parentheses (by family)

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

6. Psychological Results

In this section we make use of the module of the survey which was designed by researchers of the Mexican Institute of Psychiatry to diagnose depressive syndrome among the Mexican population[14]. The questionnaire consists of 21 questions which can be answered negatively by a no or positively by sometimes, many times and all the times. Calderon (1997) presents a criterion to use the first 20 questions in order to categorize people into: normal person, certain level of anxiety, average depression and severe depression. We build this variable by following his methodology. We first assign a score to each answer and sum them up in order to make a scale where we classify the level of depression.

Table 16 of the Appendix B shows the percentages of people who fall into each mental state. Around 88 percent of the sample is considered to be in a normal mental state, 9.27 percent is considered to have a level of anxiety, 1.86 percent has average depression and only 0.39 percent is considered to have severe depression. In our classification of fear, around 67 percent of the sample is not afraid.

Table 8 shows the results for a probit regression of risk aversion as a dependent variable when we add the psychological variables into the model. The effect of the variable for crime is still significant and the only psychological variable that seems to play a role is average depression. Anxiety, severe depression and fear are not significant in explaining risk aversion. According to these results having average depression is correlated with less risk aversion because of the negative sign. These results do not present evidence in favor of the appraisal-theory framework by Lerner & Keltner (2001) who showed that people with fear expressed pessimistic risk estimates and risk averse choices. Therefore, we cannot confirm hypothesis H_2 that states that people with a higher degree of fear are more risk averse. Our results differ from those of (Moya, 2012). He finds depression to be not significant and instead he finds that phobic anxiety is what is driving the results for risk aversion in the gains tasks. We should be careful though when comparing to other studies which make use of psychological states. Results might be sensitive to the way these variables are measured. It would be useful for future research to have a more standardized way of measuring mental states.

[14] Calderon, G.N (1997). "Un Cuestionario para Simplicar el Diagnóstico del Síndrome Depresivo" Revista de Neuro-Psiquiatría, 60:127-135.

Table 8. Psychological variables and risk aversion

VARIABLES		(1)		(2)	
		Riskav		Riskav	
		coef	se	coef	se
female		0.039	(0.026)	0.031	(0.029)
logage		0.005	(0.034)	0.008	(0.034)
education					
	primary	-0.095**	(0.043)	-0.094**	(0.043)
	secondary	-0.079	(0.051)	-0.079	(0.052)
	high school	-0.039	(0.059)	-0.040	(0.059)
	university	-0.070	(0.061)	-0.071	(0.062)
assault1		0.153***	(0.045)	0.155***	(0.045)
security					
	2.vli04a	0.007	(0.033)	0.008	(0.033)
	3.vli04a	-0.005	(0.036)	-0.005	(0.036)
	4.vli04a	-0.129**	(0.052)	-0.128**	(0.052)
	5.vli04a	-0.020	(0.104)	-0.021	(0.104)
anxiety		-0.072	(0.047)	-0.074	(0.047)
average depression		-0.215**	(0.103)	-0.215**	(0.103)
severe depression		-0.361	(0.239)	-0.363	(0.238)
fear		0.004	(0.015)	0.004	(0.015)
wlw				-0.040	(0.036)
logincome				0.003	(0.004)
Constant		-0.767***	(0.155)	-0.764***	(0.155)
Observations		12,018		12,018	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9 presents the results for a bivariate ordered probit including the psychological variables. We can observe that only severe depression is significant, the negative sign implies that people who are severely depressed are more impatient. Therefore we cannot claim that the mechanism through which crime has an effect on preferences is depression, since the effect goes in the opposite direction. All the other new variables are not significant for model (1) and anxiety is significant at 10% level in model (2). We do not have studies to compare our results to since there are none which have integrated time preferences into the analysis combined with the psychology variables mentioned above.

Both of our results from this section point towards another possible mechanism through which crime and violence can have an effect on preferences. Our expected results were that fear was possibly one of the reasons for the impact on preferences but we found no evidence for this.

Another possibility for the lack of evidence is that the classification of fear through one question in the survey is not a good measure. Depression seems to have an effect which is opposite to the effect of crime and violence. Depressed people seem to exhibit more risk taking.

Table 9. Psychological variables and Time Preferences

	(1)		(2)	
VARIABLES	timepref		timepref3	
female	0.050**	(0.022)	0.015	(0.023)
couple	0.020	(0.024)	-0.018	(0.024)
age group				
agegp2	-0.216***	(0.030)	-0.186***	(0.029)
agegp3	-0.386***	(0.034)	-0.363***	(0.035)
agegp4	-0.446***	(0.045)	-0.476***	(0.046)
education				
primary	-0.051	(0.037)	-0.067*	(0.038)
secondary	-0.068	(0.043)	-0.168***	(0.044)
high school	0.005	(0.048)	-0.122**	(0.049)
university	0.038	(0.050)	-0.109**	(0.050)
assault1	0.271***	(0.037)	0.103***	(0.036)
wlw	0.085***	(0.028)	0.027	(0.029)
logincome	-0.007**	(0.003)	-0.002	(0.003)
vli04a	-0.010	(0.011)	0.002	(0.011)
fear	-0.005	(0.012)	-0.009	(0.012)
anxiety	-0.032	(0.035)	-0.058*	(0.035)
average depression	0.051	(0.076)	0.064	(0.080)
severe depression	-0.460**	(0.184)	-0.538***	(0.194)
Constant	0.915***	(0.015)		
cut1	-0.383***	(0.071)	-0.408***	(0.072)
cut2	-0.071	(0.071)	-0.039	(0.072)
cut3	0.269***	(0.071)	0.284***	(0.072)
cut4	0.543***	(0.071)	0.621***	(0.072)
cut5	1.054***	(0.070)	1.174***	(0.072)
rho	0.7234	(0.0073)		
Observations	12,011		12,011	

Note: Cluster robust standard errors in parentheses (by family)
*** p<0.01, ** p<0.05, * p<0.1

7. Conclusions

The study of the relationship between individual preferences and exposure to violence and crime can be of great economic relevance. First we motivated our analysis by mentioning the relevance of preferences in the determination of one economic decision which is savings. We see that risk and time preferences are significant in explaining the savings decisions of individuals. Therefore, studying possible situations where these individual preferences might be affected is of great economic relevance.

This study analyzes how individual preferences towards risk and time can be altered due to an episode of crime or violence. This issue can lead to a change in individual behavior which might result in suboptimal decision making. For example, the decisions to save and invest for better education, technology, prevention of diseases and others.

In order to perform our analysis, the first part of our research describes these preferences in detail for the Mexican population. We make use of Mexican data which was collected in 2005 and contains information on 18,783 people who are older than 15 years of age. The questionnaire to measure risk attitudes was elicited as a lottery experiment. We dropped part of our sample that seemed to exhibit inconsistent behavior by picking a weakly dominated option. We observe that people in general tend to be risk-seeking and individual characteristics such as education, age, gender are not significant in explaining variation in risk attitudes. The questionnaire designed to elicit time preferences included two time periods where we could see an indication of hyperbolic discounting. We also observe a tendency for people to be very impatient in general. We find a small correlation between risk aversion and time preferences and therefore perform our analysis separately.

This research finds that crime and violence have an impact on our variables for risk and time preferences. The effect is positive for risk aversion. Propensity score matching and probit regressions show that being involved in an episode of crime increases the likelihood that a person will be risk averse. We compare the size of both effects and find similar estimations. A plausible argument to justify that our estimates are not driven by "selection into violence" effects is that our estimates show a positive correlation. If people who take more risks were those being involved in crime, it would imply that we show a lower bound on the true effect and the effect might even be stronger. We find that the effect lasts more than four years after the incident. This is an interesting result since a long lasting effect can be even more relevant for changing economic outcomes and welfare of individuals. We also compare the means of risk aversion among the people who have been subject to crime once versus those who have been multiple times. We find that those robbed more than once are more risk averse but the difference is not significant.

The results for the bivariate ordered probit regressions show that being subject to crime is correlated with an increased level of patience of people. It might be the case that people would rather postpone receiving money due to fear of being robbed in the present. This would be one way to justify the positive relationship between patience and crime incidence. There might be some reverse causality and more patient people behave in ways which make them more likely to be robbed. We find that education, age group and gender are significant in explaining variation in the subjective interest rates. Our results indicate that women are more patient than men, older people are more impatient than younger people and that people having only one or two levels of education are more impatient. The dummy included to control for having worked the week before the survey is significant and positive. People who have worked recently, are more patient on average. This is an intuitive result since these people have less urgency to receive income than those unemployed.

When we control for the psychological variables, we find that the effect of crime is still very significant in explaining risk and time preferences. For risk preferences, the level of fear appears not to be significant and the only significant psychological variable is average depression. We cannot claim that the mechanism for crime to affect risk preferences is through depression since the effect of depression is negative. People with average depression are more risk-seeking.

For the case of time preferences, we find that anxiety and severe depression are significant once we include them as controls in our models. But again, the sign of the effect is the opposite of that of crime incidence. On the other hand, the level of expectations is significant for those who expect safety to improve in the next three years. These people are more risk-seeking when they have a positive outlook of the future. It might be the case that these levels of optimism influence how people behave with respect to risk.

Therefore, from this study we can conclude that these variables are not the mechanism through which crime and violence have an impact on preferences. Further research could be directed at testing for other possibilities or improving the measurements of the psychological index.

We conclude that while there is an impact of crime and violence on individual preferences, the mechanism through which this is working is not clear. Some psychological elements are significant in explaining risk aversion, but are not in the same direction as the effect of crime. Our analysis was carried out with a single wave of the survey. It would be interesting for further research to incorporate the next available wave once it is available publicly. Having two observations would allow us to try to establish causality with better tools.

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Appendix A

Savings attitudes

Since we might be interested in how these variables of violence impact financial decisions, the next probit presents as a dependent variable save (yes=1, no=0). Out of a sample of 18,780 people, only 2,144 claim to save (this is reasonable since only a small fraction works and I include a dummy to control for this). Afterwards, I present an estimation of a tobit model with the amount of savings. This model takes into account the fact that we have censored data because we only observe savings of those people who report a positive amount of income.

The following table shows the results of the probit in model (1), it appears that the variables for risk aversion and time preferences are significant on the decision to save or not, even if when include the variable of being robbed and other insecurity questions. People who are more patient and more risk averse are more likely to save. Other variables like couple and female appear not to be significant. Education is positively correlated and significant with the propensity to save as well as the amount of savings. The second model (2) is a tobit model with the amount of savings as dependent variable. Most coefficient are also significant.

Table 10. Savings and individual preferences

VARIABLES	(1)	Column1	(2)	Column2
	realsave1 Probit coef	se	monsaved Tobit coef	model
education				
primary	0.379***	(0.065)	34,651.510***	(8,651.745)
secondary	0.676***	(0.069)	64,686.107***	(12,133.575)
high school	0.960***	(0.071)	90,973.849***	(15,596.295)
university	1.215***	(0.073)	122,682.211***	(20,398.685)
couple	0.035	(0.032)	4,350.898	(3,635.031)
female	-0.029	(0.028)	-5,576.253*	(2,991.532)
age group				
2.agegroup	0.023	(0.038)	5,802.623	(3,695.849)
3.agegroup	0.009	(0.047)	9,395.880	(5,845.979)
4.agegroup	0.142**	(0.065)	15,512.532**	(7,578.968)
ls_n	-0.018*	(0.010)	-2,133.002**	(1,035.769)
wlw	0.238***	(0.037)	22,898.041***	(5,818.705)
logincome	0.010***	(0.004)	593.290	(471.177)
riskav	0.082***	(0.032)	8,409.581**	(3,906.814)
timepref	0.084***	(0.007)	8,453.123***	(1,622.205)
Constant	-2.270***	(0.085)	-252,619.535***	(39,988.215)
sigma			109,062.359***	(16,564.239)
Observations	18,729		18,730	

Note: Clustered robust standard errors in parentheses (by family)
*** p<0.01, ** p<0.05, * p<0.1

Appendix B

List of Tables

Table 10. Difference in means of risk aversion according assault1

Risk Aversion	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
0	17360	0.203111	0.0030535	0.4023257	0.1971254	0.2090958
1	1376	0.239826	0.0115147	0.4271321	0.2172373	0.2624139
combined	18736	0.205807	0.0029537	0.4043009	0.2000175	0.2115965
diff		-0.03672	0.0113201	-0.0589033	-0.0145266	
	diff = mean(0) - mean(1)					
	Ho: diff = 0					
	t = -3.2434					
	Pr(|T| > |t|) = 0.0012					

Table 11. Marginal effect of being robbed on risk aversion

Variable	dy/dx	Std. Err.	z	P>z	[95% Conf. Interval]	
assault1	0.037575	0.0113968	3.3	0.001	0.0152379	0.0599125
	Number of obs =	18720				

Table 12
Probit for Risk Aversion and years after the robbery

Risk Aversion	(1)	
	riskav	Std. Err.
female	0.042**	(0.020)
logage	0.028	(0.029)
couple	0.018	(0.024)
education		
primary	-0.047	(0.038)
secondary	-0.043	(0.044)
high school	-0.009	(0.050)
university	-0.017	(0.052)
duration		
1 year	0.051	(0.227)
2 years	-0.091	(0.110)
3 years	0.080	(0.108)
4 years	0.200*	(0.114)
5 years	0.313**	(0.123)
6 years	0.197	(0.159)
2.vli04a	0.041	(0.029)
3.vli04a	0.014	(0.031)
4.vli04a	-0.136***	(0.042)
5.vli04a	0.289***	(0.094)
vli01	-0.000	(0.013)
Constant	-0.937***	(0.131)
Observations	18,718	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14. ATET Results

Risk Aversion	**(1)**	**(2)**
	riskav	riskav
ATET	0.063**	0.059***
	(0.031)	(0.016)
Observations	1,376	18,739

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
Model (1) presents the results for the limited sample of those people who have been robbed only once and the treatment is being robbed 4 or more years ago. Model (2) compares the people who have been not robbed with the treatment of being robbed 4 or more years ago.

Table 15. T-test for mean of risk aversion of people who have been robbed once vs. the rest.

Risk Aversion	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
0	318	0.27044	0.024948	0.444887	0.221356	0.319525
1	1058	0.230624	0.0129564	0.421431	0.205201	0.256047
combined	18736	0.205807	0.0029537	0.404301	0.200018	0.211597
diff		0.039816	0.0273047	-0.01375	0.09338	
	diff = mean(0) - mean(1)					
	Ho: diff = 0					
	t = 1.4582					
	Pr(T > t) = 0.0725					

Table 16. Psychological States

Descriptive Statistics

Variable	Percentage
normal	88.49
anxiety	9.27
average depression	1.86
severe depression	0.39
fear	
very afraid	3.33
somewhat afraid	11.51
bit afraid	17.78
not afraid	67.38
security perceptions	
very unsafe	27.10
unsafe	32.85
the same	27.07
safer	10.51
much safer	2.47