THE ROLE OF EMOTIONS ON RISK AVERSION: A PROSPECT THEORY EXPERIMENT

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Abstract

This study measures risk and loss aversion using Prospect Theory and the impact of emotions on those parameters. Our controlled experiment at two universities in Mexico City, using uncompensated students as research subjects, found results similar to those obtained by Tanaka et al. (2010). In order to study the role of emotions, we provided subjects with randomly varied information on rising deaths due to drug violence in Mexico and also on youth unemployment. In agreement with previous studies, we find that risk aversion on the gains domain decreases with age and income. We also find that loss aversion decreases with income and is less for students in public universities. With regard to emotions, risk aversion increases with sadness and loss aversion is negatively influenced by anger. On the loss domain, anger dominates sadness. On average, anger reduces loss aversion by half.

JEL: C93; D03; D12; O12; O54

Keywords: Risk Aversion; Emotions; Prospect Theory; Experiment; Mexico.

Highlights:

- We conducted a Prospect Theory experiment in Mexico.
- The experiment randomly framed students into different emotions.
- Emotions were prompted by information on the rising number of deaths due to drug violence in Mexico and on youth unemployment.
- Sadness increases risk aversion over gains, and anger decreases loss aversion.
- On average, anger reduces loss aversion by half.

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1 Introduction

Understanding human preferences over uncertain outcomes is a key issue in many subjects in the field of economics. Risk attitudes can create speculative bubbles and crashes in financial markets (De Long et al., 1991). High risk aversion can explain why some countries do not invest in business opportunities, capital, or human capital (Shaw, 1996; Hartog and Diaz-Serrano, 2007; Yesuf and Bluffstone, 2009). In fact, the effects of public policy depend on the level of risk aversion in a society (credit incentives, fiscal taxation programs, etc.). These are only a few examples of why decision making under conditions of uncertainty is important, and there are still many unanswered questions in the field.

Risk aversion is generally associated with the properties of the utility function that are consistent with expected utility theory (Harrison and Rutström, 2008). Recent literature provides many well-documented examples, under diverse scenarios, that suggest Prospect Theory (PT) as the best way to model choice under uncertainty (an important example can be found in List, 2004, where participants in a well-functioning marketplace behave according to PT). In order to achieve a deeper knowledge of human preferences, a behavioral approach like PT seems essential. Nevertheless, the literature addressing differences in specific characteristics at the time of decision making is still under development and remains mostly unclear.

One important element missing from this work is the role of the emotions in Prospect Theory, mainly because they are difficult to measure. It is well documented that humans behave differently depending on their emotional states.[1] Under specific circumstances, people, cities, and even countries can become emotionally affected. This

[1] For example, depressed people tend to overeat (Smith, 2009), frightened individuals tend to react impulsively, and angry people tend to act recklessly (Ahn, 2010).

emotional impact is one reason for the importance to economists of the effect of emotions on risky decisions. Public policy, market prognosis, and mechanism design may have different implications if we consider the emotional impact on risk behavior.

The goals of this study are to measure risk and loss aversion using Prospect Theory and the impact of emotions on the parameters that characterize them. We conducted a controlled experiment at two universities in Mexico City. The experimental design, which followed that of Tanaka et al. (2010) except in our use of uncompensated subjects, allowed us to obtain the parameters of the Cumulative Prospect Theory (CPT) value function and the probability weights for each individual. The CPT and the probability function are characterized by three parameters: the curvature of the function that assigns value to the prospects (i.e. lotteries) (σ), the coefficient of loss aversion (λ), and the one-parameter in Prelec's weighting function (α). The average individual in our sample has values of 0.47, 2.29, and 0.71 for σ, λ, and α, respectively. Although our study used only uncompensated subjects, these values are similar to those obtained in the study by Tanaka et al. (2010). We were also able to gather respondents' socioeconomic variables and information about their emotions after reading about different dramatic situations.

To gather data on emotions, we randomly varied different questions across subjects just before the elicitation of the structural parameters of CPT. One third of the subjects received a questionnaire that asked them how they felt about rising violence and deaths in Mexico.[2] Another third received an additional questionnaire about their feelings regarding youth unemployment. The final third, a control group, did not receive any information about violence or unemployment. Consistent with Lerner et al. (2003), we

[2] According to the Attorney General's Office the number of deaths caused by the drug war in 2005 was 2,221, while for 2010 this number increased to 15,273.

find that risk aversion is related to emotional state; in particular, we find that sad people are more risk averse in the gain domain. We also find that angry people are less loss averse, and that anger has a larger impact on the loss domain than sadness. While sad people become more risk loving on the loss domain than the norm, anger reduces the loss aversion by half.

To our knowledge, ours is the first attempt to explain the effect of emotions on the parameters that characterize a Cumulative Prospect Theory value function, and it may also be the first risk aversion analysis for Mexico. Hence, this paper makes a contribution to the literature of Prospect Theory, the literature of behavioral economics, and to public policy design research, especially in the case of Mexico. Literature of the relevant economic theory is reviewed in Section 2, experimental design is explained in Section 3, data analysis is presented in Section 4, the main results are shown in Section 5, and Section 6 provides some concluding remarks.

2 Review of the Literature and Economic Theory

2.1 Prospect Theory

Developments in the field of psychology led Kahneman and Tversky (1979) to the development of Prospect Theory. One important finding in the PT literature was evidence against classical Expected Utility Theory (EU), which tested the hypothesis that the weighting probability parameters are different from one. Another line of investigation--the approach we take--attempts to explain how certain individual characteristics affect the degree of loss aversion or risk aversion.

We use an extension of PT known as Cumulative Prospect Theory (CPT), proposed by Tversky and Kahneman (1992). The general model of CPT is described by the following equation:

$$V(x_i) = \sum_{i=0}^{n} \pi_i^+ (p) v(x_i) + \sum_{i=-m}^{0} \pi_i^- (p) v(x_i) \qquad (1)$$

where the first sum is over the positive prospects (non-negative outcomes only) associated with nonlinear weights (from $\mathbf{0}$ to $\boldsymbol{n}$), and the second over negative prospects (non-positive outcomes only, $-\boldsymbol{m}$ to $\mathbf{0}$). Hence, a parametric representation of CPT has parameters that identify the curvature of the value function of prospects, parameters that identify the weights of the probabilities, and parameters that indicate the degree of loss aversion.

The literature of PT includes a variety of different methods for elicitation of the parameters that identify risky decisions. Abdellaoui et al. (2008) propose a method that begins with the certainty equivalent (CE) for gains; they then recover the CE for losses and finally link them. Because this method requires subjects to make calculations to propose a certainty equivalent, agents may not give their true CE value. For example, in an experiment with time constraints, calculations performed under pressure may be less accurate.

Tanaka et al. (2010) propose the TCN Eliciting Method.[3] In TCN there are three ordered sequences of lotteries. In the first two, they identify the parameter of the curvature in the gains domain and the one-parameter of the Prelec (1998) probability weighting function. In the last sequence they identify the loss aversion parameter. This is a simpler procedure, but it has some restrictive assumptions.[4] In spite of these

[3] Following Harrison and Rutström (2008) we denominate TCN as the method used in Tanaka et al. (2010).

[4] The method assumes the same probability weighting function for gains and losses and elicits the loss aversion parameter assuming a previously correct elicitation of the parameter that identifies the curvature of the function. Although some may argue that assuming the same value for the curvature over gains and losses is restrictive, several papers have found the same value estimating the parameters separately, see Abdellaoui (2000), Abdellaoui et al. (2005), Andersen et al. (2006), Donkers et al. (2001), Fehr-Duda et al. (2006) and Tversky and Kahneman (1992).

restrictions, we use this approach; our application of the method will be described in full in Section 3.

In the experiment of Tanaka et al. (2010), using data from rural Vietnamese villages and a national survey, the elicited parameters were 2.63 for loss aversion and 0.59 for the curvature of the value function (i.e., the average agent is loss averse, risk averse over gains, and risk loving over losses). Their empirical regression allowed them to conclude, among other things, that being older reduces the level of risk aversion. However, their sample comes from a particular experimental population, so additional studies are needed to demonstrate external validity.

Holt and Laury (2002) carried out a study with 175 people to determine the constant relative risk aversion (0.26). They outline some important observations for such research, among them that hypothetical payments do not affect the estimated coefficient of risk aversion, at least for low outcomes.[5] This evidence is important given that the subjects of our study are not compensated.

2.2 Emotions and Behavioral Economics

Framing effects are quite useful in obtaining relevant information from subjects. DellaVigna (2009) discusses a number of experiments where modification in the way a question is framed produces different results. In our study, we randomly frame subjects into different emotions and analyze how they make risky decisions.

Using the Wechsler Adult Intelligence Scale, Dohmen et al. (2010) carried out a risk aversion study with cognitive implications. They asked approximately 1,000 individuals to choose between ordered pair lotteries, and used the results to propose a measure of risk willingness. Subjects were also asked to take a cognitive exam, and the

[5] Their study used low outcomes of $2-4 USD, and then scale the payoff by 20, 50 and 90 times the low payoff. They varied hypothetical and real payoffs.

researchers found a significant negative correlation between the level of risk willingness and the exam results. In our study we recorded respondents' self-reported average grades from the previous semester, allowing us to control for cognitive abilities.

According to behavioral theories, emotions can affect agents' decisions. Turvey et al. (2010) show that fear can shape the way individuals make economic decisions, in particular fear can diminish the optimal levels of consumption. In choice under uncertainty, Lerner et al. (2003) show that frightened people are more risk averse and that angry people are more risk loving.[6] Feagin (1988) established the differentiation of an empathic and a sympathetic reaction to feelings, arguing that people imagine beliefs with which they can generate an empathic emotion related to a fictional character. People worry about the troubles of fictional characters mainly because they believe that something bad will happen to them. These beliefs are not real but imagined, but fictional beliefs lead to real emotions and real decisions.

Drawing on these ideas, we use the unfortunate situation of crime and violence in Mexico to elicit risk preferences under emotional treatments. We frame the respondents into different emotional states (anger, sadness, and fearfulness) in order to gauge variation in their risk and loss aversions.

3 Experimental Design

Our experiment was conducted in two different universities in Mexico City, one public and the other private, during November 2011. All respondents were students at their respective universities. We went to classrooms and asked if we could conduct an experiment; if we got a positive answer we would return, usually 25 minutes before the

[6] These results on emotions are also observed in Lerner and Keltner (2000, 2001).We do not find significant results in such emotions with respect to risk aversion, however the authors do not use prospect theory and loss aversion is not considered by them. Indeed, we find a significant result for anger in the loss aversion parameter.

class ended. We had no special order of selection; we walked randomly around each campus, knocking on classroom doors. However, it is important to mention that students majoring in economics make up 38% of our sample.[7] We offered no compensation for participation in the experiment; we told subjects they would be participating in a study to understand job employment prospects for recent college graduates, and that it was important to answer questions truthfully.[8] Each experiment took no longer than 20 minutes, and was divided into three sections: sociodemographic characteristics, emotional framing, and risk aversion.[9]

The main part of the experiment consisted of choosing lotteries. In many experiments described in the literature, respondents are compensated after completing lotteries.[10] We decided against compensation, mainly because in Mexican universities such procedures are not common or culturally appropriate. Holt and Laury (2002) find that behavior towards risk taking is affected if high incentives are offered as a possible outcome. Nevertheless, the largest theoretical payoff in our experiment is only $1,700 pesos (approximately $125 USD). This amount is relatively small given that it represents only 12% of the self-reported expected monthly salary after graduation ($1,077 USD). Moreover, the median payoff in the high payment lottery we implement is $167 MXP ($12 USD). Hence, we believe the results of our experiment are not biased as a result of the use of volunteer subjects. In fact, we find results similar to those of

[7] This is mainly because we are more acquainted with the professors that teach economics.

[8] In Mexico it is unusual to conduct experiments using college students as subjects, or even to use them as assistants. However, we found no resistance to participation in the experiment; in general, students were enthusiastic about taking part in the study. As we told students that the main goal of the questionnaire was to understand job prospects, we included queries on expectations regarding salary and labor force participation.

[9] Two pilot studies were conducted before the experimentat a different university. Based on students' responses and recommendations about the instructions and the pool of available answers, we constructed a new experimental design. No further improvements were suggested in the second pilot, implying that respondents felt comfortable with the experiment.

[10] Occasionally they paid respondents the prize of the lottery described or simply compensated them for answering the questionnaire.

Tanaka et al. (2010), who conducted the same experiment with compensated subjects, leading us to believe, following Holt and Laury (2002), that the experiment is not affected by small monetary payoffs.[11]

3.1 Sociodemographic Characteristics

The first part of the experiment consisted of several questions about personal sociodemographic characteristics. With these questions we were able to identify the age, sex, and academic major of the students. These data allowed us to divide the groups for distinct interpretation of the parameters of the CPT function.

In order to find control variables for wealth and socioeconomic status, we asked for information about the level of education of the subjects' parents, as well as two income proxy questions about the number of rooms in their homes and cars in their households.[12] Finally, we asked about their future salary expectations, the lapse between finishing their undergraduate degrees and finding a job, and whether they worked during the week. These answers helped us to identify the subjects' good faith participation in the experiment, as discussed in Section 4.

3.2 Emotional Framing

To create an effective framing effect, we drew upon the unfortunate social situation in Mexico of deaths related to drug violence. We gave this framing treatment to two-thirds of the study group; the other third received no framing. There were two kinds of framing treatment: strong and moderate. The strong version contained two questions,

[11] It is worth mentioning that our results are very similar to those experiments where individuals were paid. For the curvature parameter of the value function see Gonzalez and Wu (1999), Tanaka et al. (2010) , Wu and Gonzalez (1996) and Liu (Forthcoming). The loss aversion parameter is very close to Tversky and Kahneman (1992), Tanaka et al. (2010) and Fehr-Duda et al. (2006) and Liu (Forthcoming). Finally, our elicited value for the reweighting factor is very similar to Tu (2005) , Wu and Gonzalez (1996) and extremely close to Tanaka et al. (2010). Hence, we do not consider that our unpaid experiment affects our main results.

[12] In Mexico most students do not know their exact family income.

while the moderate treatment contained only one. Respondents were unable to identify whether their peers received a different questionnaire. The first question, used in both treatments, was as follows:

From 2006 to 2010 almost 40,000 people died as a result of the drug war. Insecurity levels haven't gone down in any region; on the contrary, the country is living the largest wave of violence ever seen. How does this make you feel?

The question may be shocking, but some students may not be aware of its magnitude because they may be unacquainted with the topic.[13] To avoid this issue, in the strong treatment we added an even better-known situation. The second question (used only in the strong treatment) was the following:

The financial crisis of 2008 has left the international financial markets in tatters. The newspaper *El Economista* has reported that 2010 showed the largest unemployment rate for young people worldwide. Also, experts predict another economic recession for 2012. How does this make you feel?

We believe this question may impact students more directly because most of them seek to enter the workforce after finishing their degrees (almost 97%, according to our survey). It is worth mentioning that these questions were asked before the risk aversion section, so we expect them to have a framing impact on the decisions made when choosing lotteries (as discussed in Section 2.2).

The multiple-choice options for both questions are (i) anger, (ii) sadness, (iii) fear/uncertainty, and (iv) indifference.[14] Among individuals who received the violence framing, 39% reported feeling angry, 19% sad, and 37% fearful/uncertain. Among those

[13] One of the least affected regions is Mexico City, where our experiment was conducted. Thus, a student who does not follow the news could be less aware of the subject.

[14] Because some individuals may not care about the framing situation, we decided to include an option for "indifference." With this option we intended to avoid individuals feeding us false answers, for example by responding that they experienced emotions they were not really feeling.

who received the youth unemployment framing in addition to the violence framing, 20% reported feeling angry, 11% sad, and 64% fearful/uncertain.

3.3 Risk Aversion

In order to elicit the parameters of the CPT function, we conducted a replica of the experiment designed in Tanaka et al. (2010). As mentioned before, the implementation is straightforward and simplifies the function to only three parameters. Prelec's one-parameter probability weighting function is used. Tanaka et al. (2010) mostly confirm the main findings of Kahneman and Tversky (1979). One important assumption is that the agents rethink the probabilities in the same way for gains or losses. The probability weighting function is

$$\pi^{+}(p) = \pi^{-}(p) = \frac{1}{exp[ln(1/p)]^{\alpha}} \tag{2}$$

In this experiment the prospects contain only two possible outcomes, so Equation (1) simplifies to: $(1 - \boldsymbol{\pi}(\boldsymbol{p}))\boldsymbol{v}(\boldsymbol{y}) + \boldsymbol{\pi}(\boldsymbol{p})\boldsymbol{v}(\boldsymbol{x})$ (for $\boldsymbol{xy} > 0$ and $|\boldsymbol{x}| > |\boldsymbol{y}|$) or $(\boldsymbol{p})\boldsymbol{v}(\boldsymbol{x}) + \boldsymbol{\pi}(\boldsymbol{q})\boldsymbol{v}(\boldsymbol{y})$, where $\boldsymbol{p}$ and $\boldsymbol{q}$ are the true probabilities of the outcomes $\boldsymbol{x}$ and $\boldsymbol{y}$ (for $y > 0 > x$). Tanaka et al. (2010) assume a piecewise power function defined as follows:

$$v(x) = \begin{cases} x^{\sigma} & for\ x > 0 \\ -\lambda(-x)^{\sigma} & for\ x < 0 \end{cases} \tag{3}$$

With this specification, $\boldsymbol{\sigma}$ and $\boldsymbol{\lambda}$ represent the concavity of the value function and the degree of loss aversion respectively (we use the term *value* or *utility function* in reference to Equation (3), below).

To elicit the three parameters we use the TCN method. First, the respondent faced three series of paired lotteries, as shown in Table 1. Each row contains the possible outcome in Mexican pesos for Lottery A and Lottery B. The probabilities of the outcomes in both lotteries are fixed throughout the series. The TCN experimental design enforced monotonic switching by asking the subjects at which question they would change from Lottery A to Lottery B. Respondents could change to Lottery B at the first question or they could stay with Lottery A throughout.

We follow Tanaka et al. (2010) in order to estimate the structural parameters. With the parametric function in the first series, it is possible to find an interval for σ and α. It is worth noting that we used only rounded midpoints for this interval. For example, a subject changing from A to B in the 7th scenario of the first series would first have the following rationalizable (α, σ) combinations: (0.4, 0.4), (0.5, 0.5), (0.6, 0.6), (0.7, 0.7), (0.8, 0.8), (0.9, 0.9), and (1, 1).[15] If this same subject changes from A to B in the 7th scenario of the second series, his or her rationalizable combinations of (α, σ) would be: (0.8, 0.6), (0.7, 0.7), (0.6, 0.8), (0.5, 0.9), and (0.4, 1). By intersecting both parameters we get the approximation of the parameters $(\alpha, \sigma) = (0.7, 0.7)$.

Finally, the loss aversion parameter λ is partially identified with the third series. Here the TCN method assumes that σ is correctly identified in the previous series. Using the value of σ we are able to identify λ in an interval. Series 3 was constructed to assure similar values of λ across different levels of σ. Table 2 shows examples of the interval of λ given some fixed values of σ.

4 Data Analysis

The experiment included 700 subjects; however, 93 questionnaires were discarded before data analysis because they showed a clear disregard of the instructions or an unwillingness to take the experiment seriously. Discarded questionnaires showed

[15] Rationalizable combinations are those parameters that satisfy the condition that Lottery B provides more utility than lottery A.

inconsistencies in the sociodemographic questions or errors in the risk aversion section.[16]

Our final experimental data thus consists of 607 subjects, where 53 percent of the sample comes from the private university and the remainder from the public one; summary statistics are presented in Table 3, Column 1. The average values are reasonable for the subject population of Mexican college students. Fifty-five percent of the respondents are male and the average age is almost 21 years (in Mexico most students begin college at 18). Only 30 percent of our experimental sample had scholarships, and subjects worked an average of 4 hours per week (the mean here is low because most do not work at all). The average student is in the middle of his or her education (in Mexico it takes 4.5 years to graduate from college). The average parent (father or mother) has at least a high school diploma. We use the number of bedrooms and cars in the family household as proxy variables for family income: they have on average 3.5 rooms and 2 cars. After they graduate they expect to earn an average of $14,535 Mexican pesos per month (approximately $1,100 USD).

Working with emotions is complicated because it may be argued that subjects are not feeling the emotions when they respond. Nevertheless, some psychological literature argues against this criticism. Field studies on drama advertising, like Escalas and Stern (2003), find a high degree of emotional reaction in subjects reading fictional dramatic situations. They also show that the emotional response is sympathetic and empathic, in contrast with previous studies that found only an empathic reaction. Shu et al. (2011) also found a change in moral behavior when an ethics code is read before taking a test. As already mentioned, Feagin (1988) showed that real emotions can be

[16] For example, subjects who marked multiple switching points where they were supposed to mark only one.

produced from fictional situations. With these observations in mind, the remaining concern is the causality of the emotion with respect to risky attitudes. Addressing this issue, Table 3 contains the results of the randomization test on means of the emotional treatment. None of the differences are statistically significant. This means that the characteristics of subjects are random between treatment and control groups, so we can interpret the role of emotions on risk attitudes as causal.

5 Results

In our sample the average elicited value for the curvature of the value function ($\boldsymbol{\sigma}$) is 0.471, which is reasonably close to the findings of $\boldsymbol{\sigma}$=0.58 in Tanaka et al. (2010) and $\boldsymbol{\sigma}$=0.48 in Liu (Forthcoming). If we assume that the EU axioms hold, the relative risk aversion coefficient $\boldsymbol{r}$ is 0.53. A kernel distribution of the parameter is presented in Figure 1, which shows that the majority of the respondents are located around 0.5, a common result in the risk aversion literature. This result suggests that our experiment was implemented correctly, and that an experiment with uncompensated subjects does not affect the curvature of the value function.

In order to link the demographic and socioeconomic characteristics with the curvature of the CPT function, we conducted the following OLS regression:

$$\sigma_i = \sum X_i \beta_i + \sum E_i \gamma_i + \epsilon_i \tag{4}$$

where X denotes observable characteristics and E denotes emotions. Table 4 presents the results for four different models. The first column includes sociodemographic characteristics (No Treatment). The second column adds emotions referring to questions about violence (Moderate Treatment). The third column includes dummy variables of emotions reported in both questions (Either Treatment). In other words, the dummy variable of anger takes a value of 1 when an individual responds with the emotion of anger for either the violence or the youth unemployment question. The fourth column captures the intersection of both questions (Strong Treatment).[17]

The results show a positive impact of age over the value of sigma of the value function. The same effect occurs with years left until graduation. Both effects can be interpreted as a decrease in risk aversion (higher curvature) level in the gain domain, but they may also be interpreted as a decrease in risk willingness in the loss domain. These results are in agreement with the literature (Harrison and Rutström, 2008; Halek and Eisenhauer, 2001; Donkers et al., 2001). The common explanation for this phenomenon comes from the idea that older people are capable of taking more risks when there is an opportunity to win, but they also have experience that tells them it is better to lose a little when faced with the possibility of losing a lot.

Also consistent with previous literature (Hartog and Diaz-Serrano, 2007; Dohmen et al. 2010; Shaw, 1996), the level of curvature σ in the four models increases with the proxy variables for income (automobiles and rooms). In contrast to studies reporting gender differences in risk aversion (Croson and Gneezy, 2009; Eckel and Grossman, 2008), we do not find any significant gender effect. Nor do we find any relation of cognitive ability, as measured by GPA, to the curvature of the utility function.

Estimating the effect of emotions on the curvature of the utility function was one of the key goals of this study. Columns 2 to 4 show the main results. Among possible emotions, there is a statistically significant link between sadness and the curvature parameter σ (-0.077). On average, risk aversion over gains increases strongly when

[17] We also conducted an OLS regression using just a dummy variable for treatment (equal to one when the individual received either framing). In any framing event or combination of events, there were no significant effects. This response is possibly due to the fact that emotional reactions may have opposite effects: sad people may be less risk averse but angry ones may be more risk loving.

people are sad. As a consequence, public policy relying on credit incentives or risky business opportunities may not have the desired effect if the average feeling in the population is consistent with depression. Our result also implies that sad people will take more risk when trying to avoid a certain loss. Numerous situations in real life cause sadness: natural disasters, unemployment, economic crises. Our results imply that these events may affect real outcomes through the channel of emotions. As aforementioned, fear has been associated with risk aversion in the literature, however we do not find a significant result (see Lerner et al. 2003). One possible explanation might be that our treatments did not induce the levels of fear required to affect the behavior under uncertainty. In the study of Lerner et al. (2003), the fear emotion was induced by recalling the September 11th terrorist attacks. This event was common knowledge for almost every American citizen. In contrast, in our study we only use students that reside in Mexico City where no drug war occurs. Although the students report to have fear about the situation, their security is not directly in danger. Hence, a possible explanation for not finding an effect of fear on risk is that students were not induced with the required level fear to change behavior.[18]

In our sample, the average loss aversion parameter λ is 2.29, which is close to that elicited in Tanaka et al. (2010), 2.63, but closer to the finding of Tversky and Kahneman (1992), 2.25. Figure 2 presents a kernel distribution of the lower limit of λ. It shows that agents have a loss aversion coefficient around 2.5, which then starts descending. The hypothesis of Kahneman and Tversky (1979), that people feel twice as strongly about losing something than winning it, thus seems appropriate for our sample.

[18] In fact the study of Stemmler et al. (2001) reveals that imaginative fear does not exhibit the same physical reactions than real fear. In contrast, there is no physical diference between real and imaginative anger.

To estimate the relation between the characteristics and the loss aversion coefficient, it is necessary to use a maximum likelihood interval regression. Again, we present the same four models of Equation (4), each one corresponding to different emotional treatments (or none):[19]

$$\lambda_i = \sum X_i \beta_i + \sum E_i \gamma_i + \epsilon_i \qquad (5)$$

Table 5 shows the main results. In contrast to the results in Table 4, the loss aversion parameter is not correlated with demographic characteristics. Tanaka et al. (2010) also find no strong correlations on this parameter. However, we find a significant effect of being a student in a private university on the loss aversion parameter: if the individual attends a private university, the average degree of loss aversion increases by 1.25. This result implies that students from private universities suffer more from a loss, relative to a gain, than those studying at a public institution. Although we cannot disentangle the reasons for the effect, we believe it may be due to differences in self-confidence of students across university types. The fact that newspapers, for example, generally rank students from private universities above public ones in terms of employability (*Reforma*, 2012) should reinforce self-confidence in students of private universities. Consistent with this hypothesis, Ahn (2010) finds that loss aversion increases with self-confidence in a repeated laboratory experiment.[20]

With respect to wealth, we find that an increase in our proxy variable for income decreases the level of loss aversion, although the effect is significant only at the 10% level. Tanaka et al. (2010) find a similar result and argue that wealthier villages tend to invest more, given the fact that they are less loss averse. This suggests that poor people

[19] Again, we find no evidence of a significant change in λ just for receiving the treatment.
[20] In other words, we expect that students from private universities suffer more from the endowment effect (Amir et al., 2008; Hossain and List, 2009; Kahneman et al., 1990)

would be reluctant to attempt risky business opportunities and would dislike losing, so a greater compensation for losses in terms of utility is needed to encourage poorer people to take those risks. This is an important implication for public policy.

Columns 2 to 4 in Table 5 show the role of emotions on the loss aversion parameter. In the strong emotional treatment (which is in fact the most accurate, given the fact that individuals report the same emotion in both questions), anger reduces the degree of loss aversion by 1.101. In percentage terms, other factors being equal, anger reduces loss aversion by an average of 52 percent (the mean value of loss aversion is 2.3). This implies that angry individuals are less sensitive to losses and suffer less from the endowment effect (such people would not hold their bonds too long when prices fall).

Finally, in our sample the average value of Prelec's weighting parameter α is 0.713, extremely close to the findings in Tanaka et al. (2010) (the average weighting function is shown in Figure 3). It is clear that individuals overestimate probabilities under 0.4 (overestimating even more as probabilities approach zero), but start to underestimate them above that level (underestimating more around 0.8). The kernel distribution of α is presented in Figure 4, where it clearly shows a great accumulation around 0.7 and diminishes on both sides.

We conduct the same regression analysis on α but do not find any significant effect.[21] Figure 5 presents the average value function (Equation 3) and the main results of the study in terms of emotions. On average, the function shows concavity on the gain domain and convexity on the loss domain. It also shows a steeper slope over the loss

[21] Results are available upon request.

domain than the gain domain, as in the seminal contribution by Tversky and Kahneman (1992).

Panel A of Figure 5 shows that sadness causes less risk aversion in the gain domain and more risk willingness in the loss domain. Panel B shows that anger decreases loss aversion, with the loss domain almost a mirror image of the gain domain. Indeed, anger has a larger impact on the loss domain than sadness: anger decreases loss aversion by close to 50 percent.

6 Discussion and Concluding Remarks

We conducted a controlled experiment using students in two universities as uncompensated subjects to elicit the parameters of the value and weighting function of Cumulative Prospect Theory. On average, we find (σ, λ, α) = (0.471, 2.29, 0.713), implying that people in our experiment are risk averse on gains and risk loving on losses, that they suffer from loss aversion, and that they did not use true probabilities at the time of evaluation. Although our study subjects were uncompensated, these parameters are very close to the findings of Tversky and Kahneman (1992), Liu (Forthcoming), and Tanaka et al. (2010), which is consistent with the compensated and uncompensated experiments in Holt and Laury (2002).

We also analyze the relationship between the structural parameters and sociodemographic characteristics. For the curvature function, we find evidence that older and wealthier people are less averse in the gain domain but lean toward less risk taking in the loss domain. We find that being a student in a private university increases loss aversion, and our proxy for income shows that increased income reduces loss aversion. Finally, the weighting probability function does not vary with sociodemographic characteristics.

An important contribution of this paper relates to estimation of the impact of emotions on the structural parameters in Cumulative Prospect Theory. In our controlled experiment, one-third of the subjects received a questionnaire that asked how they felt about the rising rate of violence and deaths in Mexico. Another third received in addition a question about their feelings regarding youth unemployment. The final third was a control group that did not receive any questions about violence or unemployment.

Consistent with Lerner et al. (2003), we find that risk aversion is related to emotional state. In particular, we find that sad people are more risk averse in the gain domain. We also find that angry people are less loss averse than non-angry people. In fact, on average, anger reduces loss aversion by half. This could be a sympathetic reaction, or it could be that anger fuels the strength to quickly forget a loss. Further research in neuroeconomics is needed in order to gain a deeper understanding of this mechanism.

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Table 1: Three Series of Pairwise Lottery Choices (in Mexican pesos)

Option A		*Option B*		*Expected payoff difference (A-B)*
Series 1				
P=3/10	*P=7/10*	*P=1/10*	*P=9/10*	
40	10	68	5	7.7
40	10	75	5	7.0
40	10	83	5	6.0
40	10	93	5	5.2
40	10	106	5	3.9
40	10	125	5	2.0
40	10	150	5	-0.5
40	10	185	5	-4.0
40	10	220	5	-7.5
40	10	300	5	-15.5
40	10	400	5	-25.5
40	10	600	5	-45.5
40	10	1000	5	-85.5
40	10	1700	5	-155.5
Series 2				
P=9/10	*P=1/10*	*P=7/10*	*P=3/10*	
40	30	54	5	-0.3
40	30	56	5	-1.7
40	30	58	5	-3.1
40	30	60	5	-4.5
40	30	62	5	-5.9
40	30	65	5	-8.0
40	30	68	5	-10
40	30	72	5	-12.9
40	30	77	5	-16.4
40	30	83	5	-20.6
40	30	90	5	-25.5
40	30	100	5	-32.5
40	30	111	5	-39.5
40	30	130	5	-53.5
Series 3				
P=1/2	*P=1/2*	*P=1/2*	*P=1/2*	
25	-4	30	-21	6.0
4	-4	30	-21	-4.5
1	-4	30	-21	-6.0
1	-4	30	-16	-8.5
1	-8	30	-16	-10.5
1	-8	30	-14	-11.5
1	-8	30	-11	-13.0

Note: This table is the same as Table 4 in Tanaka et al. (2010).

Table 2: Lambda Identification Given Sigma

Switching Scenario	$\sigma = 0.1$	$\sigma = 0.5$	$\sigma = 1.5$
0	λ <0.123	λ <0.184	λ <0.445
1	0.123< λ <1.237	0.184 < λ <1.346	0.445 < λ <1.771
2	1.237< λ <1.955	1.346 < λ <1.733	1.771 < λ <1.85
3	1.955 < λ <2.371	1.733 < λ <2.384	1.85 < λ <2.91
4	2.371< λ <4.584	2.384 < λ <3.281	2.91 < λ <3.947
5	4.584< λ <5.717	3.281< λ <4.9	3.947 < λ <5.49
6	5.717 < λ <10.1693	4.9 < λ <9.17	5.49 < λ <11.787
7	10.1693 < λ	9.17 < λ	11.7872 < λ

Note: This table corresponds to Table 5 in Tanaka et al. (2010).

Table 3: Randomization Test on Means of Emotions

Variables	All	Control	Emotional Treatment	Difference
	[1]	[2]	[3]	[4]
Male	0.55	0.53	.54	-0.009
	(0.000)	(0.034)	(0.024)	(0.043)
Years before graduating	2.34	2.39	2.30	0.09
	(0.001)	(0.088)	(0.060)	(0.107)
Age	20.84	20.77	20.86	-0.09
	(0.002)	(0.162)	(0.104)	(0.192)
Last semester's GPA	84.64	85.00	84.46	0.53
	(0.008)	(0.726)	(0.490)	(0.877)
Number of bedrooms in	2.18	3.54	3.57	-0.03
the family household	(0.001)	(0.105)	(0.062)	(0.122)
Number of cars in the	3.56	2.05	2.25	-0.19
family household	(0.001)	(0.106)	(0.082)	(0.134)
Private University	0.53	0.53	0.53	0.00
	(0.000)	(0.035)	(0.020)	(0.042)
Father's educational	3.40	3.33	3.43	-0.10
level	(0.001)	(0.065)	(0.045)	(0.079)
Mother's educational	3.26	3.18	3.30	-0.12
level	(0.001)	(0.067)	(0.044)	(0.081)
Number of siblings	1.62	1.62	1.62	0.00
	(0.001)	(0.080)	(0.054)	(0.097)
Scholarship	0.31	0.31	0.31	0.00
	(0.000)	(0.032)	(0.023)	(0.040)
Hours worked last week	4.73	5.10	4.50	0.55
	(0.009)	(0.793)	(0.548)	(0.964)

Notes: Calculations by the authors. Means and standard errors obtained from the final data set. The third column (Emotional Treatment) contains the information of those students who took the experiment with one question (moderate treatment) or two questions (strong treatment). Educational options were: 1. Completed Primary or less (less than 8 years of schooling), 2. Completed Junior High School (9 to 11 years of schooling), 3. Completed High School (12-15 years of schooling), 4. Completed College (16 and more years of schooling).

Table 4: Regression Analysis: Curvature Parameter (σ)

Variable	No Treatment	Moderate Treatment	Either Treatment	Strong Treatment
	[1]	[2]	[3]	[4]
Male	-0.033	-0.032	-0.030	-0.032
	(0.025)	(0.026)	(0.025)	(0.026)
Years before Graduation	0.025*	0.026**	0.025**	0.026**
	(0.013)	(0.013)	(0.012)	(0.013)
Age	0.015**	0.016**	0.014**	0.015**
	(0.007)	(0.007)	(0.007)	(0.007)
Last Semester Average GPA	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Number of Bedrooms	0.023*	0.022*	0.024*	0.023*
	(0.012)	(0.013)	(0.012)	(0.013)
Number of Automobiles	0.024*	0.023*	0.023*	0.024*
	(0.012)	(0.013)	(0.012)	(0.013)
Private University	-0.031	-0.032	-0.028	-0.028
	(0.032)	(0.032)	(0.0324)	(0.032)
Anger	/	0.036	0.020	0.034
	/	(0.040)	(0.029)	(0.056)
Sadness	/	-0.111***	-0.096***	-0.077***
	/	(0.049)	(0.035)	(0.039)
Fear	/	0.009	0.002	0.017
	/	(0.037)	(0.025)	(0.040)
Constant	-0.107	-0.120	-0.075	-0.103
	(0.202)	(0.197)	(0.703)	(0.199)
No. of Observations	577	577	577	577
R-squared	0.034	0.045	0.047	0.037

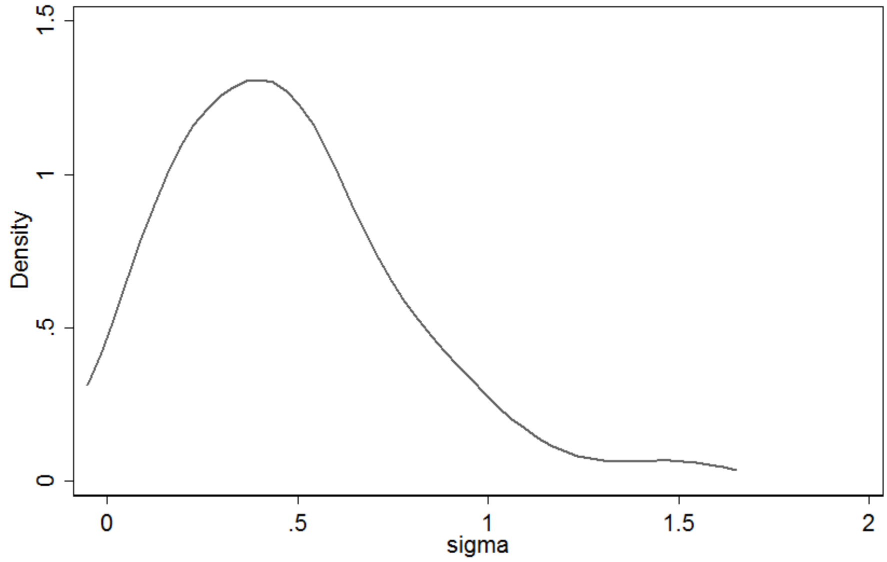
Notes: Calculations by the authors. Significance levels are denoted as * 10%, ** 5% and *** 1% respectively. Standard errors are in parentheses.

Table 5: Interval Regression Analysis. Loss aversion (λ)

Variable	No Treatment	Moderate Treatment	Either Treatment	Strong Treatment
	[1]	[2]	[3]	[4]
Male	0.591	0.596	0.558	0.542
	(0.402)	(0.404)	(0.398)	(0.404)
Years before Graduation	-0.122	-0.114	-0.117	-0.141
	(0.209)	(0.210)	(0.208)	(0.208)
Age	-0.072	-0.068	-0.064	-0.068
	(0.110)	(0.110)	(0.109)	(0.110)
Last Semester Average GPA	0.023	0.025	0.022	0.023
	(0.016)	(0.016)	(0.016)	(0.016)
Number of Bedrooms	-0.060	-0.066	-0.061	-0.056
	(0.145)	(0.144)	(0.144)	(0.145)
Number of Automobiles	-0.219*	-0.203	-0.242*	-0.225*
	(0.129)	(0.128)	(0.127)	(0.129)
Private University	1.306***	1.200**	1.234***	1.258***
	(0.483)	(0.482)	(0.479)	(0.482)
Anger	/	-0.369	-0.566	-1.101***
	/	(0.474)	(0.412)	(0.497)
Sadness	/	1.172	1.054	-0.183
	/	(0.821)	(0.704)	(0.978)
Fear	/	0.583	0.947**	0.056
	/	(0.471)	(0.405)	(0.458)
Constant	-0.107	1.064***	1.469***	1.687***
	(0.202)	(2.990)	(2.962)	(2.962)
No. of Observations	577	575	575	575

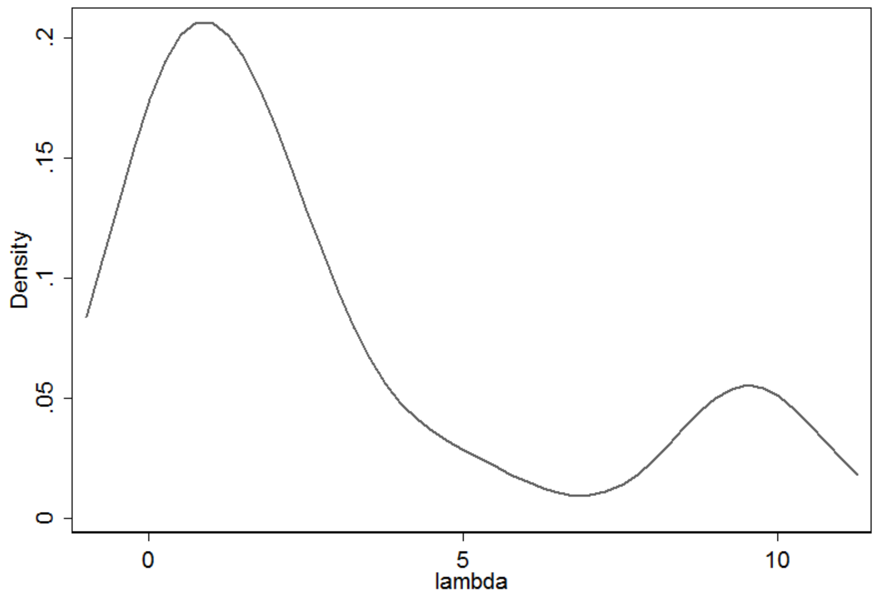
Notes: Calculations by the authors. Significance levels are denoted as * 10%, ** 5% and *** 1% respectively. Standard errors are in parentheses.

Figure 1: Curvature Parameter (σ) Kernel Density Estimate



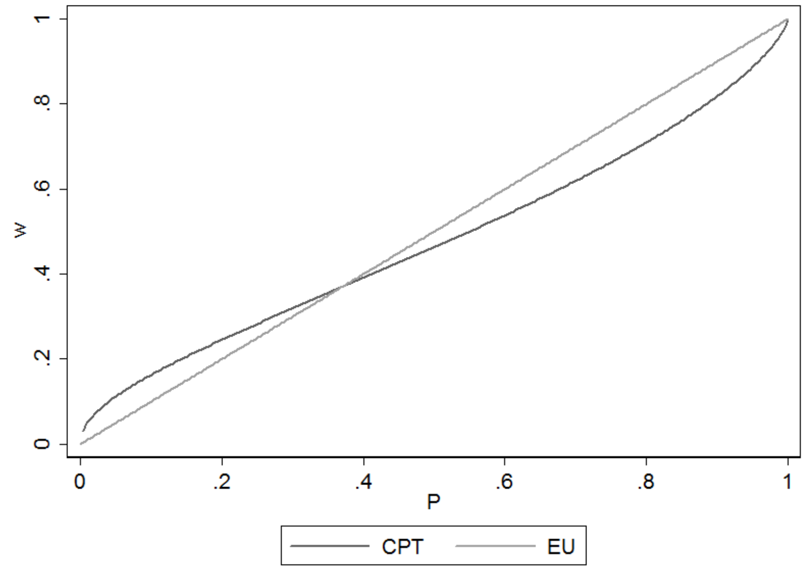
Notes: Calculations by the authors. Gaussian kernels with a bandwidth of 0.15. The kernel estimation was conducted with 607 observations from the final data set where sigma was different from missing.

Figure 2. Loss Aversion Parameter (λ) lower bound Kernel Density Estimate



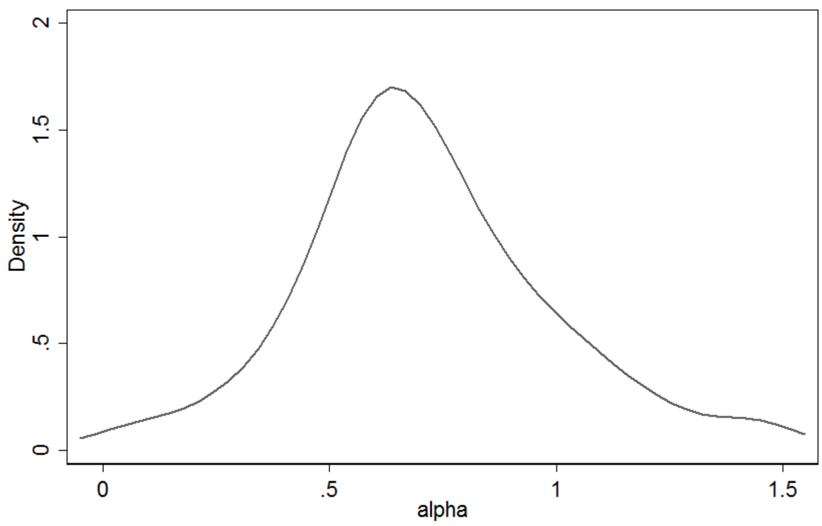
Notes: Calculations by the authors. Gaussian kernel with a bandwidth of 1.1.,The kernel estimation was conducted with 607 observations from the final data set where lambda was different from missing.

Figure 3: Average Weighting Function



Notes: Calculations by the authors. Simple average of α taken from the final data set.

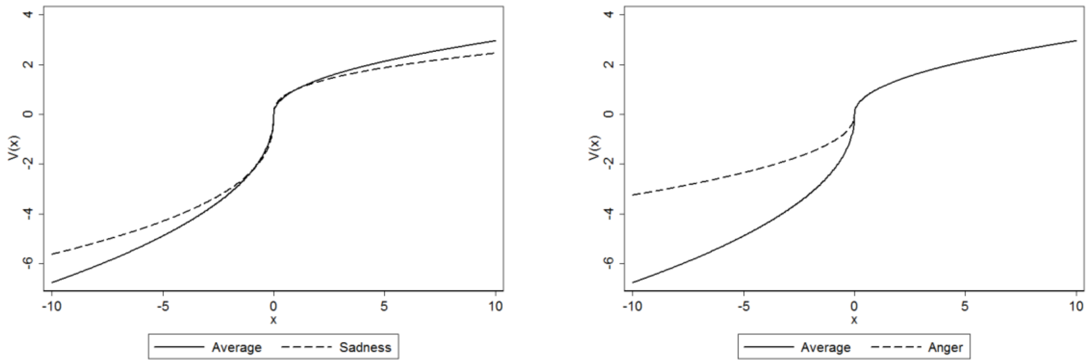
Figure 4: Prelec's One-Parameter (α) Kernel Density function



Notes: Calculations by the authors. Gaussian kernels with a bandwidth of 1. The kernel estimation was conducted with 607 observations from the final data set where alpha was different from missing.

Figure 5: Average Value Function and Emotions

Sadness   Anger



Notes: Calculations by the authors. Simple average taken from the final data set using Equation (3). Panel A uses σ = 0.47 and λ= 2.29 in the average function; the function with sadness uses σ = 0.39 and λ= 2.29. Panel B uses uses σ = 0.47 and λ= 2.29 in the average function; the function with anger uses σ = 0.47 and λ= 1.19.