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The Relationship between Farmers' Shock Experiences and their Uncertainty Preferences – Experimental Evidence from Mexico

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Abstract

A farmer's uncertainty preferences can play a large role in how he makes production decisions on the farm. We attempt to understand how farmers' household characteristics as well as past harvest shocks affect uncertainty preferences of maize farmers in southern Mexico. By using a series of incentivized lottery games, we estimate coefficients that correspond to Cumulative Prospect Theory, namely the probability weighting function, the curvature of the value function and loss aversion, along with a coefficient for ambiguity aversion. These are estimated controlling for survey data of sociodemographic characteristics as well as maize harvest losses incurred between 2012-2014. Our results provide evidence that having experienced more severe harvest losses leads to more risk aversion and stronger overweighting of small probabilities. Higher losses are not related to loss aversion or ambiguity aversion.

JEL classifications: D810; Q120; Q540

Keywords: Risk Aversion; Prospect Theory; Ambiguity; Natural Disaster; Farmers

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1. Introduction

There is now vast evidence that farmers in developing countries tend to be risk averse, as first analyzed by Binswanger (1980), and face high degrees of uncertainty with respect to their production (Roumasset 1974; Just and Pope 1979). It is also a well-known finding that risk aversion inhibits the use of new, productivity increasing technologies and inputs, such as fertilizers and improved seeds (Feder et al. 1985; Rosenzweig and Binswanger 1993; Knight et al. 2003; Engle-Warnick et al. 2011; Dercon and Christiaensen 2011; Liu 2013; Verschoor et al. 2016). In this way, risk aversion may lock poor agricultural households into poverty traps (e.g. Carter and Barrett 2006).

To better understand the lack of consensus on how farmers' sociodemographic background, decisions and experiences are related to their risk preferences, researchers have gained interest in eliciting these preferences experimentally in the field (Binswanger 1980; Miyata 2003; Engle-Warnick et al. 2011; Tanaka et al. 2010; Liu 2013; Gloede et al. 2015; Said et al. 2015). As compared to deriving risk preferences from observational data, experiments allow for the distinction between mere risk response, which could originate from other constraints, rather than from more innate risk preferences (Just and Pope 2003). The majority of studies to date however elicit only a single parameter of the utility function, namely its curvature, assuming a certain functional form grounded in Expected Utility Theory, or use ordinal, non-parametric measures for risk aversion based self-assessment scales. These may not allow accommodating a range of observed anomalies of behaviors in the field (Just and Pope 2003). Also, if loss aversion is not accounted for, it may act as a confounding factor for risk aversion (Crosetto and Filippin 2013).

Only a few authors have broken down risk preference along the lines of (Cumulative) Prospect Theory (Kahneman and Tversky 1979; Tversky and Kahneman 1992), estimating separately individual parameter for the curvature of the value function, loss aversion and non-linear probability weighting. The seminal contribution by Tanaka et al. (2010) offers an experimental approach to do so. Allowing for a wider range of individual-specific parameters describing behavior under uncertainty also proved more accurate in predicting individual choices (Gloeckner and Pachur 2012).

Furthermore, broader concepts of decision making take into account uncertainty as the sum of risk (the measurable component) and ambiguity (the immeasurable component). Ambiguity theory considers the cases where individuals are not able to assign unique probabilities to possible outcomes, but form subjective beliefs over probability distributions (Ellsberg 1961). These subjective beliefs are not neutral, as proposed by subjective Expected Utility Theory, but utility is decreased through uncertainty about probabilities depending on the degree of ambiguity aversion (Halevy 2007). Ambiguity aversion hence describes the relative disutility generated by subjective beliefs about probability distributions of payouts, compared to uncertainty generated by objective lotteries (Klibanoff et al. 2005). In the context of farming, research has shown that ambiguity aversion plays a role in technology adoption, as with new technologies such as improved seeds the probability distributions of the harvest output are generally unknown ex-ante (Barham et al. 2014; Engle-Warnick et al. 2011; Liu 2013).

Researchers have yet to build a consensus on how risk preferences vary with different sociodemographic characteristics or past experiences, such as the experiences of catastrophic shocks and losses (Said et al. 2015). Why is this important? If one aims to predict, for example, the technology adoption behavior of farmers from their experimentally elicited risk preferences, the meaningfulness of this relies on the assumption that these preferences are stable over time and with changing circumstances (Zeisberger et al. 2012), such as recent severe harvest loss experiences.

Against this background, the objective of this paper is to (1) estimate farmers' risk aversion, loss aversion, probability weighting and ambiguity aversion parameters, (2) relate them to the sociodemographic characteristics of their households, and furthermore (3) to analyze how the severity of experienced harvest losses affects them. Thereby we extend the existing literature explaining variation in uncertainty preferences by past adverse shock experiences by looking at a broader set of variables that characterize one's behavior under uncertainty. We, therefore, exploit survey data of Mexican maize farmers regarding their recent experiences of harvest shocks and use them in our estimations of prospect theory preference parameters and ambiguity aversion. Evidence suggests that shocks by natural disasters are a significant driver of poverty dynamics in Mexico (Rodriguez-Oreggia et al. 2013). While the works by Li et al. (2011) and Reynaud and Aubert (2013) address the more general effect of natural disasters on risk aversion and probability weighting, this is the only study to investigate the relationship of harvest loss experiences on all three prospect theory parameters, simultaneously also taking into account ambiguity aversion. Additionally, we include a wide range of sociodemographic variables into our analysis that allows us to put our findings in the context of the existing literature, for which we also give an extensive overview, which has not been systematically done up to date.

The rest of the paper is structured as follows. In Section 2, we present a review of the literature on stability of uncertainty preferences and the factors found to explain preference variation. Section 3 explains our sampling region and data collection strategy. In Section 4 we present our conceptual framework to elicit preference parameters according to Cumulative Prospect Theory as well as ambiguity aversion, followed by the experimental design in Section 5. Section 6 presents our estimation strategy, Section 7 and 8 present our results and Section 9 concludes the paper with a discussion of the results and policy implication.

2. Literature review and hypotheses generation

2.1. Stability of uncertainty preferences

There have been various attempts to investigate the long-term stability of risk preferences, or related to that, how risk-taking is affected by prior gain or loss experiences. For example, Harrison et al. (2005) show that constant relative risk aversion (CRRA) coefficients measured at two distinct points in time over a span of 5-6 months do not change significantly. Andersen et al. (2008) find similar results. However, there are only a few studies that look at the stability of preferences derived from Cumulative Prospect Theory (in the following, CPT) over time. Baucells and Villasis (2006) confirm the stability of the “reflection effect” over time, i.e. the phenomenon of risk averse behavior for gains and risk seeking behavior for losses. Zeisberger et al (2012) and Wölbert and Riedl (2013) show that respondents’ probability weighting, loss aversion and value function remain consistent over several weeks’ time. Duersch et al. (2017) find stability over time for the ambiguity aversion estimates for 57% of their subjects.

These results indicate a general tendency of preference stability over time, which is in line with normative economic theory, insisting that decision makers only take into account incremental outcomes. However, it is rarely the case that decisions are truly made in temporal isolation, but are generally taken in the light of preceding outcomes (Thaler and Johnson 1990). Behavioral theories leave room for behavioral learning, for example for changes in observable exogenous factors (Brunnermeier and Nagel 2008; Malmendier and Nagel 2011), or more specifically, shocks (Voors et al. 2012; Said et al. 2015).

2.2. Shock experiences and uncertainty preferences

Several behavioral heuristics may play a role when risk preferences change after experiencing a shock, even without having direct personal consequences in form of losses: the availability heuristic, inducing decision makers to assess likelihood of an event based on most readily available information, the representative heuristic that causes subjects to overweight more salient events (Tversky and Kahneman 1974) and the associativeness heuristic (Mullainathan 2002). Associativeness refers to the notion that events may affect beliefs through the memories they invoke and may result in an overreaction to contemporary information, as completely uninformative signals can influence beliefs by affecting what one recalls. By these heuristics, however, the direction of a change in risk preferences after a shock, i.e. inducing more or less risk aversion, is not predetermined.

The experience of natural disasters and shocks may also change individuals' perceptions of the background risk they are facing, even when they do not involve personal losses (Cameron and Shah 2015). Background risk refers to non-diversifiable, non-insurable risk, usually thought of as zero-mean and independent of other risks. What is the effect of an increase background risk on risk preferences? There is contradicting evidence, both from theory and empirics. On the one hand, Gollier and Pratt (1996) demonstrate in their model that a rise in background risk causes expected utility maximizing individuals to make less risky choices; a behavior referred to as "risk vulnerability". Providing an empirical test, Guiso and Paiella (2008) support this hypothesis, finding that investors facing income uncertainty or a risk of becoming liquidity constrained exhibit a higher degree of absolute risk aversion. Beaud and Willinger (2014) provide additional evidence for this phenomenon. Hence, when perceived background risk increases over time, it may make subjects become more risk averse. On the other hand, there is empirical evidence of marginal diminishing sensitivity, suggesting that in already risky environments the addition of a small independent risk should not have an influence on behavior or even decrease risk aversion (Kahneman and Tversky 1979). This notion is supported by the theoretical work of Quiggin (2003) for different utility function specifications.

Treating successive harvests as a form of sequential gambles, CPT would predict an increase in risk taking following losses when decisions are evaluated jointly in the same choice bracket (Read et al. 1999), i.e. losses are integrated with subsequent outcomes and reference points are not (yet) updated accordingly. Then, from their perspective, subjects make choices in the "loss" domain, where they act risk loving (Kahneman and Tversky 1979). Thaler and Johnson (1990) argue that more risk taking will only occur if the risky prospect gives subjects the probability to break-even, i.e. to return to the prior reference point. When each gamble is evaluated separately within a single choice bracket, i.e. when decisions are narrowly framed, then reference points change after experiencing losses, in which case CPT would predict a decrease in risk taking. When the subsequent risky prospect does not allow the possibility to break-even, then quasi-hedonic editing comes into play. Under quasi-hedonic editing, subjects cannot integrate future outcomes with prior outcomes. Hence, more risk aversion would be observed after losses and more risk taking after gains; the latter is referred to as house money effect (Thaler and Johnson 1990). Accommodating these contrasting findings, Imas (2016) presents a model distinguishing between "realized" losses, those leading to an updating of the reference point and not integrated with future outcomes, and "paper" losses, those evaluated in the same mental account with future outcomes. In empirical studies it is hard to determine the appropriate reference point for a decision maker; usually the status quo or current assets holdings are referred to (Kahneman and Tversky 1979). When estimating risk and loss aversion in experiments one generally sets the reference point exogenously at zero for simplicity (e.g. Bocquého et al. 2014). In our context, that seems reasonable as it appears unlikely that harvest losses from the last season(s) are evaluated in a joint mental account with outcomes in the lab, which involve lower stakes the do not allow for the recapturing of potential severe harvest failures.

Nevertheless, it is proposed in the literature that losses, even when not evaluated in a joint mental account, may make individuals more loss averse in future decision making situations involving losses (Barberis et al. 2001). Losses, they argue, are more painful after prior losses because of an increased sensitivity. Alternatively, the experience of losses may make the possibility of losses appear more salient in current choice options, for which decision makers overweight loss outcomes and behave more loss aversely (Bordalo et al. 2012).

Personal experience of losses can also lead to a change in subjectively perceived probabilities of incurring the same losses again. Menapace et al. (2013) find that past harvest loss experiences significantly increased farmers' perceived likelihood of recurring losses in the current growing season. Whether this changes the generic probability weights they give to any risky outcome is not clear, though. From this result however it seems plausible to infer that the experience of losses may change how farmers view small probabilities of outcomes and potentially change the weight they give to them. Heterogeneity in probability weighting has been scarcely studied to date (Fehr-Duda et al. 2011). Walther (2003) presents a model in which non-linear probability weighting emerges as a result of anticipating either elation or disappointment when the uncertainty of a prospect is resolved. His model predicts that higher sensitivity to anticipated emotions when resolving uncertainty leads to a higher degree of probability distortion. In a similar vein, Fehr-Duda et al. (2011) show that the degree of probability weighting is affected by current mood, and that subjects reporting a below-normal mood had a more inflected weighting function, a result similar to Kliger and Levy (2008) analyzing US investor data. Even though the conceptual link is not so straight forward, it seems very reasonable that probability weighting is affected by the experience of low-probability shocks (Reynaud and Aubert 2013). It could be the case that after experiencing severe harvest losses, farmers may generally be in a more aggrieved mood, which could distort their weighting of probabilities over risky outcomes. Similarly, it could make them more wary towards ambiguity and hence less likely to choose ambiguous gambles.

Only a few empirical field experiments explicitly address the effects of exogenous shocks on uncertainty preferences, finding little consensus. Table 1 gives an overview of relevant studies and the found effects. Most of them deal with risk preference changes after natural disasters in a between-subject comparison. In the follow we highlight select studies involving samples from developing countries. Bchir and Willinger (2013), for instance, find more risk seeking behavior amongst the poorer population in areas affected by mudflows. Gloede et al. (2015) analyze how self-reported risk preferences are related to the number and type of shocks experienced by a large sample. The authors find that having experienced agricultural shocks made respondents more risk averse in Thailand, while in Vietnam demographic and idiosyncratic shocks led to more risk aversion. Said et al. (2015) elicit risk preferences in the aftermath of the 2010 flood in Pakistan. They find that people living in a flood-affected area display, on average, more risk-seeking behavior, while personally having experienced flood losses made people behave more risk aversely. Cameron and Shaw (2015) relate risk preferences to experiences of earthquakes and floods. They find that those subjects recently affected by one of those natural disasters were more likely to be risk averse, while the number of disasters or the total value of the damage experienced had only minor effects. Apart from that, the authors also find that flood experiences cause people to update the probability of another flood, and this perceived increase in background risk leads to higher risk vulnerability. Broadening the scope beyond just developing countries, Page et al. (2014) look at behavior in the aftermath of floods in Australia. They find that people who have lost large amounts in a flood are more risk seeking after the flood, hypothesizing that this is because they have hopes of gaining back what they had lost, which would be in line with the break-even hypothesis (Thaler and Johnson 1990).

Most research into the role of shocks on risk preferences to date, however, uses either simple non-parametric ways to classify risk preferences, or explicit utility function specifications within Expected Utility Theory (EUT) (Eckel et al. 2009; Gloede et al. 2015; Cameron and Shah 2015). Nevertheless, there is broad evidence of non-EUT preferences of both farmers in developed (Bocquého et al. 2014) and in developing countries (Tanaka et al. 2010; Brauw and Eozenou 2014; Petraud 2014). This makes it worthwhile to further study the effect of shocks in a CPT framework, which has only been done partially by a few authors before for developing countries. Voors et al. (2012) look at the effect of exposure to violent conflict in the context of the Burundi Civil War, on risk preferences while allowing for the reflection effect (Kahneman and Tversky 1979). The authors find that exposure to conflict increases risk seeking in the positive domain while it does not affect attitudes in the negative domain. Li et al. (2011) look at people in southern China who suffered from large amounts of snow in 2008 and people affected by the Sichuan earthquake in 2008. Their results show that after a shock respondents tended to be more risk seeking in the positive and more risk averse in the negative domain. They also find that respondents were more likely to overweight small probabilities. Reynaud and Aubert (2013) analyze the CPT parameters with rural Vietnamese household heads after a large flood. They find, similar to Voors et al. (2012), that respondents who experienced the flood were more likely to pick the safe lottery game in the loss domain and the riskier lottery in the gain domain. Expecting a future flood made people additionally behave more risk aversely, while the floods had no effect on the probability weighting function.

Table 1: Shock experience and uncertainty preference parameters by paper

Variables	**Risk aversion** Eckel et al. (2009)[1]	Li et al. (2011)[2]	Voors et al. (2012)[3]	Bchir & Willinger (2013)[4]	Reynaud &Aubert (2013)[5]	Page et al. (2014)[6]	Gloede et al. (2015)[7]	Said et al. (2015)[8]	Cameron & Shah (2015)[9]	**Probability weighting** Li et al. (2011)[2]	Reynaud &Aubert (2013)[5]
Shock experience:											
-positive domain		-**	-**		-**						
-negative domain		+**	Ns		+**						
-no distinction	-			-***		+	+***	+* (personal loss) -** (no personal loss)	+*	+**	Ns

* p < 0.1, ** p < 0.05, *** p < 0.01. P-values from tests used in the respective papers (where it applies).
Ns: not significant. + denotes a positive, - a negative effect of the respective variable on the parameter.
Blanks: variables were not tested in respective study.
Shocks and catastrophes analyzed:
1 Hurricane in the USA
2 Earthquakes and Major Snow in China
3 War in Burundi
4 Mudflows in Peru
5 Flooding in Indonesia
6 Flooding in Australia
7 Household survey with data on demographic, social, economic and agricultural shocks
8 Flooding in Pakistan
9 Flooding and Earthquakes in Indonesia

Source: Authors' own illustration

In the light of the aforementioned mixed findings, we formulate the following hypothesis without attempting to predict the direction of the relationships:

> **H1:** The severity of past harvest losses affects farmers' uncertainty preferences, namely probability weighting, risk, loss and ambiguity aversion.

2.3. Sociodemographic characteristics and uncertainty preferences

Research so far has not been able to build some consensus regarding the relation of a range of sociodemographic variables with uncertainty preferences. Table 2 and Table 3 show the fluctuation in evidence from selected studies with rural samples from developing countries on the role of most commonly used sociodemographic variables.

Table 2: Sociodemographic characteristics and risk aversion by paper

Variables	Binswanger (1980)[1]	Miyata (2003)[2]	Yesuf & Bluffstone (2009)[3]	Tanaka et al. (2010)[4]	Engle-Warnick et al. (2011)[5]	Liu (2013)[6]	Said et al. (2015)[7]	Gloede et al.(2015) *Sample 1*[8]	*Sample 2*[9]
Age	Ns	+*	+**	+**	Ns	Ns	-	+***	- **
Gender (Female)	+**		Ns	Ns	Ns	+**	Ns	Ns	Ns
Education	Ns	-***	Ns	+**	Ns	Ns		-***	-***
Income/ Wealth	-**	-**	-***	-*	-*	+**		-***	-***
Distance to Market				Ns					
Land Owned			-**		Ns	Ns			
Household Size		-*	Ns		-**				

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. P-values from tests used in the respective papers (where it applies).
Ns: not significant. + denotes more risk aversion, - denotes less risk aversion.
Blanks: variables were not tested in respective study.
[1] India; [2] Indonesia; [3] Ethiopia; [4] Vietnam; [5] Peru; [6] China; [7] Pakistan; [8] Thailand; [9] Vietnam

Source: Authors' own illustration

Table 3: Sociodemographic characteristics and prospect theory parameters by paper

	Loss aversion		Probability weighting	Ambiguity aversion	
Variables	Tanaka et al. (2010)[1]	Liu (2013)[2]	Tanaka et al. (2006)[1]	Engle-Warnick et al. (2011)[3]	Liu (2013)[2]
Age	Ns	Ns	Ns	Ns	Ns
Gender (Female)	Ns	Ns	-***	Ns	Ns
Education	Ns	Ns	Ns	Ns	Ns
Income/Wealth	-***	Ns	Ns	Ns	Ns
Distance to Market	Ns		Ns		
Land Owned		Ns		Ns	Ns
Household Size				+***	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. P-values from tests used in the respective papers (where it applies).
Ns: not significant. + denotes a positive, - a negative effect of the respective variable on the parameter.
Blanks: variables were not tested in respective study.
[1] Vietnam; [2] China; [3] Peru

Source: Authors' own illustration

To start with, there is strong evidence that age plays a role in risk preference. Said et al. (2015), Tanaka et al. (2010) and Miyata (2003) all find that older farmers tend to be more risk averse. Gloede et al. (2015) look at farmers in both Thailand and Vietnam and find that age affects the two samples differently: Thai farmers become more risk averse with age whereas the opposite occurrs with their Vietnamese counterparts. The role that gender plays has had a less definite result. Liu (2013) finds that women are more risk averse than men. Biswanger's (1980) results show a slightly higher degree of risk aversion among women. Many of the other studies could not find a statistically significant link between gender and risk preference (Tanaka et al. 2010; Engle-Warnick et al. 2011; Gloede et al. 2015; Said et al. 2015). Education's role in risk aversion is very unclear. Tanaka et al. (2010) find more years of education to be positively associated with risk aversion, whereas Binswanger (1980), Miyata (2003), and Gloede et al. (2015) find the opposite. The role of wealth in risk aversion is somewhat less muddled. Higher wealth is associated with less risk aversion in most studies (Miyata 2003; Yesuf and Bluffstone 2009; Tanaka et al. 2010; Engle-Warnick et al. 2011; Gloede et al. 2015). Liu (2013), however, finds the opposite; greater wealth is related to more risk aversion. Both Miyata (2003) and Engle-Warnick et al. (2011) find that farmers from larger households are less risk averse. Miyata (2003) hypothesizes that this could be from the increases in generations living in a household, as respondents that still live with their parents are also less risk averse.

For the parameters beyond utility function curvature, few conclusive correlations have been found with respect to sociodemographic characteristics. Tanaka et al. (2010) find that farmers with greater wealth were less averse to losses. Tanaka et al. (2006) find that women's probability weighting function is less inflected. Ward and Singh (2015) find that women are more ambiguity averse, while Engle-Warnick et al. (2011) only find that a greater household size is associated with higher levels of ambiguity aversion.

Again, in the light of the mixed prior evidence, we formulate the following general hypothesis, without attempting to predict the direction of the relationships:

> **H2:** Sociodemographic characteristics affect farmers' uncertainty preferences, namely probability weighting, risk, loss and ambiguity aversion.

3. Study region and data collection

Data for this study was acquired through surveys and lottery-based experiments with Mexican maize farmers in the southern state of Chiapas. Maize holds a special status in Mexican agriculture as the crop's origins lay within the country (Hellin et al. 2014). It accounts for the highest percentage of agricultural land and is still a core part of the Mexican diet and remains a vital part of the rural economy (Eakin et al. 2014). Currently, the state is one of the poorest states in Mexico. Chiapas' GDP per capita in 2013 was $54,605 MXN or $4,113 USD[3] (Rodriguez and Luna 2014). Of those that are employed in either transitional or subsistence agriculture, 42% live in poverty (2014). Climate risk poses a growing challenge for rural Mexico (Vermeulen 2014). Nationally, between 1980-2000, Mexico experienced over 3,000 floods and over 1,000 types of other weather related shocks (Monterroso et al. 2014). The state of Chiapas is in the very high vulnerability category for weather risks.

[3] Exchange rate for 2013 was $13.275MXN to $1USD according to US IRS (irs.gov).

Data was collected from April to July 2015 in the maize growing region La Frailesca in Chiapas. The sample encompasses 282 farmers from 10 villages in the neighboring municipalities of Villaflores and Villa Corzo. The region belongs to Mexico's pacific lowland tropics and forms part of a maize mega-environment with around 100,000 active small and medium scale farmers- an environment of "modernized smallholder agriculture" (van Heerwaarden et al. 2009).

Participants were selected based on a stratified sampling procedure. First, 10 villages were selected.[4] In the sampled villages, the sessions were announced publicly with help of the village head, and people could sign up to participate. The only criteria were that they were older than 18, had basic numeric skills and carried the major responsibility for production decisions on their farms. Experiments were then conducted in small groups of 5 to 15 people in the village assembly rooms. The researcher and four enumerators were always present. Experiments were incentivized.

4. Conceptual framework

Despite the relatively large literature on stability of risk preferences after experiencing shocks, these studies generally rely on Expected Utility Theory and accordingly, a one-dimensional utility function with its curvature being the only parameter describing risk preference. However, as formalized Tversky and Kahneman (1979) in CPT, people (1) behave differently when confronted with losses or gains and (2) tend to overweight small probabilities and underweight large probabilities. When confronted with risky prospects that involve a potential loss, for equal probabilities, a loss will reduce the value of that prospect by a larger factor than an equal gain would increase it. Also, we incorporate a measure of ambiguity aversion that we estimate simultaneously.

The estimation of the CPT parameters is based on the functional forms proposed by Tversky and Kahneman (1992). The utility of a prospect ξ is given by two separate value functions, one for the situation where both possible outcomes x and y of a risky option fall into the gain domain, i.e. are larger than the reference point r (x>y>r or y>x>r), and where the lower outcome falls into

[4] The villages were drawn purposefully to cover a wide variability of the degree of technology adoption, namely of hybrid seed.

the loss domain (x<r<y or y<r<x). For simplicity, we set the reference point in our experiments equal to zero. The utility of a prospect can then be written the following way (Ward, Singh 2015):

$$\mathrm{EU}(\xi)=\begin{cases}\mathrm{v(y)+w(p)}\left[\mathrm{v(x)-v(y)}\right] & \text{for } x>y>0 \text{ or } y>x>0\\ \mathrm{w(p)v(x)+(1-w(p))v(y)} & \text{for } x>0>y\end{cases} \tag{1}$$

The value functions are defined as a piecewise power value function

$$\mathrm{v(x)}=\begin{cases}x^{\sigma} & \text{if } x\geq 0\\ -\lambda|x^{\sigma}| & \text{if } x<0\end{cases} \tag{2}$$

The letter λ denotes the loss aversion coefficient and σ the risk aversion coefficient. The probability weighting function is defined as in Prelec (1998), with exponent α denoting the degree to which probabilities p are systematically over- or underweighted:

$$\mathrm{w(p)}=\exp\left[-\left(-\ln(p)\right)^{\alpha}\right] \tag{3}$$

Ambiguity aversion is incorporated simultaneously and represented through an additional function Φ(·) as proposed by Ward and Singh (2015), which is based on the model by Klibanoff et al. (2005):

$$\Phi(\xi)=\mathrm{U}(\xi)^{\theta} \tag{4}$$

The parameter θ denotes an additional sanction on utility when unique probabilities are unknown to a decision maker. Our experimental design and econometric approach allows us to estimate simultaneously the four parameters α, σ, λ and θ.

5. Experimental design

A set of 5 series of lottery choice games totaling 57 decisions based on Ward and Singh (2015) were conducted to determine four behavioral coefficients, i.e. value function curvature (σ), loss aversion (λ), ambiguity aversion (θ) as well as the probability weighting parameter (α). A piecewise power value function as shown in equation (1), a probability weighting function as in equation (3) and a functional representation of ambiguity aversion as in equation (4) is assumed. The experiment by Ward and Singh (2015) is a simplified version of the seminal approach by Tanaka et al. (2010), but easier to communicate in contexts of low education, as the safe option generally consists of a certainty equivalent instead of a “safer” lottery. Both methods allow for estimation of both EUT and CPT consistent parameters. We simplified the approach further by using colored balls (green for winning and orange for losing draws) instead of numbered chips, as in the original version of the experiment. Payout values were used as in Ward and Singh (2015) where they were calibrated by the authors in order to allow for a simultaneous and unique identification of the behavioral parameters. For this study, the values were scaled to Mexican pesos ($MXN). The nominal value of payouts given in the lottery was converted 1/100 to the experimental payout (i.e., for every $1,000 MXN in the lottery, participants could earn $10 MXN in cash). Participants received an endowment of $10.50 MXN for this first experiment, which represented $1,050 MXN in experimental monetary units.

With exception of Series 1, the colored balls for the respective lottery option were put in the bag at the sight of the participants and visualized on a poster, so participants always knew the composition of balls for the respective lottery round. The first two series of the experiment consist of two identical lottery choice lists (see Table 4). The only difference in Series 1 was that participants did not know the composition of the balls, but were informed that there are 10 balls in the bag in total, and that there are between 0 and 10 winning (green) and losing (orange) balls. The payoff for the losing draw (orange ball) in the lottery declines successively for each choice row from being higher to lower than the respective safe payout, while the probabilities remain constant within each series, so the expected value of the lottery option is decreasing with each decision. The participants know so as they get the complete table with all the decision rows for the respective lottery series at a time as depicted in Table 4, Table 5, and Table 6. Monotonic switching is enforced as done in Ward and Singh (2015) and Tanaka et al. (2010) by telling participants they could only switch once from choosing the lottery to choosing the safe payout. Not switching, or switching in the first round are explicitly considered as possible options.[5]

Lottery Series 1 and 2 serve to identify ambiguity aversion. In Series 1 the number of winning or losing balls is not revealed, so participants must form a subjective probability $\hat{p}$ of drawing a green ball. As pointed out by Ward and Singh (2015), it is reasonable to assume that $\hat{p} = 0.5$ since Laplace's principle of insufficient reason should hold. After making their decisions in Series 1, participants are revealed the true probability of $p=0.5$ In Series 2, while the payoffs remain the same, the only difference is that participants are now shown the content of the bag, revealing equal odds (five green and five orange balls). Under ambiguity theory, as opposed to subjective utility theory, it is assumed that individuals' utility is lowered when no unique

[5] Additional to the example of never switching and switching in the first decision, we gave in each session additional examples of switching in decision 6 and 10.

probabilities but only expected probabilities can be assigned to possible outcomes. For given σ and α, if participants were indifferent to ambiguity, they would not change the point at which they change their decision to switch from the lottery to the riskless option. If participants were ambiguity averse, they would switch at an earlier round in the ambiguous lottery than in the unambiguous, equal odds lottery. If participants were ambiguity loving, they would switch later in the ambiguous lottery than in the unambiguous one.

Series 3 and 4 vary the probabilities of winning in the lottery option from 0.1 and 0.7, respectively. This allows estimating the degree of probability overweighting. As opposed to the first two series, the winning payoffs in the lottery option B are rising, ceteris paribus, within each series, i.e. the expected value of the lottery option increases, while probabilities stay the same within the series for all decision rows (see Table 5). Again, monotonic switching was enforced. Switching in the first decision row as well as not switching at all was explicitly allowed for in all series.[6]

Series 5 is used to determine loss aversion parameters. Here, participants chose between two lottery options, where the losing draw in both options implies a loss (see Table 6). However, option B involves both higher possible gains and losses. In case a participant loses, the loss amount is subtracted from their initial endowment.

After the experiment, an individual survey on agricultural production, experienced harvest shocks as well as sociodemographic characteristics of their households was conducted with all participants. For the payment of the experiment, one of the total 57 decisions was selected randomly for all participants in one session. Those who chose the safe payout in the respective round, received this nominal amount divided by 100 in $MXN. Among those who opted for the lottery option B, one participant volunteered to draw from a bag containing the respective number of green and orange balls applying to the selected decision row. If green was drawn, participants received the higher payout. When orange was drawn, participants received the lower or negative payout which was subtracted from the initial endowment.

[6] For round 3, we gave the examples of not switching, switching in the first round, switching in round 28 and 36.

Table 4: Lottery series 1 and 2

	Option A	Option B	
Decision		Green	Orange
1	$1,000	$2,000	$1,000
2	$1,000	$2,000	$800
3	$1,000	$2,000	$750
4	$1,000	$2,000	$500
5	$1,000	$2,000	$400
6	$1,000	$2,000	$350
7	$1,000	$2,000	$300
8	$1,000	$2,000	$250
9	$1,000	$2,000	$200
10	$1,000	$2,000	$100
11	$1,000	$2,000	$0

	Option A	Option B	
Decision		5 Green	5 Orange
12	$1,000	$2,000	$1,000
13	$1,000	$2,000	$800
14	$1,000	$2,000	$750
15	$1,000	$2,000	$500
16	$1,000	$2,000	$400
17	$1,000	$2,000	$350
18	$1,000	$2,000	$300
19	$1,000	$2,000	$250
20	$1,000	$2,000	$200
21	$1,000	$2,000	$100
22	$1,000	$2,000	$0

Table 5: Lottery series 3 and 4

	Option A	Option B	
Decision		1 Green	9 Orange
23	$500	$1,300	$250
24	$500	$1,400	$250
25	$500	$1,600	$250
26	$500	$1,800	$250
27	$500	$2,050	$250
28	$500	$2,350	$250
29	$500	$2,800	$250
30	$500	$3,150	$250
31	$500	$3,600	$250
32	$500	$4,250	$250
33	$500	$5,200	$250
34	$500	$6,650	$250
35	$500	$9,050	$250
36	$500	$14,000	$250

	Option A	Option B	
Decision		7 Green	3 Orange
37	$2,000	$2,800	$250
38	$2,000	$2,850	$250
39	$2,000	$3,000	$250
40	$2,000	$3,100	$250
41	$2,000	$3,250	$250
42	$2,000	$3,450	$250
43	$2,000	$3,650	$250
44	$2,000	$3,850	$250
45	$2,000	$4,100	$250
46	$2,000	$4,350	$250
47	$2,000	$4,750	$250
48	$2,000	$5,250	$250
49	$2,000	$5,950	$250
50	$2,000	$6,850	$250

Table 6: Lottery series 5

	Option A		Option B	
Decision	5 Green	5 Orange	5 Green	5 Orange
51	$1,250	-$200	$1,500	-$1,050
52	$200	-$200	$1,500	-$1,050
53	$50	-$200	$1,500	-$1,050
54	$50	-$200	$1,500	-$800
55	$50	-$400	$1,500	-$800
56	$50	-$400	$1,500	-$700
57	$50	-$400	$1,500	-$550

6. Estimation

6.1. Parameters

To estimate the four preference coefficients, we utilize the maximum likelihood (ML) approach illustrated in Harrison (2008) and applied in Bocquého et al. (2014). Expected utility for each option is the sum of the product of the probabilities weighted as in equation (3) and utility values from equation (2) for each outcome in each lottery decision row i with n possible payoffs:

$$EU_i = \sum_{k=1,n} \left[p_k \times v_k \right] \tag{5}$$

For the lottery decisions with ambiguity, the expected utility is additionally exponentiated by θ as in equation (4). The difference in expected utilities for the prospects displayed on the right and left hand side of the lottery choice lists is calculated for each participant i and each of the 57 choice rows:

$$\Delta_i^{EU} = {EU_i}^R - {EU_i}^L \tag{6}$$

where EU_i^R denotes the expected utility of the right and EU_i^L of the left hand option in the lottery series, respectively. This latent index, based on the unknown parameter σ, is linked to the observed choices using a standard cumulative normal distribution function $\Phi(\Delta_i^{EU})$. This “probit” function specification transforms Δ_i^{EU} into a number between 0 and 1. We assume decisions are made with random error, so the binary choice between lottery option A and B is described by:

$$\delta^*_i = \Delta_i^{EU}(X_i) + \varepsilon_i \text{ and } \delta_i = \begin{cases} 1 \text{ if } \delta^*_i > 0 \\ 0 \text{ otherwise} \end{cases} \tag{7}$$

We are looking for the parameters σ, λ, α and θ that maximize the following log-ikelihood function for the given choice δ and payout amounts X:

$$\ln L^{CPT}(\delta;X;\sigma;\lambda;\alpha;\theta) = \sum_k \ln\Phi(\Delta_k^{EU}) \times I(\delta_k=1) + \ln[1-\Phi(\Delta_k^{EU})] \times I(\delta_k=0) \tag{8}$$

Here, k denotes lottery choices pooled over individuals, X denotes a vector of observables that are commonly related with risk preferences or are relevant controls in relation with shocks.

6.2. Definition of shocks

Furthermore, we specify two different variables to account for an individuals’ harvest loss severity. Shock experience is defined based on loss percentages S_{it}, i.e. absolute loss in year t of subject i, v_{it}, divided by the sum of absolute loss v and harvest amount Y of farmer i in t, multiplied by 100:

$$S_{it}=\frac{v_{it}}{v_{it}+Y_{it}}\cdot 100 \tag{9}$$

We use two variables specified as follows as measures for severity of harvest loss experience:

- A continuous variable for the average percentage of harvest lost over the years 2012-2014, i.e. $\frac{\sum_{t=2012}^{2014} S_{it}}{3}$.
- A dummy variable taking the value 1 if the average percentage of harvest lost over the years 2012-14, i.e. $\frac{\sum_{t=2012}^{2014} S_{it}}{3}$, is greater than the 80th percentile of the sample. This corresponds to an average loss from 2012-14 of 25% of the harvest. This binary variable allows us to identify a "treatment group", i.e. those farmers most severely hit by harvest shocks.

6.3. Confounding factors and omitted variables

When estimating the effect of shocks on risk preferences, we must take into account several potential obstacles. One drawback is a potential selection bias. Self-selection into more or less shock and loss prone plot types could have occurred based on their risk preferences, as was supposed by Olbrich et al. (2011). However, we argue that self-selection is not an issue in the Mexican context. The possibility of farmers choosing their plots based on their uncertainty preferences is largely ruled out due to Mexico's "ejido" system. This form of land titling was installed after the Mexican revolution and redistributed large estates to the farmers in the form of small plots that could not be sold (e.g. Sweeney et al. 2013). More than 73% of landholdings in our sample are under the "ejido" system.

If our shock variable does not suffer from self-selection, there may still be observed variables that could act as confounding factors. Uncertainty preferences could affect input level choices and thereby affect loss severity. For example, farmers who are less risk averse might generally use less pesticides and herbicides, or use more fertilizer and higher quality seed (Knight et al. 2003; Liu 2013; Verschoor et al. 2016). This could mean that more risk seeking farmers are also more likely to incur harvest losses. In order to deal with this potential endogeneity, we ideally must know the counterfactual, i.e. how the same farmers that suffered from harvest losses would have decided in the lotteries, had they not experienced harvest shocks. We cannot use an experiment to randomly introduce harvest shocks, so we need to another way to approach this issue. We therefore present a propensity score matching (PSM) approach, as done similarly by Said, Afzal, and Turner (2015). As treatment variable, we use our loss dummy, indicating average harvest losses of 25% from 2012-14, as stated in Section 5. We then create the propensity score for by running logit estimation on the binary treatment variable controlling for all observable variables that might affect shock severity:

$$T_i=\beta_0+\beta^{'}X_i+e_i \tag{10}$$

In equation (10), T_i refers to the treatment status of individual i and e_i refers to the individual specific error term. The vector X_i contains all of the variables that could determine treatment assignment, i.e. whether one incurred a severe maize harvest loss. Besides the control variables from our prior section we include production variables such as maize area, logged per hectare expenditures for fertilizer, pesticides and herbicides as well as the average maize area 2012-14, and the share of maize land devoted to improved maize varieties. Conditioning on the propensity score, the preference parameter outcomes are independent of treatment assignment (Caliendo and Kopeinig 2008). Kernel density estimates of the propensity score, i.e. predicted probability of belonging to the treatment group based on observables (Figure A1 in the appendix) provide evidence for common support. Each treated subject was matched with two untreated based on nearest neighbor matching.

A further issue might arise because of potentially omitted variables, such as levels of precaution or ability, which cause higher loss shares in maize, and are at the same time correlated with uncertainty preferences. Therefore, in the absence of a control variable to capture precaution levels, we might have a problem of reverse causality, meaning that existing uncertainty preferences cause less precaution and thereby cause losses, rather than the other way around. Precaution is unobserved and insufficiently approximated just by looking at input levels. We therefore additionally present an instrumental variable (IV) approach. As IV, we use the village level averages of the farmers' maize loss percentages. The village averages can be regarded as exogenous in a sense that they only affect an individual farmer's preference parameters through his own experience of harvest losses, not via unobservable factors such as his own level of precaution. Given a relatively large number of observations per village, whether losses were high on the village level should be uninfluenced by an individual farmers' precaution or risk preferences. At the same time, it is hard to imagine that there are other (unobservable) factors on the village level that affect both risk preferences and harvest losses apart from exogenous shocks, so estimators can be expected to be consistent (Angrist and Krueger 2001; Gormley and Matsa 2013). To create IV-based estimates, we first run the following first stage OLS regression:

$$S_{ij}=\beta_0+S_j\beta_1+\beta^{'}X+e_{ij} \tag{11}$$

In equation (11), S_{ij} refers to the harvest loss share 2012-14 of individual i from village j, and e_{ij} refers to the individual specific error term. The IV S_j is the average of all S_{ij}, over all individuals i in the village j. The linear predictions for harvest losses $\hat{S}_{ij}$ from equation 11 are then used in the second stage, i.e. the ML estimation from equation 8. To correct the standard errors we apply bootstrapping over the two stages.

The parameter estimation based on maximum likelihood as proposed by Harrison (Harrison 2008) was implemented in STATA13, with modifications to include ambiguity aversion and standard errors clustered by subject. Those households that did not produce maize during all of the years 2012-14 for which data was collected were excluded. This reduces our sample size to 265 participating farmers.

7. Results for sociodemographic characteristics

7.1. Descriptive results

First, we give an overview of the sociodemographic characteristics of our participants (Table 7). The average respondent age is around 47 years old. The sample is overwhelmingly male, with only 8% being female, due to our respondents being farm decision makers, which is a predominantly male responsibility. On average, respondents achieved relatively low levels of formal education, with an average of 5.47 years. Only around 4% of the sample had an indigenous parent. The sampled villages are on average rather remote, with an average travel time to the nearest municipal capital of 80 minutes. As a proxy for wealth, we developed an asset index based on principal component analysis. Unlike income, which measures a respondent's current economic position, an asset index looks at a respondent's long-term economic status (Filmer and Pritchett 2001). Our index incorporates and weights a list of owned household and farm goods. The mean maize area over the three years prior to the survey is 2.66 ha. Of the total land used to cultivate maize, the respondents used on average 56% for hybrid maize. While 92% of respondent stated maize production to be their main income source, on average respondents had a total of 4 income sources, which includes both additional farm and off-farm incomes.

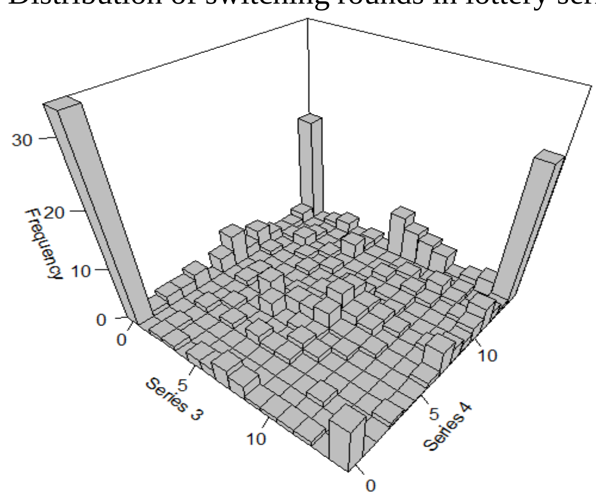
Table 7: Sociodemographic characteristics of participants

VARIABLE	Mean	SD
Education (years)	5.44	3.79
Female (dummy)	0.08	0.28
Asset Index[1]	0.25	0.16
Household Size	3.98	1.67
Producer Age (years)	46.76	14.15
Reunions Attended (share)	0.55	0.43
Parents Indigenous (dummy)	0.04	0.21
No. of Income Sources	4.05	1.55
Time to City (minutes)	80.12	42.17
Avg. Maize Area 2012-14 (ha)	2.66	1.81
Observations	265	

[1] based on principal component analysis scores for one component and the following assets: TV, concrete floor, fridge, cellphone, washing machine, separate bathroom inside/outside, draft animals, tractor, maize degraining machine, transport vehicle, livestock.

Figure 1 gives some insights into the decisions during the lotteries and shows the distribution of switching rounds between Series 3 and 4. The high frequency bars at the extremes show that a large number of respondents either switched immediately or did not switch at all from option A to B, which corresponds to high degrees of risk aversion and/or non-linear probability weighting.

Figure 1: Distribution of switching rounds in lottery series 3 and 4



Source: Authors' own illustration

7.2. Estimation Results

Table 8 shows the sample average values CPT parameters without including any covariates, as result of our ML estimation. We can strongly reject that our subjects are expected utility maximizers, which would imply neither probability weighting nor loss aversion, i.e. respective coefficients equal to 1. However, we do find significant loss aversion, non-linear probability weighting, concave value function curvature and, with a coefficient of 0.94, a slight tendency towards ambiguity loving preferences (Chi-square test p-values<0.00).

Table 9 shows the results of the ML estimation of the parameters controlling for sociodemographic variables. When looking at specific variables we find that we can help build toward the consensus that previous researchers have started. An increase of the value function curvature σ in the interval (0,1) means decreasing concavity and therefore, less risk aversion. Our results show that higher levels of education are related to lower levels of risk aversion. This is in contrast to the results from Tanaka et al. (2010) but in line with both the samples of Gloede et al. (2015). Household size increases risk aversion, which is in contrast to the finding by Miyata et al. (2003). This difference could be that in our case, the subjects were almost invariably household heads. Instead of a larger household representing a safety net as argued by Miyata et al. (2003), when looking at household heads exclusively a larger household might imply a larger responsibility burden and therefore a more considerate and risk- averse behavior. Subjects with indigenous parents were on average significantly more risk averse, as were those with a more diversified income.

An increase in the loss aversion parameter λ for any value of $\lambda>1$ is associated with an increase in loss aversion. We find that the number of people living in one's household is related to higher levels of loss aversion, which is consistent with previous findings and could be explained similarly to the higher degree of risk aversion amongst heads of larger households. More education is associated with less loss aversion. We could not find any other study in the literature that could make a significant connection between loss aversion and household size.

A reduction in the probability weighting coefficient α in the interval (0,1) denotes an increase in overweighting of small probabilities and deweighting of large probabilities. Hence, we find that probability overweighting is decreasing in wealth and distance to the nearest city. We do not find

Table 8: CPT coefficients using maximum likelihood estimation

PARAMETER		
Value Function Curvature (σ)	0.490^{***}	(18.82)
Loss Aversion (λ)	2.406^{***}	(19.52)
Probability Weighting (α)	0.777^{***}	(32.05)
Ambiguity Aversion (θ)	0.940^{***}	(39.29)
Noise	0.696^{***}	(26.52)
Observations	15,105	
Cluster	265	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. t statistics in parenthesis.

Table 9: CPT coefficients and sociodemographic variables using maximum likelihood estimation

	Value Function Curvature (σ)	**Loss Aversion (λ)**	**Probability Weighting (α)**	**Ambiguity Aversion (θ)**
Education (years)	0.026^{***}	-0.079^{**}	0.003	0.003
	(3.92)	(-2.17)	(0.54)	(0.49)
Female (dummy)	0.122	0.441	0.073	0.037
	(1.27)	(0.88)	(0.95)	(0.58)
Asset Index[1]	0.102	-0.959	0.344^{**}	-0.039
	(0.51)	(-1.40)	(2.45)	(-0.41)
Household Size	-0.026^{**}	0.266^{***}	-0.005	-0.005
	(-2.01)	(2.58)	(-0.34)	(-0.33)
Producer Age (years)	0.003^{**}	0.005	0.002	-0.002
	(2.11)	(0.45)	(1.12)	(-0.79)
Reunions Attended (share)	0.062	-0.216	-0.069	0.034
	(0.85)	(-0.71)	(-1.16)	(0.61)
Parents Indigenous (dummy)	-0.270^{***}	-0.213	0.048	-0.859^{***}
	(-4.88)	(-0.11)	(0.13)	(-10.38)
No. of Income Sources	-0.026^{**}	-0.102	-0.004	0.019
	(-2.36)	(-1.25)	(-0.21)	(1.30)
Time to City (minutes)	0.000	-0.001	0.001^{**}	-0.001
	(0.33)	(-0.32)	(2.03)	(-1.01)
Constant	0.311^{*}	2.559^{***}	0.527^{***}	0.998^{***}
	(1.94)	(3.15)	(3.59)	(6.36)
Noise Constant	0.623^{***} (9.55)			
Observations	15,105			
Cluster	265			
Prob > Chi2	0.012			
Wald Chi2(9)	21.05			

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. t statistics in parenthesis.

[1] based on principal component analysis scores for one component and the following assets: TV, concrete floor, fridge, cellphone, washing machine, separate bathroom inside/outside, draft animals, tractor, maize degraining machine, transport vehicle, livestock.

a significant relationship between probability weighting and any of the other sociodemographic variables.

Looking at the ambiguity aversion coefficient θ, an increase in the interval (0,1) means a decrease in ambiguity loving preference towards ambiguity neutrality, while an increase in the interval (1, θ) would mean an increase in ambiguity aversion. However, we only find a significantly higher degree of ambiguity aversion for subjects with an indigenous parent. Unlike Engle-Warnick et al. (2011) we do not find an effect of household size on ambiguity aversion. All in all, hence, we cannot reject hypothesis H1, that sociodemographic characteristics explain variation in the CPT parameters and ambiguity aversion, while the direction of influence is only partly in line with past studies.

8. Results for harvest loss experiences

8.1. Descriptive results

Table 10 presents descriptive statistics on subjects' maize shock frequency and severity experienced from 2012-2014. During the studied years, the average respondent reported to have suffered from 1.77 incidents in which maize harvest was lost. Over the years 2012-14, drought accounted for 51% of the total losses, followed by excessive rain (20%) and pest shocks (14%). Those farmers that experienced harvest shocks, lost on average 19% of their harvest in the incident.

Table 10: Summary statistics of maize losses

	Mean	SD
No. of Losses, 2012-14	1.79	(1.00)
Average Yearly Losses 2012-14 (% of Harvest)[1]	18.74	(24.27)
Average Loss >=25% (dummy)	0.21	-
Loss to Drought (% of Total Maize Loss)	51.19	-
Loss to Rain (% of Total Maize Loss)	20.06	-
Loss to Pest (% of Total Maize Loss)	13.61	-
Loss to Wind (% of Total Maize Loss)	4.89	-
Loss to Other (% of Total Maize Loss)	10.25	-
Observations	265	

[1] Given a loss occurred

8.2. Estimation results

Models 1 and 2 in Table 10 show the results of the ML estimation of the CPT parameters controlling for the average severity of maize losses in 2012-14, expressed either as average loss percentages or as a dummy for a harvest losses of over 25%. In all specifications we control for sociodemographic variables. In columns (1) and (2) we can infer from both the continuous and the dummy variable that subjects who experienced a larger loss severity in 2012-14 do not score significantly differently on parameters of the value function curvature (σ), loss aversion (λ), or ambiguity aversion (θ). Even though not significant, the sign on λ is positive which suggests a tendency of increased loss aversion after more severe loss experiences as proposed by Barberis et al. (2001). However, we do find a significant relationship with maize loss severity and the increased overweighting of small probabilities, corresponding to a negative coefficient on the probability weighting coefficient α. This result is in line with Li et al. (2011) who also find that subjects overweighted small probabilities events after a shock and in contrast to Reynaud and Aubert (2013) who find no such effect for flood loss experiences. Li et al. (2011) argue that experiencing a low-probability disaster may cause an overestimation of the frequency of low probability events in general through the availability and representative heuristics that subjects follow (Tversky and Kahneman 1974).

As argued before, to deal with potential endogeneity, nevertheless, we extend our analysis by a propensity score matching (PSM) and an instrumental variable (IV) approach laid out in the following. In order to assess whether a matching approach is justified in our case, we check for the balance of covariates in the treatment group, i.e. the group of farmers with average loss shares between 2012-14 of over 25%, and the control group before matching. Indeed we find some significant differences in fertilizer and herbicide expenditures per hectare, as well as total maize area (Table 12). However, t-tests on the explanatory variables after matching indicate that balance on observables was achieved (Table A1 in the annex). Results for propensity score matched data are presented in column (3) of Table 10. The treatment dummy, i.e. having incurred average maize loss shares above 25% in 2012-14, shows up significantly negative in explaining probability weighting. This confirms our results from the last section, finding that shock severity

Table 11: Effect of losses on CPT parameters using maximum likelihood estimation

	(1) Non-IV	(2) Non-IV	(3) PSM	(4) IV
Value Function Curvature (σ)				
Loss (%)	0.001			-0.014^{**}
	(1.40)			(-2.29)
Loss >=25% (dummy)		0.005	-0.090^{**}	
		(0.14)	(-2.10)	
Constant	0.590^{***}	0.583^{***}	0.427^{***}	0.489^{***}
	(5.77)	(5.64)	(6.03)	(2.82)
Loss Aversion (λ)				
Loss (%)	0.001			0.074
	(0.09)			(1.48)
Loss >=25% (dummy)		0.446	0.360	
		(1.31)	(0.96)	
Constant	2.540^{***}	2.584^{***}	2.912^{***}	2.389^{**}
	(3.19)	(3.22)	(6.21)	(2.19)
Probability Weighting (α)				
Loss (%)	-0.003^{***}			-0.022^{**}
	(-3.09)			(-2.53)
Loss >=25% (dummy)		-0.133^{**}	-0.115^{*}	
		(-2.26)	(-1.91)	
Constant	0.351^{**}	0.342^{**}	0.890^{***}	0.247
	(2.15)	(2.09)	(12.64)	(1.03)
Ambiguity Aversion (θ)				
Loss (%)	0.000			-0.006
	(0.14)			(-0.79)
Loss >=25% (dummy)		-0.006	-0.031	
		(-0.11)	(-0.57)	
Constant	0.930^{***}	0.933^{***}	0.912^{***}	0.902^{***}
	(6.21)	(6.23)	(14.26)	(5.56)
Noise (Constant)	0.631^{***}	0.630^{***}	0.515^{***}	0.638^{***}
	(9.55)	(9.64)	(9.53)	(9.59)
Socio-Demographics[1]	Yes	Yes	Yes	Yes
Observations	15,105	15,105	9,405	15,105
Cluster	265	265	165	265
Prob > Chi2	0.000	0.003	0.093	0.059
Wald Chi2	31.63	26.50	4.75	16.37

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. t statistics in parenthesis.
Model (3): Propensity Score Matched Data. Treatment= Loss 25% (dummy). Each treated was matched with two untreated observations based on nearest neighbor matching.
Model (4): IV Estimation. IV=Village level average of respective loss variable. Standard Errors were bootstrapped.
[1] In Model 3: Propensity Score

Table 12: Balance of covariates by loss affected status

	Treatment[1]		Control		
	Mean	SD	Mean	SD	p^2
Education (years)	5.49	3.84	5.27	3.64	0.71
Female (dummy)	0.08	0.27	0.09	0.29	0.81
Asset Index[3]	0.25	0.15	0.27	0.17	0.36
Household Size	3.92	1.60	4.22	1.92	0.24
Producer Age (years)	46.23	13.97	48.67	14.78	0.25
Reunions attended (share)	0.59	0.42	0.52	0.46	0.27
Parents Indigenous	0.04	0.20	0.05	0.23	0.72
No. of Income Sources	3.97	1.51	4.35	1.65	0.11
Time to City (minutes)	81.70	41.93	74.09	42.90	0.23
Avg. Maize Area 2012-14 (ha)	2.57	1.60	3.02	2.45	0.10*
Log. Fertilizer Expenditure ($MXN/ha)	7.69	1.08	7.97	1.25	0.09*
Log. Pesticide Expenditure ($MXN/ha)	2.69	2.36	3.34	2.37	0.07*
Log. Herbicide Expenditure ($MXN/ha)	6.42	1.02	6.39	1.37	0.89
Avg. Hybrid Maize Land Share, 2012-14	0.57	0.44	0.53	0.34	0.60
Observations	210		55		

[1] Treatment refers to subjects with average maize loss shares 2012-14 above the 80th percentile of the sample distribution, i.e. >= 25%.
[2] p-values from two-sided T-test. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
[3] based on principal component analysis scores for one component and the following assets: TV, concrete floor, fridge, cellphone, washing machine, separate bathroom inside/outside, draft animals, tractor, maize degraining machine, transport vehicle, livestock.

increases probability weighting. However, when looking at the coefficient of the shock dummy variable in estimating the value function curvature, we find a significant negative treatment effect. This means that when comparing subjects with the same probabilities to incur severe maize losses as predicted by their sociodemographic and production characteristics, subjects that actually suffered severe maize losses are more risk averse. This result is in line with Reynaud and Aubert (2013) and Cameron and Shaw (2015) who report higher risk aversion for individuals in that experienced natural disaster related shocks and points towards risk vulnerability.

Regarding the IV results, the validity of our instrument is confirmed in the first stage regression (Table A2 in the annex), confirming a strong correlation between the instrument, village average loss shares, and our variable of interest, individual loss severity. In the IV-estimation results are presented in column (4) of Table 11. The instrumented loss percentages, i.e. the variation in shock severity that is explained exogenously, shows up significantly negatively in explaining probability weighting. This confirms our results from before, finding that shock severity increases the overweighting of small probabilities. When looking at the coefficient of the instrumented loss shares for the value function curvature, we find a negative significant coefficient for loss percentage. This denotes an increase in risk aversion following larger maize harvest loss shares and is in line with the PSM results. For loss aversion and ambiguity aversion, we find no significant effect.

9. Conclusion

Starting with Binswanger (1980), economists have been trying to understand how smallholder farmers make decisions under uncertainty. Previous authors have tried to work towards an understanding of the relationship between the experience of shocks and risk preferences, but have not been able to come to a consensus. This paper helps to further the at times hazy understanding of the role of shocks on uncertainty preferences. Not only do we add to the literature surrounding the effects of shocks, in our case maize harvest shocks, on risk aversion only, we use Cumulative Prospect Theory and additionally estimate ambiguity aversion, i.e. aversion to uncertainty over the probabilities of a risky payout. To do so we used lab-in-the-field experiments conducted with smallholder maize farmers in Chiapas, Mexico, and furthermore collected data on sociodemographic characteristics, agricultural production and maize harvest losses. Our results show a strong rejection of Expected Utility Theory in favor of Cumulative Prospect Theory. We find significant probability weighting, risk and loss aversion amongst our sample, and a weaker degree of ambiguity aversion.

Our results are notable because they allow for conclusions regarding the effects of sociodemographic variables and harvest loss experiences beyond just risk aversion. First, we use a wide range of sociodemographic variables to explain parameters of risk aversion, loss aversion, probability weighting and ambiguity aversion. We find that coefficients are partially in line with the existing literature that attempts to explain variation in Cumulative Prospect Theory parameters with sociodemographic characteristics. Most notably, subjects from richer households displayed less overweighting of small probabilities, while subjects from larger households were more risk and loss averse. Farmers with more diversified on- and off-farm income sources were on average more risk averse. Subjects from indigenous families were more risk and also more ambiguity averse, while ambiguity aversion was not significantly related to any other sociodemographic factor. Second, using propensity score matching and an instrumental variable approach to control for potential endogeneity of harvest losses, we find that farmers having experienced more severe losses become more risk averse and more strongly overweight small and underweight large probabilities. No such effect is found on loss aversion or ambiguity aversion.

If farmers become more risk averse in the aftermath of shocks, this could well affect their future investment and technology adoption behavior, potentially making them more hesitant to engage in risky but productivity enhancing practices. Additionally, the more severe the experienced harvest losses, the more distorted is the farmers' assessment of probabilities and the likelihood of future shock may be overestimated. The risk of shocks by itself is already considered a driver of persistent poverty; if the occurrence of shocks furthermore causes preferences to change endogenously towards risk avoidance, they might furthermore lead to "behavioral poverty traps" (Barrett and Carter 2013). Before this background, it is not encouraging that weather shocks with adverse impacts on harvests are likely to further increase. Taken all together, as stressed by the World Bank (2014), this makes the case for policies facilitating risk management, disaster relief and safety nets in poor rural regions even stronger. The Mexican catastrophic risk management program CADENA that reinsures municipalities providing emergency assistance to farmers is certainly a step in the right direction (Cabestany-Noriega et al. 2013). Farmers in our sample so far did not benefit from this governmental assistance, for which it is of vital importance to ensure that in the future also smallholder farmers will be reached.

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Annex

Table A1: Balance of covariates after propensity score matching

	Control		Treatment[1]		
VARIABLE	Mean	SD	Mean	SD	p^2
Education (years)	5.27	3.45	5.27	3.64	1.00
Female (dummy)	0.08	0.28	0.09	0.29	0.84
Asset Index[3]	0.28	0.17	0.27	0.17	0.79
Household Size	4.23	1.97	4.22	1.92	0.98
Producer Age (years)	48.98	13.70	48.67	14.78	0.89
Reunions Attended (share)	0.37	0.42	0.46	0.46	0.21
Parents Indigenous	0.02	0.13	0.05	0.23	0.20
No. of Income Sources	3.95	1.45	4.35	1.65	0.12
Avg. Maize Area 2012-14 (ha)	2.61	1.75	3.02	2.45	0.22
Logged Fertilizer Expenditure ($MXN/ha)	7.81	1.23	7.97	1.25	0.41
Logged Pesticide Expenditure ($MXN/ha)	3.61	2.09	3.34	2.37	0.46
Logged Herbicide Expenditure ($MXN/ha)	6.26	0.89	6.39	1.37	0.46
Avg. Land Share with Hybrid Maize, 2012-14	0.51	0.45	0.53	0.34	0.70
Time to City (minutes)	73.33	36.63	74.09	42.90	0.91
Observations	110		55		

Propensity score matched data.
[1] Treatment= Loss 25% (dummy). Each treated was matched with two untreated observations based on nearest neighbor matching.
[2] p-values from two-sided t-test. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2: First stage OLS regression

Village Average of Loss (%)	0.868***
	(3.17)
Constant	-15.863
	(-1.49)
Socio-Demographics	Yes
Observations	265
Adjusted R^2	0.073

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *t* statistics in parentheses.

Figure A1: Kernel density estimates for propensity scores