Risk, Insurance and Technology Adoption in Rural Development - Evidence from Southern Mexico

Dissertation

to obtain the Ph. D. degree

in the International Ph. D. Program for Agricultural Sciences in Göttingen (IPAG)

at the Faculty of Agricultural Sciences,

Georg-August-University Göttingen, Germany

presented by

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born in Munich

Göttingen, March 2017

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Date of dissertation: 18.05.2017

Acknowledgements

The present work was developed during my time as a research associate within the Research Training Group (RTG) “Transformation of Global Agri-Food Systems: Trends, Driving Forces and Implications for Developing Countries” (GlobalFood), which is affiliated with the Department of Agricultural Economics and Rural Development at the University of Göttingen. This research was made possible with funding of the German Research Foundation (DFG).

I am greatly indebted to many people for their advice, encouragement and support, which was invaluable for the successful completion of this work. In the following, some of the people who have made this work possible are gratefully acknowledged. First, I would like to thank my supervisor Prof. Dr. Oliver Musshoff, of the Chair of Farm Management, for his persistent support, concerted supervision, indispensable guidance and feedback throughout the entire period of my doctoral studies. I also wish to express my gratefulness to Prof. Marcela Ibanez, PhD, Leader of the Junior Research Group 'Development Economics', for being my second supervisor in my doctoral thesis committee and making a great collaboration with much encouraging feedback and rewarding discussions possible that motivated me to excel in my work. I also owe thanks to Prof. Dr. Matin Qaim, of the Chair of International Food Economics and Rural Development, for being the third supervisor and, above all, for making the RTG GlobalFood possible and such a one-in-a-kind academic and personal experience.

I would also like to thank all my colleagues within the GlobalFood RTG and at the Chair of Farm Management, especially to my office-mate Birgit Gassler, for their support and encouragement during my doctoral studies as well as for creating such a friendly work atmosphere. In particular, I would like to thank my colleagues Sabine Fischer and Kerstin Grosch for being frequent discussants of my doctoral seminars and providing excellent feedback. I would also like to thank my co-authors for their indispensable contributions and collaboration, namely Stephan Dietrich and Benjamin Wiercinski.

My sincere gratitude also goes to the International Maize and Wheat Improvement Center (CIMMYT) in Mexico, especially to Jon Hellin, for allowing us to use their networks in order to enable my field work. I am especially grateful to Prof. Francisco Guevara-Hernandez, of the Faculty for Agronomic Science at Universidad Autónoma de Chiapas, Mexico, for his collaboration and support in recruiting qualified enumerators and assistance during field work in general. This time was a unique and unforgettable learning experience. I would furthermore like to thank the enumerators who worked with me in Chiapas, Mexico, namely Anixe Velazquez Sanchez, Sergio Fabian Nunez Grajales, Silverio Hernandez Martinez, Diego Alberto Simuta Masson and Moises Ivan Arguello Aguilar. Their reliability, great commitment and local knowledge ensured that we collected the most accurate information from the farmers during the experimental sessions and survey.

Finally, I wish to express my sincere gratitude to my parents Elfriede and Franz, my brother Markus, and my life-long friend Maria for their confidence in me, their strong interest in my academic career and their ongoing encouragement and moral support throughout my PhD.

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I General Introduction

1. Decision making under risk and agricultural development

Agricultural production is subject to various risks which make uninsured agricultural outputs and incomes highly volatile (Cole et al. 2013; Dercon 2002; Rosenzweig and Binswanger 1993). Given the continuous importance of agricultural production in developing countries together with the high exposure of farmers to output volatility, uninsured risk is today regarded to be closely related to rural poverty (Dercon 2005).

The two major sources of risk in agriculture are output risks, especially due to adverse weather events, and price risks, which are partly due to an inelastic demand for food (Chavas et al. 2010). In this dissertation the focus lays on output risk. In the standard agricultural economics literature, output risk is referred to as the variance of agricultural output, or yield (Just and Pope 1978). By this definition, agricultural inputs such as fertilizer and improved seed, are considered to be risk-increasing, while pesticides or herbicides are considered to be risk-reducing (e.g. Just and Pope 1979b).

Climate change will further exacerbate output risks, as extreme weather events will increase with global warming (IPCC 2015). This is especially problematic with regards to poverty, as during the last 20 years, the countries most affected by extreme weather events were developing countries (Kreft et al. 2014). However, only 5 percent of the target population in Latin America, 15 percent in Asia and 0.5 percent in Africa have agricultural insurance (McCord and Biese 2015).

Why do risky events exist? In the classical economic theory, risk is referred to as a “mean-preserving spread” in the distribution of a random variable, such as the yield (Rothschild et al. 1971). Risk exists because of our inability to control and/or measure all causal predictors of events, as well as our limited ability to process information, referred to as bounded rationality (Chavas 2004). Risk analysis presumes that we know or can approximate the probability distribution of the random variable. Independently of which of the different approaches for probability assessment is drawn on, an individual is faced with a decision on how to behave when exposed to a risky event.

The most wide-spread model to predict behavior under risk is Expected Utility Theory (EUT), going back to von Neumann and Morgenstern's seminal work (Neumann and Morgenstern 1944). Within this prominent theory, subjects make decisions by maximizing expected utility of outcomes, not the monetary outcome itself, based on risk preferences captured in the curvature of their utility function. Recent advances in experimental economics came up with ways of designing experiments to identify the latent risk attitude under some rationality assumptions (Cox and Harrison 2008). The most widely used experimental methods usually involve an incentivized choice where subjects trade-off higher monetary payoffs against higher probabilities of obtaining them (Binswanger 1980; Charness and Gneezy 2012; Eckel and Grossman 2002; Gneezy and Potters 1997; Holt and Laury 2002). These techniques involve a relatively low cognitive load and are fairly easy to implement (Crosetto and Filippin 2016). Most studies attempting to measure individual risk preferences within rural populations in developing countries, starting with the work of Binswanger (1980), confirm that the average farmer behaves aversely to risk (e.g. Hill 2009; Menapace et al. 2013; Verschoor et al. 2016).

The following papers presented in this dissertation highlight various aspects of risk aversion and risk management with regards to rural development. They result from the analysis of farmer surveys and framed field experiments (Harrison and List 2004) which were conducted from April to September 2015 in the state of Chiapas in southern Mexico. The study area is a major maize growing region, forming part of Mexico's pacific lowland tropics and a maize mega-environment with around 100,000 active small and medium scale farmers (van Heerwaarden et al. 2009). Nevertheless, 52 percent of the population live below the poverty line (CONEVAL 2010). The specific aspects analyzed in each paper are summed up in the following.

2. Risk management and technology adoption

In a growing strand of literature, risk aversion and the lack of insurance or comparable risk management tools such as state-contingent credits or savings have been identified as major explanatory factors for the underinvestment in productivity-enhancing inputs, especially so in agriculture (Barnett et al. 2008; Cole et al. 2016; Dercon and Christiaensen 2011; Drèze and Modigliani 1972; Fafchamps 2010; Feder et al. 1985; Just and Pope 2003; Kurosaki and Fafchamps 2002; Liu and Huang 2013; Lybbert and Barrett 2007; Rosenzweig and Binswanger

1993; Sandmo 1971). Instead, risk-averse farmers may be left locked into low-risk, low-return production activities (Barrett and Carter 2013).

Crop insurance could play a vital role as a risk management instrument to enable poor farmers in developing economies to cope with weather related production risk, hence contributing to poverty alleviation (Hazell 1992; Hazell et al. 1986; World Bank 2013). Besides allowing ex-post consumption smoothing, insurance and comparable risk management tools are argued to help overcoming the situation of low-risk, low-return livelihoods (Dercon 2005; Fan et al. 2013). Arguably, this can happen either by directly encouraging ex-ante input use and technology adoption or via reduced credit rationing (Boucher et al. 2008; Brick and Visser 2015; Carter et al. 2016; Elabed and Carter 2015b; Emerick et al. 2016; Farrin and Murray 2014; Ghosh 2001; Giné and Yang 2009; Hill and Viceisza 2012; Karlan et al. 2014).

Rural insurance markets in developing countries suffer from many constraints, such as moral hazard, adverse selection and high transaction costs (Hazell 1992). Innovative insurance schemes that circumvent these constraints, such as weather index insurance, could therefore be promising tools for poor farmers to cope with weather risk (Binswanger-Mkhize 2012; Miranda and Farrin 2012; Skees and Barnett 1999). However, a main challenge of index insurance is basis risk, the supposed reason for the low demand of farmers for it (Carter et al. 2016; Clarke 2016; Elabed et al. 2013; Jensen et al. 2014; McIntosh et al. 2013). Indemnity payouts of index insurance are based on an objective index value, rather than the individual farmer's loss (Miranda 1991; Woodard and Garcia 2008). Since the chosen index never perfectly correlates with the individual farmers' output, there will be situations in which an insured farmer faces a loss, but will not receive an indemnity payment, or vice versa. This risk is referred to as basis risk. Independent from that, a promising way of insurance marketing lies in bundling index insurance contracts to loans or inputs (Binswanger-Mkhize 2012; Lybbert and Carter 2014; Ward et al. 2015), which could induce a positive effect on insurance take-up and technology adoption at the same time.

The case study area to test these issues is the maize growing region La Frailesca in the southern state of Chiapas, Mexico. The main staple crop in Mexico is maize, and in total, 60 percent of Mexican maize supply comes from smallholders (Appendini 2014), of whom there are around 3 million in Mexico (Cabestany-Noriega et al. 2013). The changing consumption patterns as a consequence of urbanization, especially the trend of increased meat demand, will increase the demand for yellow maize for livestock feed and industrial use, where Mexico is currently not self-sufficient, and challenge the production of white maize for human consumption (Appendini 2014). Improving land productivity is therefore of vital policy interest in order to ensure food security and self-sufficiency (SAGARPA 2013; UNCTAD 2013).

Land productivity is currently stagnating at arounds 2.7 tons per hectare (SAGARPA 2010). Improved maize varieties, especially hybrids, were found to increase land productivity, farm household welfare and to reduce poverty in Mexico (Becerril and Abdulai 2010). Even though improved maize has been available in Mexico for more than 40 years, the degree of adoption by farmers is relatively low. In total, only about 30 percent of the production units sow improved seed varieties (INEGI 2014). Farmers were found to favor local varieties because of their “known quantities” and distrust the unfamiliar improved seeds’ performance (Arellano and Arriaga 2001; Badstue et al. 2007), which points towards risk aversion as a relevant driver of non-adoption. At the same time, in the poor south, only around 8.6 percent of agricultural production units have insurance (Arias 2013). Governmental programs providing insurance subsidies have been installed to increase coverage (Cabestany-Noriega et al. 2013; Fuchs and Wolff 2011). Considering this background it is very relevant to study the potential effects that innovative insurance mechanisms could have on hybrid seed adoption.

In the paper *“Insurance for Technology Adoption: An Experimental Evaluation of Schemes and Subsidies with Maize Farmers in Mexico”* (Chapter II), the effect of bundling a higher yielding hybrid maize variety with different insurance schemes on total hybrid seed adoption is estimated experimentally. In different treatments, the levels of risk coverage, premium subsidies, and basis risk are varied, and farmers’ risk preferences are taken into account. Thereby, it can be established whether index-based insurance, bundled with hybrid seed, could be a viable tool for incentivizing adoption. This is the first paper to address bundling of insurance and inputs experimentally while systematically varying premium cost, coverage level and basis risk.

3. Explaining variation in uncertainty preferences

The existence of a utility function is based on four restrictive axioms: Completeness, Transitivity, Independence, and Continuity. However, the empirical evidence shows that these axioms are often violated in standard experiments (e.g. Buschena 2003). Against this background, several alternative models for decision making under risk have been formulated, with one gaining particular attention, namely (Cumulative) Prospect Theory (in the following CPT) (Kahneman and Tversky 1979; Tversky and Kahneman 1992). At the core of this theory lies the observation of a value function that is steeper for losses than for gains, which reflects loss aversion. In addition to that, it was found that people care about small risks, i.e. they tend to overweight small probabilities and underweight large probabilities. This is referred to as probability weighting. In experiments with farmers, a violation of EUT in favor of CPT could be confirmed (Bocquého et al. 2014; Cardenas and Carpenter 2013; Fafchamps 2010; Tanaka et al. 2010; Ward and Singh 2015).

In the real world, decisions under uncertainty often involve only vague probabilities (Kocher and Trautmann 2008). If one takes into account that uncertainty about probabilities, similarly to uncertainty about outcomes, affects utility, this leads to a broader concept of decision making under uncertainty. Uncertainty can then be defined as the sum of risk (i.e. the measurable component of uncertainty) and ambiguity (i.e. the immeasurable component). Ambiguity aversion describes disutility generated when individuals are not able to assign unique probabilities to prospects (Ellsberg 1961). The full range of parameters characterizing behavior under uncertainty (risk aversion, loss aversion, probability weighting, ambiguity aversion) will therefore be referred to as uncertainty preferences.

What happens to uncertainty preferences when one experiences a random adverse shock that incurs income losses? Normative economic theory would stress that preferences remain stable, as decision makers should not be affected by past, but only incremental outcomes, which is, however, rarely the case in practice (Thaler and Johnson 1990). Behavioral theories, in contrary, allow for behavioral learning, for example of changes in observable exogenous factors (Brunnermeier and Nagel 2008; Malmendier and Nagel 2011). Several authors have confirmed that risk preferences of subjects in developing countries that experienced natural disasters or income shocks differed from the average (Callen 2015; Cameron and Shah 2015; Gloede et al. 2015; Said et al. 2015; Voors et al. 2012). However, the direction of the effect is not consistent across studies. The same holds for predictions from different conceptual frameworks that could explain these preference shifts: behavioral heuristics (Tversky and Kahneman 1973), changes in background risk perceptions (Bchir and Willinger 2013; Cameron and Shah 2015; Gollier and Pratt 1996; Guiso and Paiella 2008; Quiggin 2003), or mental accounting (Imas 2016; Kahneman and Tversky 1979; Thaler and Johnson 1990). However, these conceptual frameworks and some empirical studies suggest that uncertainty preferences beyond EUT may be affected by the experiences of shocks (Barberis et al. 2001; Fehr-Duda et al. 2011; Li et al. 2011; Reynaud and Aubert 2013; Walther 2003). Furthermore, research so far has not been able to build a consensus regarding the relation of a range of sociodemographic variables with individual uncertainty preference parameters.

Why is this important? If one aims to predict the behavior of farmers from their uncertainty preferences, the meaningfulness of this relies on the assumption that these preferences remain stable with changing circumstances (Zeisberger et al. 2012). Also, understanding which aspects of a person's sociodemographic background precisely affect their risk preferences can help identifying the reasons for variation in risk preferences across the population in general.

It is very worthwhile to study these questions in rural Mexico. Natural disasters have been identified as a significant driver of poverty dynamics in Mexico (Rodriguez-Oreggia et al. 2013). Furthermore, the country is expected to be among the most negatively affected countries by climate change (IPCC 2014). Particularly, a large percentage of poor rural communities is located in environments that may experience a drying and warming trend during the main maize season (Bellon et al. 2005).

The objective of the paper *"The Relationship between Farmers' Shock Experiences and their Uncertainty Preferences - Experimental Evidence from Mexico"* (Chapter III) is therefore to estimate the full range of CPT preferences as well as ambiguity aversion parameters with Mexican farmers. The parameters are related to sociodemographic characteristics of their households and to the severity of experienced harvest losses. Thereby, the existing literature explaining variation in uncertainty preferences with past shock experiences and sociodemographic characteristics is extended by looking at a broader set of variables that characterize behavior towards uncertainty.

4. Informal risk management, insurance and other-regarding preferences

As has been laid out, the access of rural populations to formal insurance or comparable risk management tools is to date still very limited. This is why they often times rely on informal insurance mechanisms such as informal risk sharing amongst family members or cooperative groups to protect against adverse income shocks (Besley 1995; Jalan and Ravallion 1999;

Townsend 1994). It has been argued that solidarity mechanisms emerge quite naturally in societies that are subject to economic insufficiencies, rather than under affluence (Fafchamps 1992). More specifically, when members of informal social networks engage in risk sharing and make transfers amongst each other after a member suffered an income shock, this can strengthen social capital among network members (Dietrich 2013). Interaction amongst individuals can create social ties, or more precisely, other-regarding preferences. Other-regarding preferences refer to the weight individuals attach to the well-being of others (Camerer et al. 2011; Kagel and Roth 1995). They allow explaining a range of non-selfish behaviors from charitable giving to contributions to public goods (Cooper and Kagel 2016), and, on a macro level, in societies with stronger other-regarding preferences, economic growth is higher (Cardenas and Carpenter 2008; Zak and Knack 2001). Other-regarding preferences have been demonstrated to depend on the history of the interaction between individuals and are therefore dynamic (van Dijk and van Winden 1997). The introduction of formal insurance to informal networks has been found to modify the interactions amongst individuals in the network, namely by crowding-out the exchange of informal transfers (Landmann et al. 2012; Lin et al. 2014). Whether this crowding-out effect might also affect the dynamics of other-regarding preferences is still an open question. The relevance of this potential effect in the sample region is given by the documented importance and long history of social capital in rural Chiapas (Fox and Tversky 1995; Rico García-Amado et al. 2012). Therefore it is highly relevant to study how it could be affected by an increase in formal insurance coverage as sought by the government.

The paper *"Formal Insurance, Risk Sharing, and the Dynamics of Other-regarding Preferences"* (Chapter IV) analyzes theoretically and experimentally if and under which circumstances the introduction of formal insurance affects the dynamics of other-regarding preferences. Importantly, the structure of the shocks is taken into account. An experimental design similar to van Dijk and van Winden (1997) is applied to measure other-regarding preferences before and after a group of individuals interact in a repeated solidarity game, resembling a risk sharing network (Selten and Ockenfels 1998). By exogenously making formal insurance available to some members of the risk sharing network, the crowding-out effect on risk sharing transfers and other-regarding preferences causal to insurance can be estimated.

5. Outline of the dissertation

The dissertation is structured as follows. After this introductory part, Chapter III presents the paper titled *"Insurance for Technology Adoption: An Experimental Evaluation of Schemes and Subsidies with Maize Farmers in Mexico"*, which is to be published in Journal of Agricultural Economics. Chapter III presents the paper titled *"The Relationship between Farmers' Shock Experiences and Uncertainty Preferences - Experimental Evidence from Mexico"* which is published GlobalFood Discussion Paper Series (No. 92). Chapter IV presents the paper titled *"Formal Insurance, Risk-Sharing, and the Dynamics of Other-Regarding Preferences"*. Finally, Chapter V provides a summary of the results, discusses some potential limitations, and puts the findings into the context of related research.

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II Insurance for Technology Adoption: An Experimental Evaluation of Schemes and Subsidies with Maize Farmers in Mexico[1]

Publication reference: *Journal of Agricultural Economics,* DOI: 10.1111/1477-9552.12226.

Abstract

For farmers in developing countries, the combination of both risk aversion and the lack of insurance is often a major impediment to adoption of productivity-enhancing technologies, such as higher yielding hybrid seed. In a framed field experiment with Mexican maize farmers, we investigate whether bundling hybrid seed with an insurance scheme can increase its adoption, while also controlling for risk aversion. We test insurance schemes with different levels of risk coverage and premium subsidies and find that (1) all schemes significantly increase the degree of adoption of the higher yielding seed, (2) partial insurance schemes perform worse than full insurance, (3) weather index insurance with geographical basis risk performs no worse than indemnity insurance, and (4) premium subsidies significantly increase the adoption effect of indemnity insurance, but not that of index insurance.

JEL classifications: Q120; O31; C910

Keywords: Insurance; risk aversion; technology adoption; Mexico

[1]This chapter is co-authored by Oliver Musshoff. The authors' contributions are as follows: HF and OM designed the research. HF collected, analyzed, and interpreted the data. OM assisted in the analysis and interpretation of the results. HF wrote the paper.

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III The Relationship between Farmers' Shock Experiences and Uncertainty Preferences - Experimental Evidence from Mexico[2]

Publication reference: *GlobalFood Discussion Paper 92,* University of Göttingen. http://www.uni-goettingen.de/de/213486.html.

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 harvest loss severity is not related to loss aversion or ambiguity aversion.

JEL classifications: D810; Q120; Q540

Keywords: risk aversion; Prospect Theory; ambiguity; natural disaster; farmers

[2]This chapter is co-authored by Ben Wiercinski and Oliver Musshoff. The authors' contributions are as follows: HF developed the research idea and collected the data. HF analyzed and interpreted the data. BW and OM assisted in the analysis and interpretation of the results. HF and BW wrote the manuscript.

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 (Just and Pope 1979a; Roumasset 1974). 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 (Dercon and Christiaensen 2011; Engle-Warnick et al. 2011; Feder et al. 1985; Knight et al. 2003; Liu 2013; Rosenzweig and Binswanger 1993; 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; Engle-Warnick et al. 2011; Gloede et al. 2015; Liu 2013; Miyata 2003; Said et al. 2015; Tanaka et al. 2010). As compared to deriving risk preferences from observational data, experiments allow for the distinction between mere risk response, which could originate from other constraints, from 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 on 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 preferences along the lines of (Cumulative) Prospect Theory (Kahneman and Tversky 1979; Tversky and Kahneman 1992) when analyzing behavior of rural populations, estimating separately individual parameters 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 the technology adoption behavior of farmers from their experimentally elicited risk preferences, the meaningfulness of this relies on the assumption that these preferences remain stable over time and with changing circumstances (Zeisberger et al. 2012), such as recent 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. Therefore we 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. This 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 on the relationship between sociodemographics and past shock experience and uncertainty preferences. Section 3 explains details on 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 implications.

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. 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 to 6 months did 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 curvature remained consistent over several weeks' time. Duersch et al. (2017) find stability over time for the ambiguity aversion estimates for 57 percent 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 from changes in observable exogenous factors (Brunnermeier and Nagel 2008; Malmendier and Nagel 2011), or more specifically, shocks (Said et al. 2015; Voors et al. 2012).

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 the form of losses: the availability heuristic, inducing decision makers to assess likelihood of an event based on the 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 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 the 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 that 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 low-probability 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 III-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 following, 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 in Thailand and Vietnam. 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 caused people to update the probability of another flood, and this perceived increase in background risk lead to higher risk vulnerability. Broadening the scope beyond just developing countries, Page et al. (2014) look at preferences in the aftermath of floods in Australia. They find that people who have lost large amounts in a flood were more risk seeking afterwards, possibly because they had hopes of gaining back what they had lost, a finding that is in line with the break-even hypothesis (Thaler and Johnson 1990).

Most research on 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 (in the following, EUT) (Cameron and Shah 2015; Eckel et al. 2009; Gloede et al. 2015). Nevertheless, there is broad evidence of non-EUT preferences of both farmers in developed (Bocquého et al. 2014) and in developing countries (Brauw and Eozenou 2014; Petraud 2014; Tanaka et al. 2010). This makes it worthwhile to 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 increased 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 a safer lottery in the negative domain and the riskier lottery in the positive domain during a risk experiment. Expecting a future flood made people additionally behave more risk aversely, while the flood experience had no effect on the probability weighting function.

Table III-1: Shock experience and uncertainty preference parameters by paper

	Risk aversion									**Probability weighting**	
VARIABLES	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]	Li et al. (2011)[2]	Reynaud &Aubert (2013)[5]
Shock experience:											
-positive domain		-**	-**		-**						
-negative domain		+**	Ns		+**						
-no distinction	-			-***		+	+***	+* (personal loss) -** (no personal loss)	+*	+**	Ns

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0$. 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 indicate that variables were not tested in the 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 III-2 and III-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 III-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		-**				

* $p < 0.1$, ** $p < 0.05$, *** $p < 0$. p-values from tests used in the respective papers (where it applies).
Ns: not significant. + denotes more risk aversion, - denotes less risk aversion.
Blanks indicate that variables were not tested in the 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 III-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				+***	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0$. 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 indicate that variables were not tested in the 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 (Engle-Warnick et al. 2011; Gloede et al. 2015; Said et al. 2015; Tanaka et al. 2010). 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 (Engle-Warnick et al. 2011; Gloede et al. 2015; Miyata 2003; Tanaka et al. 2010; Yesuf and Bluffstone 2009). 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 are 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, is still a core part of the Mexican diet, and remains of vital importance for 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 (Rodriguez and Luna).[3] In the studied municipalities, 52 percent live below the poverty line (CONEVAL 2010). Climate risk poses a growing challenge for rural Mexico (Vermeulen 2011). 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.

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

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

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 sampled based on a stratified 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 EUT 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 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 (Tversky and Kahneman 1992):

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

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

The value functions are defined as a piecewise power value function

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

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:

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

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

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

The parameter θ denotes an additional sanction on utility when unique probabilities are unknown to a decision maker. Our experimental design and econometric approach allow 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) are 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 earned \$10 MXN in cash). Participants received an endowment of \$10.50 MXN for this 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 consisted of two identical lottery choice lists (see Table III-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 III-4, Table III-5, and Table III-6. Monotonic switching was 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 had to 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 were revealed the true probability of $p = 0.5$ In Series 2, while the payoffs remained the same, with the only difference that participants were shown the content of the bag, revealing equal odds, i.e. five green and five orange balls. Under ambiguity theory, it is assumed that individuals' utility is lowered when no unique 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 switched from the lottery to the riskless

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

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 to 0.7, respectively. This allows estimating the degree of probability overweighting. As opposed to the first two series, the winning payoffs in Option B are rising, ceteris paribus, within each series, i.e. the expected value of the lottery increases, while probabilities stay the same within the series for all decision rows (see Table III-5). Again, monotonic switching was enforced. Switching in the first decision row as well as not switching at all was explicitly allowed 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 III-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 amount. Among those who opted for the lottery option, 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 then subtracted from the initial endowment. All nominal earnings were then divided by 100 before they were paid out in cash.

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

Table III-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 III-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 III-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 also applied by 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 the value function in equation (2) for each outcome in each lottery decision row i with n possible payoffs:

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

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 side (Option B) and left hand side (Option A) 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 hand option (Option B) and EU_i^L of the left hand option (Option A) 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 Option A and B in the lottery-based experiment is described by:

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

We are looking for the parameters σ, λ, α and θ that maximize the following log-likelihood 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 and X denotes a vector of sociodemographic characteristicscommonly related with risk preferences or relevant controls in relation to shocks, as well as variables indicating the severity of harvest shock experiences.

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 maize harvest loss in year t of subject i in tons, v_{it}, divided by the sum of the absolute loss v and harvest amount Y of farmer i in t in tons, 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 80$^{\text{th}}$ percentile of the sample. This corresponds to an average loss from 2012-14 of 25 percent 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, one 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 farmers' uncertainty 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 percent 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 lottery-based experiment, 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 et al. (2015). As treatment variable, we use our loss dummy, indicating average harvest losses of 25 percent from 2012-14, as stated in the previous section. We then create the propensity score for by running a logit estimation on the binary treatment variable controlling for all observable variables that might affect shock severity:

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

Here, 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. Here we include relevant sociodemographic control variables as stated before and the following production variables: maize area, logged per hectare expenditures for fertilizer, pesticides and herbicides, average total maize area 2012-14, and the share of maize land devoted to improved maize varieties (Table A1 in the annex of this chapter shows all the variables included). Conditioning on the propensity score, the preference parameter outcomes are independent from 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 annex of this chapter) 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. To deal with this potential source of endogeneity, we therefore additionally present an instrumental variable (IV) approach.[7] 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:

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

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 $\overline{S_j}$ is the average of S 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 (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 III-7). The average respondent is around 47 years old. The sample is overwhelmingly male, with only 8 percent being female, due to our respondents being farm decision makers, which is a predominantly male responsibility. On average, respondents achieved relatively low levels of

[7] To restrict the analysis on seemingly losses due to exogenous types of shocks such as self-reported drought losses is not sufficient, as the severity of these shocks might be related to precaution or ability, too.

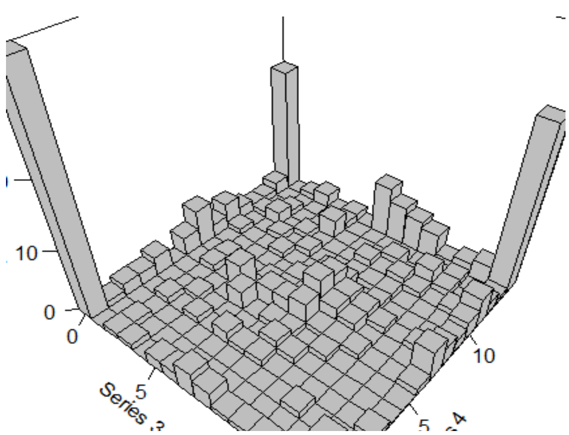
formal education, with an average of 5.44 years. Only around 4 percent of the sample had an indigenous parent. The sampled villages are on average rather remote, with an average travel time to the nearest municipal capital of 80 minutes. As a proxy for wealth, we developed an asset index based on principal 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 devoted on average 56 percent to hybrid maize. While 92 percent of respondent stated maize production to be their main income source, on average they had a total of 4 income sources, which includes both farm and off-farm incomes.

Table III-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
Village 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 III-1: Distribution of switching rounds in lottery Series 3 and 4



Source: Authors' own illustration

Figure III-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.

7.2 Estimation results

Table III-8 shows the sample averages of the CPT parameters resulting from ML estimation without including covariates. We can strongly reject that our subjects are expected utility maximizers, which would imply neither probability weighting nor loss aversion, i.e. $\alpha = \lambda = 1$. 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 III-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 III-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). Risk aversion increases with household size, which is in contrast to the finding by Miyata et al. (2003). This difference could be due to the fact that our subjects were almost invariably household heads. Instead of a larger household representing a safety net as argued by Miyata et al. (2003), from the perspective of the head a larger household might imply a larger responsibility burden and therefore a more considerate and risk-averse behavior. Subjects with indigenous

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

VARIABLES	**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)
Village 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		0.623***		
Constant		(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.

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

VARIABLES	**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)

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 de-weighting of large probabilities. Hence, we find that probability overweighting is decreasing in wealth and distance to the nearest city. We do not find 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 $[1,\theta]$ denotes an increase in ambiguity aversion. However, we only find significantly higher ambiguity aversion for subjects with an indigenous parent. Unlike Engle-Warnick et al. (2011) we find no significant effect of household size. 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 III-11 presents descriptive statistics on subjects' maize shock frequency and severity experienced from 2012-14. During those years, the average respondent suffered from 1.77 incidents in which maize harvest was lost. Drought accounted for 51 percent of the total losses, followed by excessive rain (20 percent) and pest shocks (14 percent). Those farmers that experienced harvest shocks, lost on average 19 percent of their harvest in the incident.

Table III-11: 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

Table III-12 shows 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 an average harvest loss of over 25 percent. 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 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, 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, we check for the balance of covariates in the control and treatment group, i.e. the group of farmers with average loss shares of over 25 percent between 2012-14 before matching. Indeed, we find some significant differences in fertilizer and herbicide expenditures per hectare, as well as total maize area (Table A1 in the annex of this chapter). However, t-tests on the explanatory variables after matching indicate that balance on observables was achieved (Table A2 in the annex of this chapter). Results for propensity score matched data are presented in column 3 of Table III-12. The treatment dummy, i.e. having incurred average maize loss shares above 25 percent in 2012-14, shows up significantly negative in explaining probability weighting. This confirms our results from the non-matched data, finding that shock severity increased 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

Table III-12: 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%=1. 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 with 100 repetitions.
[1]Model (3): Propensity score

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 that experienced natural disaster related shocks and points towards the risk vulnerability hypothesis (Gollier and Pratt 1996).

Regarding the IV results, the validity of our instrument is confirmed in the first stage regression (Table A3 in the annex of this chapter), 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 III-12. 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 effects.

9. Conclusion

Starting with Binswanger (1980), economists have been trying to understand how smallholder farmers make decisions under uncertainty. Also, 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 shock experience 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 a lab-in-the-field experiment 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 to a weaker degree, 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. Coefficients are partially in line with the existing literature. 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 loss severity, we find that farmers having experienced more severe losses become more risk averse, 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 experiencing 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 becomes the farmers' assessment of low 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 (2013), 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 (Cabestany-Noriega et al. 2013) is certainly a step in the right direction. 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 more remotely located smallholder farmers will be reached.

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Annex

Table A1: Balance of covariates by loss affected status before propensity score matching

	Treatment[1]		Control		
VARIABLE	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
Village reunions attended; share	0.59	0.42	0.52	0.46	0.27
Parents indigenous; dummy	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
Land with hybrid maize 2012-14; share	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, which corresponds to a loss≥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.

Table A2: Balance of covariates by loss affected status 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
Village reunions attended; share	0.37	0.42	0.46	0.46	0.21
Parents indigenous; dummy	0.02	0.13	0.05	0.23	0.20
No. of income sources	3.95	1.45	4.35	1.65	0.12
Time to city; minutes	2.61	1.75	3.02	2.45	0.22
Avg. maize area 2012-14; ha	7.81	1.23	7.97	1.25	0.41
Log. fertilizer expenditure; $MXN/ha	3.61	2.09	3.34	2.37	0.46
Log. pesticide expenditure; $MXN/ha	6.26	0.89	6.39	1.37	0.46
Log. herbicide expenditure; $MXN/ha	0.51	0.45	0.53	0.34	0.70
Land with hybrid maize 2012-14; share	73.33	36.63	74.09	42.90	0.91
Observations	110		55		

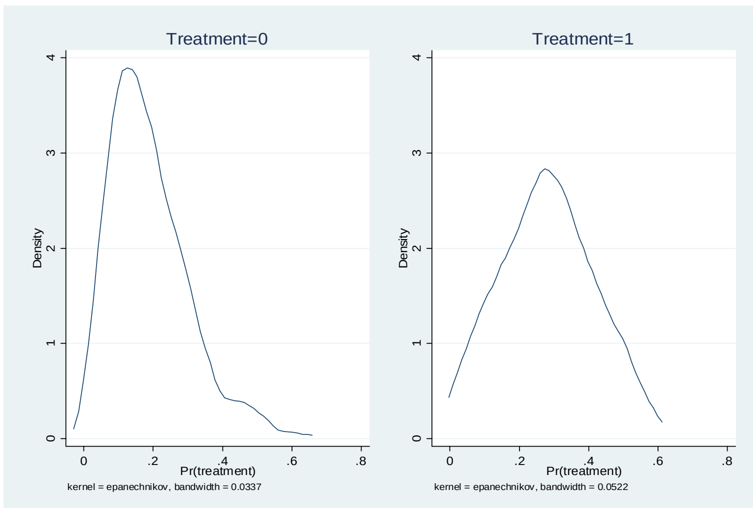
[1]propensity score matched data. Treatment refers to subjects with average maize loss shares 2012-14 above the 80th percentile of the sample distribution, which corresponds to a loss≥25%. Each treated was matched with two untreated observations based on nearest neighbor matching.
[2]p-values from two-sided t-test. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$
[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.

Table A3: First stage OLS regression

VARIABLES	
Village average of maize loss, 2012-14; %	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.
Dependent variable=farmers' share of harvest lost, 2012-14; %

Figure A1: Kernel density estimates for propensity scores



IV Formal Insurance, Risk Sharing, and the Dynamics of Other-Regarding Preferences[8]

Abstract

In the absence of formal financial markets many poor households rely on the mutual exchange within informal risk sharing networks to protect themselves against adverse events. Social interactions in the aftermath of shocks have been found to strengthen the social ties among members of such networks. In this paper, we analyze how selectively providing formal insurance to members of a risk sharing network affects risk sharing transfers and, subsequently, the dynamics of other-regarding preferences. In a framed field experiment, we find that the effect of formal insurance depends on (1) the covariance structure of shocks and (2) on the individual insurance status. When formal insurance is available to some members of a risk sharing network, it either decreases trust levels of the uninsured or increases trust levels of the insured subjects towards the other network members, depending on the degree of income covariance within the network. Trustworthiness and altruism remain unaffected by the introduction of insurance. The results are driven by a change in the dynamics of the transfer behavior within the network induced by formal insurance.

JEL Classifications: D64; A13; C91; D81

Keywords: altruism; risk sharing; social preferences; insurance

[8]This chapter is co-authored by Stephan Dietrich, Marcela Ibañez, and Oliver Musshoff. The authors' contributions are as follows: SD, MI and HF designed the research. MI developed the theoretical model. HF contributed to the model design and collected the data. HF and SD analyzed and interpreted the data. HF, SD, MI and OM wrote the manuscript.

1. Introduction

The aim of this paper is to investigate the interlink between risk sharing in informal solidarity networks, formal insurance, and the dynamics of other-regarding preferences. Other-regarding preferences, also referred to as social preferences, are the preferences of individuals over the well-being of others, additionally to their own (Camerer et al. 2011; Kagel and Roth 1995). They allow explaining decisions in various circumstances ranging from charitable behavior, bequests, contributions to public goods, and investment decisions (Cooper and Kagel 2016). Understanding the factors that affect the development of other-regarding preferences is important since societies that manage to establish norms that curb individualistic interest in favor of social well-being have been found to experience higher economic growth (Cardenas and Carpenter 2008; Zak and Knack 2001).

Providing formal, individualized insurance to previously uninsured households in developing countries is regarded as a promising instrument to decrease vulnerability to poverty (World Bank 2013): it has been argued that the risk reduction due to formal insurance could lead farmers to invest in more risky, but higher yielding technologies (Fafchamps 2010; Karlan et al. 2014), improve access to loans (Giné and Yang 2009) and prevent the use of inefficient risk coping mechanisms (Barnett et al. 2008; Dercon 2002; Fafchamps and Gubert 2007; Fafchamps and Lund 2003). Yet, theoretical and empirical literature suggests that formal insurance can crowd-out risk sharing in informal solidarity networks, potentially resulting in a net decrease in risk coverage (Lin et al. 2014). Apart from increasing households' vulnerability to adverse shocks, this could have negative effects on the development of other-regarding preferences among households. We present a model that explains the development of these preferences in informal risk sharing agreements with imperfect commitment. Other-regarding preferences are formalized as the weight the network partners' income has in one's own utility function. Similar to van Dijk and van Winden (1997), these weights are not constant over time but depend on the history of the interaction between individuals. As individuals who are affected by negative shocks receive transfers from their social network, they increase the weight that they attach to the utility of those others. Therefore, even when there is no infinite repeated interaction, positive levels of risk sharing can be achieved (Coate and Ravallion 1993; Foster and Rosenzweig 2001; Ligon et al. 2002). We extend this model by taking into account the impact of formal insurance on risk sharing. Similar to Lin et al. (2014), we are able to show that formal insurance crowds-out risk sharing under some circumstances. We show that this can also result in a subsequent crowding-out of the development of other-regarding preferences.

To test the above hypotheses, we implemented a framed field experiment (Harrison and List 2004) in rural Mexico where households, mainly relying on agricultural activities for their income, are particularly vulnerable to weather shocks and exposed to a large amount of uninsured risks. It could be shown that natural disasters are a significant driver of poverty dynamics in Mexico (Rodriguez-Oreggia et al. 2013). In an effort to reduce this vulnerability, the Mexican government has invested in the development of a subsidized federal insurance scheme for farmers (Cabestany-Noriega et al. 2013). Public expenses to promote formal agricultural insurance schemes have almost doubled between 2007 and 2010. In 2011, 2.67 million hectares of agricultural land - however mainly located in the more developed regions - were covered. By strengthening the insurance markets, many small-scale farmers could get access to formal insurance, which could have important implications for the dynamics of other-regarding preferences within communities. Moreover, the implications could be especially severe for those left uninsured; typically, these are the poorest households who are less likely to buy insurance (Eling et al. 2014).

Our experimental design is similar to van Dijk et al.'s (2002) three-stage design. In the first stage we elicit experimental measures of social preferences using a three-person dictator and trust game. Thereafter, we allow participants to interact in a three-person, repeated solidarity game similar to Selten and Ockenfels (1998). After solving a real effort task, participants can suffer from a negative shock which results in total loss of their earnings. Participants who are not affected by the shock can decide to send a transfer to affected participants. In this stage we exogenously modify (1) the number of participants simultaneously affected by a shock and (2) the availability of insurance. We allow for either one individual being affected by a shock at a time, which we will refer to as "individual shock" and corresponds to a negative income correlation, or two, which we will refer to as "collective shock" and corresponds to positive income correlation. In the treatments with insurance, two participants in the network are exogenously provided with fair insurance, while the third individual remains exposed to negative shocks. Insured participants receive a fixed payment independently of whether they are affected by a shock or not and therefore can send transfers to the shock-affected member. Finally, in the last stage we repeat the measurement of social preferences using a three-person dictator and trust game with the same three-person groups from the solidarity game. The comparison of the experimental measures before and after the solidarity game under different treatments allows tracing the dynamics of social preferences.

We find partial support for the model. The history of previous interactions in the solidarity game does affect the development of other-regarding preferences. Participants that are insured and therefore receive no transfers from their network in the solidarity game, display less trust towards the other network members than in the control treatment without insurance. Conversely, participants who are not insured and receive transfers from insured participants, display higher levels of trust. Our results, however, provide limited support for the crowding-out effects of the insurance on average informal risk sharing. We find that average transfers to non-insured network members do not change significantly when some members are insured and shocks are individual. When shocks are collective, insurance has a positive effect on the absolute value of the transfers received by non-insured network members, but a negative effect on the value of transfers received relative to the maximum amount possible. These results suggest that when formal insurance is introduced, the effects on other-regarding preferences are driven by the structure of the shocks, or covariance of incomes within the network.

Few theoretical models explain the existence of risk sharing agreements with imperfect commitment (Charness and Genicot 2009; Coate and Ravallion 1993; Foster and Rosenzweig 2001; Kimball 1988; Ligon et al. 2002). Yet, the only paper that considers the crowding-out effects of formal insurance on risk sharing is Lin et al. (2014). Following an approach similar to Foster and Rosenzweig (2001) and Lin et al. (2014), we propose a model of risk sharing with other-regarding preferences. Previously, van Dijk and van Winden (1997) and van Dijk et al. (2002) also examined the effect of interaction in public goods games on other-regarding preferences. Yet, we differ from these papers as we are the first to explicitly examine the effect of risk sharing with and without formal insurance on the development of other-regarding preferences.

There is a growing literature examining the interrelation between formal insurance and risk sharing networks (Cecchi et al. 2016; Dercon et al. 2014; Landmann et al. 2012; Lenel and Steiner 2016; Lin et al. 2014; Mobarak and Rosenzweig 2013). For example, Mobarak and Rosenzweig (2013) study how the existence of risk sharing agreements affects the demand for formal insurance. Similar to Dercon et al. (2014) and Lin et al. (2014), we take into account potential crowding-out effects of formal insurance on informal risk sharing. On the one hand, Dercon et al. (2014) show theoretically and empirically that basis risk, the risk of suffering a loss that is not indemnified by index-based insurance, can crowd-in informal transfers in risk sharing networks. On the other hand, Lin et al. (2014) show theoretically and empirically that formal insurance can crowd-out transfers in informal risk sharing networks. First, the utility of remaining in autarky relative to participating in the network increases. Second, formal insurance is a substitute for informal transfers and decreases the marginal utility of those. Similarly, Landmann et al. (2012) find that formal insurance crowds-out solidarity between network members when incomes are observable, and that this effect even persists after removing the insurance. In contrast to these studies, our focus lies on the effect of formal insurance on the dynamics of other-regarding preferences.

A similar approach to our research is the work by Cecchi et al. (2016) who analyze how the introduction of formal health insurance in Uganda affects public goods contributions. The authors find a reduction in public goods contributions in areas where insurance had been introduced. The effect is driven by lower contributions of individuals that did not take up insurance. Our work complements this research by analyzing the effects of formal insurance depending on the covariance structure of shocks. In particular, we separately consider the cases when negative income shocks affect either one or more than one network member simultaneously. This is important as the dynamics of the exchange of help and other-regarding preferences can change significantly depending on the structure of shocks (Dietrich 2013).

The rest of the paper is structured as follows. Section 2 presents the theoretical model explaining the crowding-out effects of insurance on transfers within risk sharing models. Section 3 and 4 explain the experiment design, treatments, and experimental procedures. Section 5 describes the estimation strategy and results. The results summarized and potential limitations are discussed in Section 6.

2. Theoretical model

2.1 Model set-up

We propose a risk sharing model in the spirit of well-established models of risk sharing under no or imperfect commitment (Coate and Ravallion 1993; Foster and Rosenzweig 2001; Ligon et al.

2002). Specifically, a solidarity network with altruistic preferences similar to Lin et al. (2014) is considered, composed of three individuals, $i = 1,2,3$. They interact over two periods $t = 1,2$. In each period individual i receives an income $y_{i,t}(s_{i,t})$, where s_t is the state of the world that individual i confronts in period t. There are two possible states, $s_{i,t} = 1$ or $s_{i,t} = 2$. The probabilities associated with each of these are $(1 - p)$ and p, respectively. Similar to other risk-sharing models (Foster and Rosenzweig 2001; Lin et al. 2014), we assume that individuals cannot save across periods. Income is given by:

$$y_{i,t} = \begin{cases} E_{i,t} + w_{i,t} & if\ s_{i,t} = 1 \\ E_{i,t} & if\ s_{i,t} = 2 \end{cases} \tag{1}$$

E_i is a fixed income and w_i an additional positive income only attained if $s_{i,t} = 1$, while a negative income shock corresponds to $s_{i,t} = 2$. Individuals can send transfers to network members that are affected by a shock ($s_{it} = 2$). We denote the transfer sent by individual i to the affected individual(s) j in period t by $t_{ij,t}$. We assume that transfers are only sent if at least one member in the network is affected by a shock, and that affected members cannot send transfers. Then a transfer from i to j occurs if $s_{i,t} = 1$ and $s_{j,t} = 2$ for all $j \neq i$.

We assume that individuals' utility depends on two components: (1) the utility of their own consumption and (2) utility of consumption of the other network members. Thereby we take into account that transfers can be motivated by an altruistic motive (Cox et al. 2008; Foster and Rosenzweig 2001; Lin et al. 2014). The utility of consumption $U(c_{i,t})$ is assumed to be a standard von Neumann-Morgenstern utility function that is increasing and concave in $(U'(c) > 0, U''(c) < 0)$. In period t, individual i attaches a welfare weight $\gamma_{ij,t}$ to their partner j's utility of consumption, $V(c_{j,t})$, with $V'(c) > 0$ and $V''(c) < 0$. Following the standard assumptions we define $0 < \gamma_{ij,t} < 1$, ruling out that i values j's utility of consumption more than her own.

Our innovation is that we extend this model by considering that the welfare weight $\gamma_{ij,t}$ is dynamic. Therefore we follow the notion suggested by Bault et al. (2016), who model the development of other-regarding preferences among individuals as depending on the degree of positive or negative valuation of their interaction experiences. Within a risk sharing network, we suggest that an interaction is valued more positively when higher risk sharing transfers are received. Therefore, the welfare weight $\gamma_{ij,t}$ changes over time with the history of previous transfers received by i from j, $t_{ji,t-1}$, and the previous level of altruism, $\gamma_{ij,t-1}$. Dynamics of other-regarding preferences are given by a function $\gamma_{ij,t+1} = f(t_{ji,t}, \gamma_{ij,t})$, where $\gamma_{ij,t+1}$ is increasing in transfers received in t, $t_{ji,t}$($\frac{\gamma_{ij,t+1}}{dt_{ji,t}} > 0$), and increases more for initially less altruistic individuals, ($\frac{d^2\gamma_{ij,t+1}}{dt_{ji,t}d\gamma_{ij,t+1}} < 0$). For simplicity, we assume that the discount rate is equal to one and future consumption is valued as much as present consumption.

We consider two different scenarios which we refer to as individual and collective shocks. In the scenario with individual shocks, incomes of the network members are negatively correlated and therefore only one network member is affected by a negative income shock in a given period. Hence, if a shock occurs, then $s_{i,t} = 2$ for i and $s_{j,t} = 1$ for all $j \neq i$. Under this scenario, two participants in the network can make a transfer to the affected member at a given time. In the scenario with collective shocks, incomes of the network members are positively correlated and two network members are affected by a negative income shock in a given period. In this case, $s_{i,t} = 1$ for i and $s_{j,t} = 2$ for all $j \neq i$ and only one network member can make a transfer at a time. Each shock-affected member will receive half of that transfer.

2.2 Individual shocks

2.2.1 Optimization problem

We first consider the scenario with individual shocks, in which participant j suffers an income shock and individual i (and k) can make a transfer to them. Assuming that an individual's utility is separable in two components - own consumption and weighted consumption of others in the network, the optimization problem for individual i in $t = 1$ is:

$$\underset{t_{ij,t}}{Max} \quad U_{i,t}(c_{i,t}, c_{j,t}, c_{k,t}) = U(c_{i,t}) + \gamma_{ij,t}V(c_{j,t}) + \gamma_{ik,t}V(c_{k,t}) \tag{2}$$

Subject to:

$$ci_{j,t} + t_{ij,t} = E_{i,t} + w_{i,t} \tag{3}$$

$$c_{j,t} - t_{ij,t} - t_{kj,t} = E_{j,t} \tag{4}$$

$$c_{k,t} + t_{kj,t} = E_{k,t} + w_{k,t} \tag{5}$$

$$U_{i,t}(c_{i,t}, c_{j,t}, c_{k,t}) + EU_{i,t+1}(c_{i,t+1}, c_{j,t+1}, c_{k,t+1}) \geq U_{i,t}\left(y_{i,t}, y_{j,t}, y_{k,t}\right) + EU_{i,t+1}\left(y_{i,t+1}, y_{j,t+1}, y_{k,t+1}\right) \quad (6)$$

Equations (3) to (5) refer to the budget constraints for individuals i, j, and k, while equation (6) refers to the participation constraint in the risk sharing network. This condition simply states that individual i would decide to participate in the risk sharing network and make a transfer if the discounted expected utility after the transfer is larger than the expected utility in autarky, i.e. without current or future exchange of transfers. The discounted expected utility of participating in the network, $EU_{i,t+1}$, depends on the expected probabilities of the different states of the world that i could be confronted with in $t+1$. Denoting the set of states for the world by $S = \{s_{i,t}, s_{j,t}, s_{k,t}\}$, the following sets of states are possible: $S_1 = \{1,2,1\} + \{1,1,2\}$; $S_2 = \{1,2,2\}$; $S_3 = \{2,1,1\}$; $S_4 = \{2,2,1\} + \{2,1,2\}$; $S_5 = \{2,2,2\}$ and $S_6 = \{1,1,1\}$. Let q_1 to q_5 represent the probabilities of the different sets of states.[9] The expected utility of consumption in $t = 2$ is given by the expected utility of different states of the world:

$$\begin{aligned}
EU(c_{i,t+1}) = &\\
& q_1\left(U(E_{i,t+1} + w_{i,t+1} - t_{ij,t+1}) + \gamma_{ij,t+1}V(E_{j,t+1} + t_{ij,t+1} + t_{kj,t+1}) + \gamma_{ik,t+1}V(c_{k,t})\right)\\
& + q_2\left(U(E_{i,t+1} + w_{i,t+1} - t_{ij,t+1}) + 2\gamma_{ij,t+1}V\left(E_{j,t+1} + \frac{t_{ij,t+1}}{2}\right)\right)\\
& + q_3\left(U(E_{i,t+1} + t_{ji,t+1} + t_{ki,t+1}) + \gamma_{ij,t+1}V(E_{j,t+1} + w_{j,t+1} - t_{ji,t+1}) + \gamma_{ik,t+1}V(c_{k,t})\right)\\
& + q_4\left(U\left(E_{i,t+1} + \frac{t_{ji,t+1}}{2}\right) + \gamma_{ij,t+1}V(E_{j,t+1} + w_{j,t+1} - t_{ji,t+1}) + \gamma_{ik,t+1}V\left(E_{k,t+1} + \frac{t_{ji,t+1}}{2}\right)\right)\\
& + q_5\left(U(E_{i,t+1}) + \gamma_{ij,t+1}V(E_{j,t+1}) + \gamma_{ik,t+1}V(E_{k,t+1})\right)\\
& + (1 - q_1 - q_2 - q_3 - q_4 - q_5)\left(U(E_{i,t+1} + w_{i,t+1}) + \gamma_{ij,t+1}V(E_{j,t+1} + w_{j,t+1}) + \gamma_{ik,t+1}V(E_{k,t+1} + w_{k,t+1})\right) \quad (7)
\end{aligned}$$

Here, the value of the transfer received by i tomorrow, $t_{ji,t+1}$, is a function of the welfare weight or degree of altruism γ from j to i, which increases with the transfers sent by i to j today, $t_{ij,t}$. For a finite interaction over two periods, the problem can be solved recursively, finding the optimal transfer in $t = 2$ first, and then finding the optimal transfer in $t = 1$. In $t = 2$, the participation

[9] Assuming that the probability of a shock, p_i, is the same for all i, then $q_1 = 2p_i(1-p_i)^2$; $q_2 = {p_i}^2(1-p_i)$; $q_3 = p_i(1-p_i)^2$; $q_4 = 2{p_i}^2(1-p_i)$; and $q_5 = {p_i}^3$. Hence, $(1 - q_1 - q_2 - q_3 - q_4 - q_5) = (1-p_i)^3$.

constraint is not binding. Assuming that $t_{kj,t}$ is independent from $t_{ij,t}$, the first order condition for an interior solution implies that a transfer will be sent if:

$$\gamma_{ij,t} > \bar{\gamma}_{ij,t} = \frac{U'(c_{i,t})}{V'(c_{j,t})} \tag{8}$$

This implies that when the welfare weight, $\gamma_{ij,t}$, is higher than the threshold level $\bar{\gamma}_{ij,t}$, risk sharing can be achieved in the absence of repeated interaction. However, in $t = 1$, transfers can occur even if the welfare weight is below the threshold level. This happens when the participation constraint in the risk sharing network is binding. The participation constraint states that participants' expected utility of participating in the risk sharing a network and making a transfer today is larger than the expected utility in autarky, i.e. without any exchange of transfers. If this is the case, transfers are positive even when $\gamma_{ij,t}<\bar{\gamma}_{ij,t}$. Comparative statics around the optimum transfer $t_{ij,t}{}^*$ for $t = 1{,}2$ lead to the following proposition:

Proposition 1: Optimal transfer

The optimal transfer increases with (1) the level of altruism or welfare weight, $\gamma_{ij,t}$, (2) i's income, $E_{i,t} + w_{i,t}$, and (3) the probability of attaining a low income state, p.

Proof: see annex of this chapter.

We extend this model furthermore by introducing formal insurance. We consider a scenario in which only two members of the network j and k have access to fair insurance. In this model we do not attempt to explain the decision to insure, but assume that insurance is exogenously assigned. This could for instance reflect a social protection program that just reaches some individuals within a community. Insured network members are insured for all two periods. We consider fair insurance that costs ph each period and pays h when $s_{i,t} = 2$. In order to analyze the crowding-out effect of insurance, we must distinguish three cases:

2.2.2 Case A: Non-insured participant sends transfer to insured participant

When a non-insured participant i makes a transfer to an insured participant j, the first order condition for optimization of the non-insured participant is

$$\frac{dL}{dt_{ij,t}} = (1+\lambda)(-U'(E_{i,t} + w_{i,t} - t_{ij,t}) + \gamma_{ij,t}V'(E_{j,t} + (1-p)h + t_{ij,t} + t_{kj,t})) +$$
$$\lambda\left[q_3\left(U'(E_{i,t+1} + t_{ji,t+1} + t_{ki,t+1}) - \gamma_{ij,t+1}V'(E_{j,t+1} + w_{j,t+1} - ph - t_{ji,t+1})\right) +\right.$$
$$q_4\left(\frac{1}{2}U'\left(E_{i,t+1} + \frac{t_{ji,t+1}}{2}\right) - \gamma_{ij,t+1}V'(E_{j,t+1} + w_{j,t+1} - ph - t_{ji,t+1})\right)\Bigg]\left(\frac{dt_{ji,t+1}}{d\gamma_{ji,t+1}}\frac{d\gamma_{ji,t+1}}{dt_{ji,t}}\right)] \qquad (9)$$

where λ is the Lagrangian multiplier which is assumed to be larger than zero when the participation constraint is binding, and equal to zero otherwise. The first line of equation (9) above refers to the marginal net benefit of sending a transfer today, while the second and third lines of the expression refer to the future expected utility gains of sending a transfer today. As participant i sends a larger transfer to j in $t = 1$, the welfare weight of j towards i, $\gamma_{ji,t+1}$, increases in $t = 2$. This implies that if individual i is hit by a shock in $t = 2$, transfers $t_{ji,t+1}$ from j to i will be larger. This effect is captured by the last term of the last line in equation (9). The change in utility depends on the increased marginal utility of own consumption from receiving a transfer, indicated first part of the second and third line in equation (9), versus the decreased weighted marginal utility of consumption of j, indicated in the second part of the second and third lines, respectively.

The introduction of insurance induces a substitution effect. When j receives an indemnity payment, ph, the marginal utility of additionally receiving a transfer is lower, which i takes into account when determining her own optimal transfer level and therefore reduces it accordingly. The insurance also generates an income effect. When the insured participant pays ph for the insurance in $t + 1$, he is relatively poorer compared to the scenario without insurance. This increases the marginal cost of a transfer from j to i in $t + 1$. Knowing that j is insured and expecting less transfers from j in $t + 1$ when experiencing a negative income shock, i anticipates this effect and sends less transfers to j in $t = 1$. The substitution and the income effect result in a lower $t_{ij,t}$. This also crowds-out the development of other-regarding preferences amongst i and j. As j receives lower transfers from i, her level of attachment towards i is also reduced when insurance is available compared to when it is not.

2.2.3 Case B: Insured participant sends transfer to non-insured participant

When participant i is insured, while she can still send transfers to affected participants, we assume that she cannot receive transfers in $t + 1$, since she will get an indemnity payment of

$(1-p)h$ when she suffered a shock. Therefore, $q_3 = q_4 = 0$. This reduces i's incentive to send a transfer to j in t. The first order condition for optimization for i is:

$$\frac{dL}{dt_{ij,t}} = (1+\lambda)\left(-U'\left(E_{i,t} + w_{i,t} - t_{ij,t} - ph\right) + \gamma_{ij,t}V'\left(E_{j,t} + t_{ij,t} + t_{kj,t}\right)\right) \tag{10}$$

The effect of insurance is to decrease i's disposable income in $t = 1$, which increases i's marginal cost of sending a transfer to the uninsured participant j and therefore decreases $t_{ij,t}$. Besides, the insurance changes the participation constraint. As i knows she is insured in case of a shock in $t+1$ and will receive an indemnity payment $(1-p)h$, the marginal utility of (additionally) receiving transfers from j is lower. This reduces i's incentive to make transfers today and crowds out $t_{ij,t}$.

2.2.4 Case C: Insured participant sends transfer to insured participant

In this case, the first order condition for optimization of the insured participant in the network is:

$$\frac{dL}{dt_{ij,t}} = (1+\lambda)\left(-U'\left(E + w_{i,t} - t_{ij,t} - ph\right) + \gamma_{ij,t}V'\left(E_{j,t} + t_{ij,t} + t_{kj,t} + (1-p)h\right)\right) \tag{11}$$

In this case, the effects of insurance are the following: insurance decreases disposable income of i in t, so transfers become costlier (income effect). Because j also has insurance, the marginal benefit of her receiving a transfer is lower. Since i cannot expect to receive transfers in $t+1$, i's incentive to make a transfer in t are additionally reduced (change in the participation constraint).

In conclusion, in all three cases we observe that introducing insurance to the risk sharing network results in a crowding-out effect on the value of the transfer in $t = 1$. This generates an indirect effect on the dynamics of other-regarding preferences. The welfare weights in $t+1$ are therefore expected to be lower when some network members are insured as compared to when none is insured.

2.3 Collective shocks

2.3.1 Optimization problem

The above model can be modified in order to consider the scenario in which shocks are collective and two members of the network are affected by a shock in a given period. Similar as before we first look at the case where there is no insurance available and then compare it to the scenario in which it is. As before, insurance is assigned exogenously and we do not model the decision to become insured.

In the scenario with collective shocks, we assume that the individual who is not affected by a shock, i, decides in $t = 1$ on the optimal level of transfer $t_{ij,t}$ to the two network members j and k affected by a shock. This transfer is equally shared among j and k and each of them receives $\frac{t_{ij,t}}{2}$. We further consider that the welfare weight is the same for j and k in t, $\gamma_{ij,t} = \gamma_{ik,t}$. Under the scenario with collective shocks, the budget restrictions for each of the network members are:

$$c_{i,t} + t_{ij,t} = E_i + w_{i,t} \tag{12}$$

$$c_{j,t} - t_{ij,t}/2 = E_{j,t} \tag{13}$$

$$c_{k,t} - t_{ij,t}/2 = E_{k,t} \tag{14}$$

The participation constraint and the expected utility of participating in $t + 1$ the network remain unchanged as in equations (6) and (7).

As with individual shocks, we can consider three different scenarios regarding the effect of the insurance on transfers. We explain each scenario separately below.

2.3.2 Case D: Non-insured participant sends transfer to two insured participants

The first order condition for optimization of the non-insured participant i in the network is:

$$\begin{gathered}\frac{dL}{dt_{ij,t}} = \\ (1+\lambda)\left(-U'\left(E_{i,t} + w_{i,t} - t_{ij,t}\right) + \gamma_{ij,t}2V'\left(E_{j,t} + (1-p)h + \frac{t_{ij,t}}{2}\right)\right) + \lambda\Big[q_3\Big(2U'\big(E_{i,t+1} + \\ 2t_{ji,t+1}\big) - \gamma_{ij,t+1}2V'\left(E_{j,t+1} + w_{j,t+1} - ph - t_{ji,t+1}\right)\Big) + q_4\left(\frac{1}{2}U'\left(E_{i,t+1} + \frac{t_{ji,t+1}}{2}\right) - \right. \\ \gamma_{ij,t+1}V'\left(E_{j,t+1} + w_{j,t+1} - ph - t_{ji,t+1}\right) + \\ \left.\frac{1}{2}\gamma_{ik,t+1}V'\left(E_{k,t+1} + (1-p)h + \frac{t_{ji,t+1}}{2}\right)\right)\Big]\left(\frac{dt_{ji,t+1}}{d\gamma_{ji,t+1}}\frac{d\gamma_{ji,t+1}}{d\frac{t_{ji,t+1}}{2}}\right)\end{gathered} \tag{15}$$

As the shock-affected network member j is insured and receives an indemnity payment $(1-p)h$ in t, the marginal utility of i's transfer is lower than it would be without insurance. This generates a substitution effect, reducing $t_{ij,t}$. The insurance also affects the expected benefit of the transfer in $t+1$. If state $s=1$, insured participants have a lower disposable income than non-insured participants due to the premium payment. Therefore, the marginal cost for j of making a transfer to i in $t+1$ is higher when they are insured. This income effect crowds-out $t_{ij,t}$.

2.3.3 Case E: Insured participant sends transfer to non-insured participant

In this case, the first order condition for optimization of the insured participant in the network is:

$$\frac{dL}{dt_{ij,t}} = (1+\lambda)\left(-U^{'}\left(E_{i,t} + w_{i,t} - t_{ij,t} - ph\right) + \gamma_{ij,t} V^{'}\left(E_{j,t} + \frac{t_{ji,t+1}}{2}\right)\right) \tag{16}$$

We assume that all three participants are insured, but the propositions also hold when k is not insured. The effect insurance in this case is threefold. First, the insured participant i has a lower expected benefit of making a transfer in t as being insured, she has a lower marginal utility of receiving transfers in $t+1$. This generates an incentive to decrease transfers in t. Second, the insurance generates a negative income effect in t that increases the marginal cost of making a transfer. Third, in case that two participants in the network are insured, there is a substitution effect. As participant j will also receive a positive transfer from k in $t+1$, the marginal utility of an additional transfer from i is lower and therefore i reduces her transfer to j accordingly. These three effects decrease $t_{ij,t}$. However, the total marginal benefit of a transfer is lower than in case B, wherefore the crowding effect is also expected to be larger when shocks are collective than when shocks are individual.

2.3.4 Case F: Insured participant decides to send a transfer to an insured participant

In this case, the first order condition for optimization of the insured participant in the network is:

$$\frac{dL}{dt_{ij,t}} = (1+\lambda)\left(-U^{'}\left(E_{i,t} + w_{i,t} - t_{ij,t} - ph\right) + \gamma_{ij,t} 2V^{'}\left(E_{j,t} + (1-p)h + \frac{t_{ji,t+1}}{2}\right)\right) \tag{17}$$

We assume that all three participants are insured, but the propositions also hold when k is not insured. Similar to case E, the insurance generates an income effect that increases the marginal cost for i of sending a transfer. Besides, the insurance generates a substitution effect, further crowding-out the optimal transfer level $t_{ij,t}$.

We see that in all six cases, insurance crowds-out informal risk sharing transfers. Compared to the scenario with individual shocks, crowding-out is lager in at least one of the cases when shocks are collective. Also, it is easy to see that optimal transfers are higher the larger the initial welfare weight $\gamma_{ij,t}$. Combining the above six cases, we can formulate the following proposition:

Proposition 2. Crowding-out effect of the insurance

Transfers are reduced in the insurance treatment compared to the non-insurance treatment. The crowding-out effect is larger, when (1) the participation constraint is binding, (2) the welfare weight, $\gamma_{ij,t}$, is higher, and (3) shocks are collective rather than individual.

Proof: see annex of this chapter

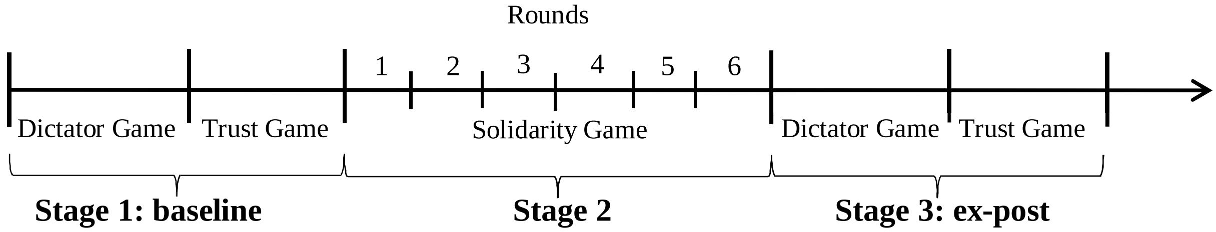
3. Experiment design

We use a three-stage experimental design similar to van Dijk et al. (2002) as displayed in Figure IV-1. In the first stage (baseline), participants were randomly and anonymously matched in groups of three. Using the strategy method, we measured initial levels of other-regarding preferences using a three-person dictator game and a three-person trust game. Participants do not receive feedback on their outcome in the baseline. In the second stage, we randomly and anonymously re-matched participants in a three-person solidarity network which we will refer to as NW. NW members participate in a repeated solidarity game over six rounds. Within this stage, we implemented a between-subject design with four treatments as explained in more detail below.

In the third stage, we repeated the measurement of altruism and trust, while keeping constant the NW from the second stage. The comparison between the first and third stages for this NW matching allows us to measure the change of altruism and trust due to the different treatments. We explain the procedures used in each stage of the game in more detail below.

Participants knew that the experiment consisted of a total of five parts (the first and the third stages consisted of two games each). Yet the exact procedures in each part were explained sequentially. Participants were also informed that only one of the five parts would be randomly selected for payment at the end of the experiment. In addition, participants received a show up fee of $20 MXN irrespective of their performance in the experiment. To avoid strategic bias between stages, participants were informed that they would receive the instructions of each part as the activity progressed.

Figure IV-1: Sequence of the experiment



3.1 Stages

3.1.1 First stage: baseline

In the first stage of the experiment subjects played two games: a one-shot dictator game (in the following DG) with two dictators and one recipient based on Panchanathan et al. (2013) and a trust or investment game (in the following TG) with two trustors and one trustee (Berg et al. 1995; Cassar et al. 2013; Cassar and Rigdon 2011). The games were implemented using a strategy method similar to Fischbacher et al. (2001). For the DG, participants first decided on their transfer as if they were all in the role of the dictator. All participants decided simultaneously and privately how much of an endowment of $150 MXN they wanted to transfer to a recipient who had not received any endowment. We used a neutral frame for the roles and referred to the two dictators as players A and the recipient as player B. Participants were informed that if this activity were chosen for payment, two participants would be randomly assigned within the triad to assume the roles of players A, and one participant would assume the role of player B. To make the decision less abstract, participants received copies of banknotes (Myrseth et al. 2015):[10] two notes of $50 MXN, $10 MXN and $5 MXN, and one note of $20 MXN. To decrease concerns of experimental demand effects in social dilemmas (Zizzo 2010), we implemented a double-blind procedure. The value to be transferred to player B was deposited in an envelope marked with the word "PASS" which was given to an enumerator who then recorded the sent amounts privately, only knowing the number of the player.

The three-person TG used a similar structure and procedure as the DG. New groups of three players were randomly and anonymously formed. All players first assumed the role of the trustor (framed as player A). They received an endowment of seven experimental banknotes of $10 MXN and decided simultaneously and privately how much they wanted to transfer to the trustee

[10]While we would have preferred to give them experimental units, we considered that this would have involved a too high cognitive load given the education level of our participants.

(framed as player B) by putting the respective number of notes in an envelope marked with the word “PASS”. They were informed that the amount they put in the envelope would be tripled and passed on to the player in role B. Following the strategy method, the player in role B decided for all possible amounts she could have received on how much to return to the players A ($30, $60, and so on, up to $210 MXN). This decision was made completing a decision table.

In both experiments we used posters to explain the structure of the games and presented different examples to illustrate how payments were calculated. Before participants made their decisions, they had to answer a set of control questions. If these were unclear, participants could raise their hands and one of the enumerators approached them individually to clarify the problems. Once it was verified that all participants understood the games, they were implemented.

3.1.2 Second stage: solidarity game

In the second stage, participants were again matched randomly and anonymously into solidarity networks, which will be referred to in the following as NW. Each NW had three participants who interacted with each other in a repeated solidarity game (in the following SG) based on Selten and Ockenfels (1998). To increase entitlement over the endowment (Reinstein and Riener 2012), participants solved a real effort task where they earned a fixed payment of $150 MXN per round. Subjects were informed that they could lose their complete earnings if they were hit by a shock after solving the task. Yet, no further information on the probability and structure of the shocks was provided. As explained in more detail in Section 3.2, the number of NW members who were affected simultaneously by a shock, as well as whether some random NW members would be formally insured, was exogenously varied by our experimental design.

After the real effort task, each participant received a note indicating whether she experienced a shock, as well as the respective earnings of herself and the two other NW members. In case a NW member suffered a shock, those in the NW who had earned a positive income had to decide if they wanted to send a predefined amount of $30 MXN to them. We kept the value of the transfers fixed to increase control over end game distributions of income. In case two NW members simultaneously suffered a shock, the transfer made by the unaffected member was equally divided between them. The solidarity game was repeated over six rounds and after each, participants received feedback on the transfers sent and received from their NW.

3.1.3 Third stage: ex-post

In this stage, we capture how interaction in the SG affects other-regarding preferences. Therefore, the DG and the TG were played again in this stage using the same procedures implemented in the baseline. To capture how participants behave towards NW members who they had interacted with before, we used a pair matching procedure and repeated the DG and TG with the same groups of three as in the SG. As the experimental design varied the possibilities of exchange in the SG exogenously, we are also able to compare whether this conditions possible differences in other-regarding preferences ex-post.

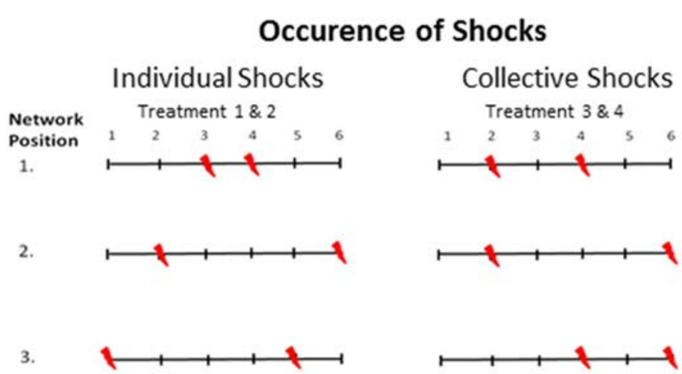
3.1.4 End of the experiment

After completing the experiment, one of the five parts was chosen for payment by randomly selecting one of five numbered cards. In the case a DG or TG part was chosen, additionally, one of three numbered cards was randomly drawn to determine who assumed the role of person A or B for payment. In case the SG was chosen, one of the six rounds was randomly selected for payment by drawing one of six numbered cards. After determining the payouts, participants were surveyed individually by the enumerators regarding their socio-demographic characteristics as these serve as important control variables when eliciting other-regarding preferences (e.g. Fehr

Figure IV-2: Structure of the shocks and treatments

Persons affected by shock in NW	No insurance	Insurance*
1	individual-control (Treatment 1)	individual-insurance (Treatment 2)
2	collective-control (Treatment 3)	collective-insurance (Treatment 4)

*insurance is mandatory for participants in NW position 2 and 3 only.



2009; Houser et al. 2010; Karlan 2005). Apart from standard demographic variables, we elicited proxies for participants' social capital. Social capital within the experimental session was proxied by the share of session participants that subjects considered to be their friends. Social capital in the villages was proxied by the number of people participants stated they could potentially lend money from, and the number of festive events they had attended in the year prior to the survey. Also, we elicit the subjects' experience of a wide range of adverse agricultural and demographic shocks during the last year. Upon finishing the survey, participants were called one by one to the experimenter's table and received their payouts individually. Average payment was $156 MXN (approx. $9.20 USD at the time of the experiment). This is around 1.5 times the average daily wage of an agricultural laborer.

3.2 Treatments

The solidarity game in the second stage involved four treatments in a between-subject design as depicted in the table of Figure IV-2. In the treatments with individual shocks, only one NW member was affected by a shock at a time, whereas in the collective shocks treatments, two NW members were affected simultaneously. In order to increase comparability across sessions and to have control over the shock pattern, we predefined the timing of shock occurence for each member of the NW triad (see lower part of Figure IV-2). In case of individual shocks, for example, the first NW member was hit by a shock in round three and in round four. The position of each participant in the NW triad is however allocated randomly. Depending on the period and treatment, one, two or none of the NW members are affected simultaneously by a shock. Over a total of six rounds, all NW members were affected twice.

In the treatments without insurance, individual-control and collective-control, none of the participants in the NW had access to formal insurance. Hence, in case of a negative shock, they received an income of $0 MXN, plus the transfers from their NW. In treatments with insurance, two NW members were assigned actuarially fair full insurance. To avoid concerns that self-selection into the insurance treatments would affect social preferences (i.e. only the less pro-social participants choose to insure), insurance was always allocated to the randomly assigned NW positions 2 and 3. Those participants remained insured during all six rounds and received a fixed income of $100 MXN in each round regardless of whether they were hit by a shock. Insured participants could still transfer $30 MXN to their fellow shock-affected NW members, but could not receive transfers from the non-affected members; neither could uninsured participants that were not hit by a shock.

4. Experimental procedures

We conducted the experimental sessions in five different villages in the region La Frailesca of the Mexican State of Chiapas. The importance and history of social capital in village communities in Chiapas is well documented (Fox 1996; Rico García-Amado et al. 2012). Our case study area is a commercially orientated maize growing environment dominated by smallholders. This region is very poor and 52 percent of the population lives below the poverty line (CONEVAL 2010). Climate risk poses a growing challenge for rural Mexico. Especially the frequency of drought shocks has increased and is endangering maize yields (Vermeulen 2011), while the state of Chiapas is particularly vulnerable to weather risks (Monterroso et al. 2014). In response to this situation, the Mexican government has invested in the development of a subsidized federal insurance scheme for farmers (Cabestany-Noriega et al. 2013). However, in 2011, only around 8.6 percent of agricultural production units in the poor south were covered on average (Arias 2013). Considering this background, it is highly relevant to study the potential impact that insurance could have on other-regarding preferences in the region. Regarding health insurance, there has been a considerable increase in coverage since a free-of-charge, federal health insurance program ("seguro popular") was introduced in 2003 (Bonilla-Chacín and Aguilera 2013). It is targeted specifically to the poor without access to other forms of social security and covers the most basic, cost-effective interventions.

Participants were selected based on a stratified random sampling procedure from villagers' lists provided by village heads ("comisariados"). We stratified the sample based on gender to obtain equal quota for men and women. Invitation to the session was given by the village heads. The selected household member was allowed to pass on their invitation to another household member or relative of the same gender if they could not attend the session.

If there are already strong pre-existing other-regarding preferences between participants, the scope to generate changes through the experiment is possibly limited. Therefore, in order to decrease the degree of pre-existing other-regarding preferences, we did not invite only participants from the same village to the session, but from two to three nearby villages. The sessions took place in the village assembly room, usually in the largest and best accessible of those villages. Up to seven enumerators assisted in conducting the sessions. To guarantee understanding, we illustrated all parts through posters and had participants answer control questions in every step. On average, participants correctly answered 92 percent of all questions.

5. Estimation strategy and results

5.1 Descriptive results

In total, 441 subjects from 12 villages participated in a total of 19 experimental sessions. Sessions were conducted with 17 to 38 persons depending on show-up. Table IV-1 gives an overview of the socio-demographic data of the participants by treatment. Wilcoxon rank-sum tests show that despite our randomization procedure, there are significant differences in the distributions of socio-demographic variables across treatments with and without insurance. Namely, for treatments with individual shocks, there are significant differences between the insurance and no-insurance treatment in the proportion of females per session, the number of people the subject could lend money from (proxy for a subject's social network), and real life shock experiences. For treatments with collective shocks there are significant differences in the distribution of age, share of friends in the session and concrete house ownership (proxy for a subject's wealth). We must control for these unbalanced variables in our further analysis. Furthermore, we find that only 2 percent of participants have had agricultural insurance before, while 54 percent have had some form of public social insurance ("seguro popular").

In the baseline, participants gave on average 36 percent of their endowment in the DG and around 48 percent in the TG (see Table IV-2). Consistent with the results from Cox (2004) and Ashraf et al. (2006), we find a high correlation in the giving behavior in the DG and TG (Spearman correlation is 0.36) indicating that trust behavior can partly be explained by norms of altruism. For the amounts returned in the TG, measuring trustworthiness, for the average transfer received of around $30 MXN, the share returned was 38 percent. We also find a significant correlation between giving in the DG and the share returned in the TG (Spearman correlation is 0.26). Participants who passed a larger proportion of the endowment in the TG also returned a larger proportion, indicating that trust and trustworthiness are positively correlated (Spearman correlation is around 0.22 at the expected amount received of $90 MXN).

Table IV-1: Characteristics of participants by treatment

VARIABLE	T1 individual-control Mean	SD	T2 individual-insurance Mean	SD	T3 collective-control Mean	SD	T4 collective-insurance Mean	SD	T1=T2 p^1	T3=T4 p^1
Age; years	33.56	11.99	35.92	16.14	38.26	14.16	34.29	13.63	0.55	0.02**
Agriculture main income[2]; d	0.93	0.26	0.88	0.33	0.91	0.29	0.86	0.35	0.21	0.32
Education; years	7.59	4.14	7.26	4.67	7.97	3.99	8.17	4.43	0.45	0.40
Female; d	0.60	0.49	0.44	0.50	0.58	0.50	0.47	0.50	0.02**	0.10
Friends in session; share	0.23	0.30	0.20	0.24	0.19	0.22	0.14	0.16	0.56	0.07*
HH has concrete house; d	0.28	0.45	0.26	0.44	0.25	0.43	0.28	0.45	0.72	0.54
HH owns cellphone; d	0.31	0.46	0.31	0.47	0.43	0.50	0.52	0.50	0.90	0.17
No. of festivities 2014[3]	4.64	3.35	5.75	5.37	7.41	6.59	6.82	6.14	0.16	0.56
No. of potential lenders[4]	4.60	5.45	5.72	6.21	5.65	3.61	5.33	3.55	0.03**	0.57
Shock experience[5]; d	0.20	0.40	0.45	0.50	0.46	0.50	0.25	0.43	0.00***	0.00***
Observations	114		108		117		102			

d denotes dummy variable.
[1]p-values. Categorical variables: Two-sample test of proportions. H_0: Variables have equal proportions within treatment groups. Continuous variables: Wilcoxon rank-sum test. H_0: Treatment groups are from populations with the same distribution.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***} < 0.01$
[2]Takes the value 1 if subject's household's main income source is agriculture.
[3]Festivities, such as weddings, religious events, birthdays, baptisms etc. attended in 2014.
[4]Answer to the question: "If you urgently needed $500 MXN, how many people outside your household would be willing to lend you that amount?"
[5]Takes the value 1 if subject suffered one or more of the following shocks in the last 3 years: drought, excessive rain, storm, pests, livestock illness, erosion, sales price decrease, input price increase, low sales, severe illness, death of family member, loss of income source, robbery, fire.

Despite our randomization of treatment assignment, we find some baseline differences in DG and TG transfers between collective and individual shocks. However, we find a good level of balance in initial levels of altruism and trust across treatments with and without insurance once that we condition on the type of shocks (individual and collective; see Table IV-2). The treatment groups T1 and T2 (individual shocks with and without insurance) and T3 and T4 (collective shocks with and without insurance) are not significantly different from each other regarding the average baseline DG and TG transfers (Wilcoxon rank-sum test p>0.05). For baseline trustworthiness at the average received amount of $90 MXN, we find a small significant difference for T3 and T4, but not so for T1 and T2. Across the other possible transfer amounts, initial trustworthiness is largely balanced. This means we can compare the effect of insurance separately for individual and collective shocks without having to account for initial differences.

There is consistency in behaviors across stages as the proportion of the endowment passed in the DG and TG in the first and third stage is highly correlated (Spearman correlation is 0.53 and 0.41

Table IV-2: Summary of DG/TG transfers by treatment

VARIABLE	T1 individual-control Mean	SD	T2 individual-insurance Mean	SD	T3 collective-control Mean	SD	T4 collective-insurance Mean	SD	T1=T2 p^1	T3=T4 p^1
Dictator Game										
Transfers										
Baseline	0.30	0.28	0.33	0.26	0.39	0.24	0.42	0.26	0.32	0.24
Ex-post	0.30	0.24	0.30	0.24	0.37	0.24	0.41	0.30	0.98	0.48
Difference	0.00		-0.03		-0.02		-0.01			
p^1	0.55		0.58		0.43		0.52			
Trust Game										
Transfers										
Baseline	0.47	0.25	0.42	0.22	0.52	0.24	0.51	0.24	0.21	0.89
Ex-post	0.39	0.22	0.40	0.18	0.49	0.23	0.43	0.23	0.36	0.11
Difference	-0.08		-0.02		-0.03		-0.08			
p^1	0.01**		0.66		0.12		0.01**			
Conditional Returns										
Baseline, $90 MXN	0.37	0.20	0.37	0.20	0.37	0.16	0.43	0.22	0.68	0.03**
Ex-post, $90 MXN	0.32	0.20	0.31	0.16	0.36	0.18	0.37	0.22	0.84	0.69
Difference	-0.05		-0.06		-0.01		-0.06			
p^1	0.07*		0.08*		0.60		0.01*			
Observations	114		108		117		102			

All values expressed as a shares of the endowment.
[1] *p*-value from Wilcoxon rank-sum test. H_0: Groups are from populations with the same distribution.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

for the DG and TG, respectively). Yet, there is a decrease of contributions between the baseline and the ex-post measure, although this difference is only significant for the TG in treatments T1 and T4 (Wilcoxon rank-sum test p<0.05).

The upper graph of Figure IV-3 displays the absolute transfer amounts in $MXN received in the SG (second stage) by treatment. As intended by the experimental design, insured participants in insurance treatments (light grey bars), i.e. those in NW positions 2 or 3, did not receive any transfers from their NW. Thereby we can analyze the effect of this decrease in the possibilities to receive transfers on the value of transfers they send to other NW members, and the subsequent effect on other-regarding preferences towards the whole NW. Because of the varying numbers of instances in which subjects could receive transfers across treatments, we must distinguish between the situations in which subjects know they cannot receive a transfer, and when they know they can. We thereby acknowledge that people might not only care about absolute outcomes when evaluating an interaction as positive or negative, but take the maximum value of transfers the NW partner(s) could have provided them with as a reference point, as similarly suggested by Falk and Fischbacher (2006). The authors provide evidence that the attribution of intentions indeed matter in human interactions, as opposed to standard "consequentialist" utility theory which assumes utility is derived exclusively from the consequences of interactions. While we cannot observe intentions directly in our experiment, it seems likely that network members not receiving a transfer evaluate this network transaction differently when they know their network was unable to provide transfers, as opposed to when they know it was able – even though the consequence in terms of income is identical. Therefore, we cannot only look at absolute transfers received, but at relative transfers, i.e. the proportion of the maximum possible value, conditional on the possibility to receive a transfer. The relative transfers by treatment are depicted in the lower graph of Figure IV-3, where only subjects that could receive transfers are incorporated and insured NW members are excluded. When shocks are individual, we find that the total average receipt of transfers is crowded-out by insurance (bars over "Total" in left-hand upper graph of Figure IV-3). However, contrary to the predictions of the model, we find that insurance does not crowd-out transfers received by non-insured NW members (bars over "NW1"). Instead, subjects in NW position 1, i.e. the non-insured, receive significantly more transfers both in absolute and relative terms (Wilcoxon rank-sum test $p<0.01$). In contrast, when shocks are collective, insurance increases the absolute value of transfers received by those in NW position 1 (Wilcoxon rank-sum test $p<0.01$), but decreases the relative, conditional value (Wilcoxon rank-sum test $p<0.01$).

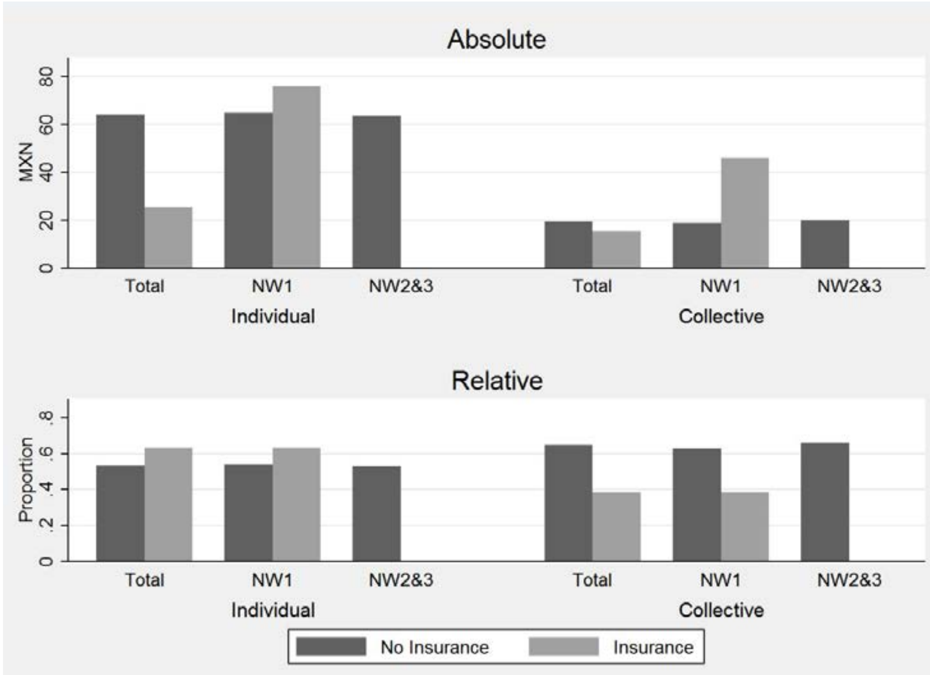
5.2 Determinants of transfers received

To control for initial differences in socio-economic characteristics of the participants, we estimate the following linear random effects model explaining transfers in the SG:

$$Y_{i,t} = \beta_0 + \beta_1 NW1_i + \beta_2 I + \beta_3 NW1_i \times I + \beta' X_i + \sum_{t=2}^{6} \alpha_t P_t + u_i + e_{it} \qquad (18)$$

In this model, the dependent variable Y is the transfer value received from the NW partner(s), expressed either as the absolute value of the transfer received in \$MXN (absolute) or the share of

Figure IV-3: Average solidarity game transfers by treatment



the maximum amount one could possibly have received, conditional on the possibility of receiving a transfer (relative). The dummy variable $NW1_i$ controls for the position within the NW. A value of 1 indicates that individual i is in NW position 1. I is a dummy variable that takes the value 1 for treatments in which some members of a NW are insured. The term $I \times NW1_i$ is the interaction of the above variables and measures the heterogeneous effect of insurance on transfers received by the non-insured NW members, compared to the insured. The vector X_i controls for individual-specific and time-invariant socio- demographic variables. This includes all variables that were not balanced across treatments: age, female dummy, the share of friends in the session, shock experience, number of potential lenders, and the concrete house dummy. P_t is a dummy for the experimental period, with $t = 2, \ldots, 6$. The time-invariant and time-variant random errors are expressed in u_i and e_{it}, respectively.

Table IV-3 displays the results of estimating equation (18) separately for individual and collective shocks, as well as absolute and relative transfers. When shocks are individual, participants on average receive an absolute value of $9.87 MXN from the NW (column 1). This number, however, includes zero values for insured NW members, who, by definition, cannot receive transfers. Conditioning on the possibility to receive transfers, subjects receive 56 percent of the maximum value of transfers possible. As intended by the insurance treatment, the absolute

Table IV-3: Effects of insurance on SG transfers received by type of shock

	INDIVIDUAL			COLLECTIVE			
	absolute		relative	absolute		relative	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NW1; d=1		0.37			-0.31		-0.02
		(0.80)			(0.26)		(0.02)
Ins.; d=1*NW1; d=1		12.26***			7.93***		
		(1.29)			(1.27)		
Ins.; d=1	-6.68***	-10.45***	0.09	-1.07**	-3.67***	-0.27***	-0.26***
	(0.89)	(0.86)	(0.07)	(0.43)	(0.29)	(0.08)	(0.08)
Constant	9.87***	8.89***	0.56***	5.01***	4.72***	0.76***	0.76***
	(1.57)	(1.29)	(0.09)	(1.22)	(1.07)	(0.14)	(0.14)
Socio-econ.[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,332	1,332	300	1,314	1,314	302	302
R^2 within	0.04	0.04	0.06	0.17	0.17	0.01	0.01
between	0.21	0.54	0.04	0.04	0.41	0.14	0.14
overall	0.07	0.12	0.04	0.14	0.22	0.08	0.08

Random effects regressions. Standard errors clustered at NW level in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$
Dependent variable: models (1), (2), (4), (5): absolute value of transfers received ($MXN); models (3), (6), (7): transfers received as share of maximum possible transfer value, conditional on possibility to receive a transfer.
d denotes dummy variable.
Ins.=1 if participant belongs to NW with insurance.
NW 1=1 if participant is in NW position 1, i.e. is never insured.
[1]Socio-economic controls include: age (years), female (dummy), friends in session (share), no. of pot. lenders, no. of shocks 2014.

Table IV-4: Heterogeneous effect on SG transfers received by network position

		INDIVIDUAL		COLLECTIVE	
		Absolute	Relative	Absolute	Relative
@NW Position 1	=1	1.81	0.09	4.26***	-0.26***
		(1.39)	(0.07)	(1.25)	(0.08)
	=0	-10.45***		-3.67**	
		(0.86)		(0.29)	

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$
Contrasts based on models (2), (3), (5), and (7) in Table IV-3. Standard errors clustered at NW level in parentheses.
Blanks: Transfers to subjects in NW positions 2 and 3 are zero in insurance treatments and not taken into account with relative transfers.

value of transfers received decreases significantly when insurance is available (columns 1 and 2). The relative value of transfers, however (column 3), does not change significantly.

A more interesting aspect is whether the effect of insurance differs among the insured and non-insured NW members. Results in columns 2 illustrate the fact that insured NW members, those in NW positions 2 and 3 in the insurance treatment, cannot receive any transfers and therefore, the average NW participant receives significantly less absolute transfers in the insurance treatment as compared to the control treatment. In contrast, the net effect of the presence of formal insurance in the NW on non-insured members, corresponding to $\beta_1 + \beta_3$ in equation (18) and presented in Table IV-4, is not significantly different from zero. Therefore, we can conclude that insurance does not crowd-out transfers to non-insured NW members facing individual shocks.

Columns 4 to 7 in Table IV-3 present the results for collective shocks. We find that on average participants receive an absolute transfer of $5.01 MXN, which again includes zero values for the insured NW members. When conditioning on the possibility to receive a transfer, we find that subjects receive 76 percent of the maximum transfer value possible. The insurance treatment has the desired effect of reducing the average absolute and relative value of the transfer (columns 4 and 6). Those in NW position 1, with no access to insurance, receive on average a significantly larger absolute transfer amount in the insurance treatment (Table IV-4). This could, however, be driven by the fact that at the time of a collective shock, with some NW members being insured, there are now two instead of one potential sender of transfers. Nevertheless, each of them is sending a significantly lower relative value. This finding confirms the predicted crowding-out effect of the model. The relatively large magnitude of the decrease in relative transfers, especially compared to the treatment with individual shocks where no significant decrease is found, could be explained by an aggravation of the crowding-out through a bystander effect (e.g. Panchanathan et al. 2013). This effect refers to the empirical finding that individuals are less likely to provide help when more potential helpers are available. Insured participants receive a constant positive income unaffected by shocks, and therefore can make transfers even though they had experienced a shock. This increases the number of potential "helpers" at the time of a shock in the NW. As a result of the bystander effect, however, each of them is less likely to provide help to the uninsured NW member suffering from a shock, as compared to a situation where there is only one potential "helper".

Result 1

Insurance does not crowd-out the absolute value of transfers received by non-insured NW members when shocks are individual, but crowds-in absolute transfers when shocks are collective. Yet, only when shocks are collective insurance induces a crowding-out effect on the value of transfers received by non-insured NW members relative to the maximum transfer value possible.

5.3 Change of other-regarding preferences

In order to analyze how other-regarding preferences are affected by the presence of insurance in informal risk sharing groups, we explore the differences in ex-post and baseline transfers in the DG and TG and estimate the following model:

$$\Delta Z_i = \beta_0 + \beta_1 I + \beta_2 DG_{i1} + \beta_3 TG_{i1} + \beta' X_i + u_i \tag{19}$$

Here, ΔZ_i refers to the difference in the ex-post versus baseline measure of other-regarding preferences. Hence, it denotes either the difference in the proportions of endowment passed in DG or TG, or returned in the TG. The sub-index i refers to each participant. DG_{i1} and TG_{i1} refer to the transfers made in the baseline DG and TG by individual i, respectively. I is defined as before. The vector X_i contains socio-demographic controls and the term u_i denotes unobserved effects. The model is estimated with OLS for the difference in proportions of endowment sent in the DG and TG. For the proportions returned in the TG, a random effects model is estimated by treating the return decisions for the different possible TG amounts received as periods, while additionally controlling for their absolute and squared value in $MXN.

To further explore the drivers of a potential change in other-regarding preferences, we disaggregate the effect of insurance on the insured and non-insured NW members by estimating the following equation:

$$\Delta Z_i = \beta_0 + \beta_1 I_i + \beta_2 I \times NW1_i + \beta_3 NW1_i + \beta_4 DG_{i1} + \beta_5 TG_{i1} + \beta' X_i + u_i \tag{20}$$

Here, $NW1_i$ is a dummy that takes the value 1 if participant i is in NW position 1 and therefore uninsured in the insurance treatments. Hence the term $I \times NW1_i$ measures the heterogeneous effect of insurance on the uninsured, as compared to the insured. Lastly, in separate regressions, we want to shed light on the mechanisms behind the changes in other-regarding preferences. Hence, we estimate an additional regression where we control for the receipt of transfers:

$$\Delta Z_i = \beta_0 + \beta_1 I_i + \beta_2 I \times T_i + \beta_3 T_i + \beta_4 DG_{il} + \beta_5 TG_{il} + \beta' X_i + u_i \tag{21}$$

With T_i we denote the transfers received by subject i, either as the absolute amount in $MXN or expressed as proportion of the maximum amount that she could have received during the SG. The coefficient of the term $I \times T_i$ furthermore tells us if the effect of transfers on other-regarding preferences is different for those in NWs where some members have insurance.

Table IV-5: Effect of insurance on altruism, trust and trustworthiness by type of shock

	(1) DG	(2) DG	(3) TG	(4) TG	(5) TG return	(6) TG return
INDIVIDUAL						
Ins.; d=1	0.01	-0.01	0.02	0.02	0.01	0.01
	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)
DG1	-0.63***	-0.64***	0.16*	0.17**	-0.03	-0.03
	(0.08)	(0.08)	(0.06)	(0.06)	(0.03)	(0.03)
TG1	0.32***	0.34***	-0.78***	-0.75***		
	(0.07)	(0.07)	(0.08)	(0.07)		
TG amount; $MXN					-0.00*	-0.00*
					(0.00)	(0.00)
TG amount; $MXN^2					-0.63**	-0.63**
					(0.05)	(0.04)
Constant	0.03	0.05	0.24***	0.30***	0.25**	0.24**
	(0.03)	(0.06)	(0.03)	(0.05)	(0.03)	(0.04)
Socio-econ.	No	Yes	No	Yes	No	Yes
Observations	222	222	222	222	222	222
R^2	0.41	0.42	0.48	0.51	0.35	0.36
COLLECTIVE						
Ins.; d=1	0.04	0.02	-0.06**	-0.08**	-0.01	-0.02
	(0.03)	(0.04)	(0.03)	(0.03)	(-0.56)	(-0.78)
DG1	-0.54***	-0.55***	0.18***	0.18***	0.03	0.03
	(0.07)	(0.07)	(0.06)	(0.06)	(0.63)	(0.59)
TG1	0.38***	0.36***	-0.63***	-0.64***		
	(0.07)	(0.07)	(0.06)	(0.06)		
TG amount; $MXN					-0.00***	-0.00***
					(0.00)	(0.00)
TG amount; $MXN^2					0.00*	0.00*
					(0.05)	(0.04)
Constant	-0.01	0.13	0.22***	0.32***	0.28***	0.31***
	(0.04)	(0.08)	(0.03)	(0.07)	(0.04)	(0.05)
Socio-Econ[1]	No	Yes	No	Yes	No	Yes
Observations	219	219	219	219	219	219
R^2	0.29	0.32	0.33	0.34	0.29	0.36

Standard errors clustered at NW level in parentheses.
OLS regressions for models (1) to (4) and random effects regression for models (5) and (6). $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
Dependent variable=difference of post- and baseline DG/TG transfer shares sent/ returned.
d denotes dummy variable.
Ins.=1 if participant belongs to NW with insurance.
DG1/TG1 refers to the share of endowment sent in the baseline of the DG/TG.
[1]Socio-economic control variables include: age (years), female (d), friends in session (share), concrete house (d), no. of pot. lenders, no. of shocks experienced 2014.
Additional controls in models (5) and (6): amount received in TG ($MXN) refers to amount received from the sender in the TG.

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The results for the estimation of equation (19) are presented in Table IV-5. The upper panel presents the result for the treatments with individual shocks, whereas the lower panel presents the results for collective shocks. Columns 1 and 2 present the effects on changes in the proportions of endowment given in the DG, columns 3 and 4 on changes in proportions given in the TG, and columns 5 and 6 present changes in the proportions returned in the TG. As can be inferred from columns 1 and 2, there is considerable stability in the proportion of the endowment passed in the DG, both in the control and in the insurance treatment and for individual and collective shocks. Yet, we observe some convergence, as participants with higher baseline DG transfers decreased their transfers in the ex-post measurement. In contrast, we find that transfers in the TG increased about 30 percentage points from the baseline to the ex-post measurement in the control treatment without insurance, both for individual and collective shocks (column 4). Whereas the insurance does not crowd-out other regarding preferences in treatments with individual shocks, we find a significant crowding-out effect of around 8 percentage points with collective shocks. Results in columns 5 and 6 indicate that, on average, in the post-test subjects display higher levels of trustworthiness, measured by the proportion returned in the TG, both for individual and collective shocks. Yet, no significant difference is observed for trustworthiness in the insurance treatment.

Table IV-6 presents the results from estimating equation (20), where the effects of insurance are disaggregated for non-insured and insured participants.[11] We find that while there are no significant differences between control and insurance treatment on altruism and on trustworthiness, there are significant effects on trust. Interestingly, however, we find that the direction of the effect that insurance within the informal NW has on subsequent trust depends on whether the shocks are individual or collective. Whereas for individual shocks, insurance crowds-in trust of non-insured NW members towards their NW partners, it crowds-out trust levels of the insured NW members towards their NW when shocks are collective.

Result 2

Formal insurance crowds-in trust levels of the non-insured when shocks are individual, but crowds-out trust levels of the insured when shocks are collective. Formal insurance has no effect on altruism and trustworthiness.

[11]The effect for insured NW members corresponds to the coefficient β_1 in equation (20), while the effect for non-insured participants corresponds to the coefficients $\beta_1 + \beta_2$.

The positive effect of insurance on trust levels of non-insured subjects towards their NW is consistent with a perceived positive valuation of the transfer interaction. Non-insured NW members could have anticipated that insured members have no incentive to send them transfers.

Table IV-6: Heterogeneous effect of insurance on DG/TG by network position

		INDIVIDUAL			COLLECTIVE		
		DG	TG	TG return	DG	TG	TG return.
@NW Position 1	=1	-0.04	0.10**	0.04	0.07	-0.02	-0.01
		(0.05)	(0.04)	(0.03)	(0.05)	(0.05)	(0.03)
	=0	0.04	-0.02	-0.01	0.00	-0.10***	-0.02
		(0.03)	(0.03)	(0.02)	(0.04)	(0.04)	(0.02)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Contrasts based on OLS estimation of models (2), (4), and (6) in Table IV-5.
Standard errors clustered at NW level in parentheses.

Yet, we find that insurance does not crowd-out transfers received by the non-insured in the SG. In response to this positive surprise, non-insured NW members could have increased the degree of attachment towards the NW that provided them with transfers and perceived them as more trustworthy. In contrast, in the treatment with collective shocks, we find opposite effects of insurance on the absolute and relative value of the transfers received by non-insured subjects. Therefore, whether they value the interaction with their NW as positive or negative will depend on whether they care more about absolute or relative transfers when evaluating a transfer interaction as positive or negative. We will shed light on this issue when estimating equation (21), controlling separately for absolute and relative transfers, as discussed below.

The negative effect of the insurance treatment on trust levels expressed by participants in NW positions 2 and 3, the insured NW members, is consistent with the hypothesis that reduced opportunities for positive interaction, in our case defined by the receipt of transfers, decreases the attachment towards NW members. Yet, it remains an open question why this negative effect is observed only in the case of collective and not in the case of individual shocks. In both cases, when hit by a shock, insured members receive no transfers from their NW, but an insurance compensation, so they have a constant income across periods. So why is it that the insured NW members reduce trust in their NW only in the collective shock treatment? In case of experiencing a shock, the income of insured NW members, consisting of the indemnity payment, is framed as a loss. Hence, the only difference induced by the introduction of insurance in the collective compared to the individual shock treatment is that when insured subjects experience a shock, they are still asked to provide a transfer to the other shock-affected, but non-insured NW member. With individual shocks, there is only one NW member affected by a shock per period and so with insurance there are no instances in which an insured member suffers a shock and could provide transfers to another affected NW member at the same time. When the insured subjects' income is framed as a loss when experiencing a shock, this may imply a reduction in utility. Rather than providing transfers, these subjects might hope to receive transfers from the NW, which they cannot. The negative effect on trust levels of the insured towards their NW might therefore be more pronounced in the collective as compared to the individual shocks treatment, where there are no instances in which transfers could be made from earnings framed as losses.

To shed more light on the underlying mechanisms, results from estimating equation (21) are presented in Table IV-7 and Table IV-8. We find mainly positive coefficients on absolute or relative transfers received, indicating that these could positively affect the ex-post level of other-regarding preferences. However, there is only a significant effect of relative transfers and collective shocks on trust. This finding points to the notion that individuals care more about relative than absolute transfers when evaluating a risk sharing interaction. For collective shocks, we find that, on average, higher transfers relative to the maximum possible increase trust levels (columns 6 and 8 in Table IV-8). When controlling for insurance, the effect and significance level decreases, which captures the finding that relative transfers received by uninsured NW members are decreased by insurance. The reason why this decrease does not translate into significantly lower trust levels expressed by the non-insured could be that relative transfers must go below a certain threshold level before initiating a downward trend in trust levels. This is a matter of further investigation.

All in all, we can only partly confirm the theoretical predictions asserting that formal insurance crowds-out other-regarding preferences among members of informal risk sharing groups. While we find some crowding-out of trust, we do not find similar effects on altruism or trustworthiness. Moreover, the crowding effects seem to be context specific, as we only observe them in treatments with collective shocks, but not with individual shocks. Moreover, as expected, we find differential effects of insurance on the preference dynamics of insured and uninsured subjects within a NW.

Table IV-7: Mechanism of altruism and trust dynamics (absolute**)**

	INDIVIDUAL				COLLECTIVE			
	(1) DG	(2) TG	(3) DG	(4) TG	(5) DG	(6) TG	(7) DG	(8) TG
Ins.; d=1			0.05	0.03			0.069	-0.02
			(0.04)	(0.04)			(0.05)	(0.04)
Ins.; d=1*T.abs.			-0.13*	-0.01			-0.22	-0.25
			(0.076)	(0.06)			(0.19)	(0.17)
T. abs.	0.01	-0.00	0.07	0.016	0.08	0.08	0.28	0.29*
	(0.04)	(0.03)	(0.05)	(0.04)	(0.05)	(0.07)	(0.18)	(0.16)
DG1	-0.64***	0.17***	-0.64***	0.17***	-0.54***	0.17**	-0.55***	0.17***
	(0.08)	(0.056)	(0.08)	(0.06)	(0.07)	(0.07)	(0.07)	(0.06)
TG1	0.34***	-0.75***	0.34***	-0.75***	0.36***	-0.62***	0.36***	-0.64***
	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.074)	(0.06)
Constant	0.04	0.32***	0.00	0.29***	0.13**	0.24***	0.07	0.26***
	(0.07)	(0.05)	(0.08)	(0.07)	(0.06)	(0.06)	(0.08)	(0.08)
Socio-econ.[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	222	222	222	222	219	219	219	219
R^2	0.42	0.51	0.43	0.52	0.32	0.55	0.33	0.55

Standard errors clustered at NW level in parentheses.
OLS Regressions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Dependent variable=difference of ex-post and baseline DG/TG shares of endowment passed on.
Ins.=1 if participant belongs to NW with insurance.
d denotes dummy variable.
T. abs.=value of transfers received in SG (in $100MXN).
DG1/TG1 refers to the share of endowment passed on in the baseline of the DG/TG.
[1]Socio-economic control variables include: age (years), female (dummy), friends in session (share), concrete house (d), no. of pot. lenders, no. of shocks 2014.

6. Conclusion and outlook

Poor households are often restricted in their access to formal capital markets and thus rely on informal insurance networks. The mutual exchange of transfers facilitated by these networks has been shown to foster the development of other-regarding preferences among its members. In this paper, we analyze how the introduction of formal insurance affects the exchange of transfers in informal solidarity networks, and the subsequent effect of this change in informal exchange on the development of other-regarding preferences. We develop a theoretical model and use a framed field experiment with baseline and ex-post measures of altruism, trust and trustworthiness, and a solidarity game with different treatments. Thereby we investigate (1) how insurance, exogenously assigned to some network members, and (2) the covariance structure of negative income shocks affect the transfer behavior, as well as trust, trustworthiness and altruism.

Table IV-8: Mechanism of altruism and trust dynamics (relative)

	INDIVIDUAL				COLLECTIVE			
	(1) DG	(2) TG	(3) DG	(4) TG	(5) DG	(6) TG	(7) DG	(8) TG
Ins.; d=1			0.05	0.03			0.07	-0.02
			(0.04)	(0.04)			(0.05)	(0.04)
Ins.; d=1*T. rel.			-0.15*	-0.01			-0.01	-0.05
			(0.09)	(0.08)			(0.08)	(0.10)
T. rel.	0.01	-0.00	0.09	0.02	0.03	0.10***	0.09	0.09*
	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)
DG1	-0.64***	0.17***	-0.63***	0.17***	-0.54***	0.17***	-0.55***	0.17***
	(0.08)	(0.06)	(0.08)	(0.06)	(0.07)	(0.06)	(0.07)	(0.06)
TG1	0.34***	-0.75***	0.34***	-0.75***	0.36***	-0.63***	0.36***	-0.64***
	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)	(0.06)
Constant	0.04	0.32***	0.00	0.29***	0.14**	0.23***	0.07	0.26***
	(0.07)	(0.05)	(0.08)	(0.07)	(0.06)	(0.06)	(0.08)	(0.08)
Socio-econ.[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	222	222	222	222	219	219	219	219
R^2	0.42	0.51	0.43	0.52	0.32	0.34	0.33	0.35

Standard errors clustered at NW level in parentheses.
OLS regressions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Dependent variable=difference of ex-post and baseline DG/TG shares of endowment passed on.
Ins.=1 if participant belongs to NW with insurance.
d denotes dummy variable.
T. rel.=Transfers received in SG (proportion of max. possible transfers).
DG1/TG1 refers to the share of endowment passed on in the baseline of the DG/TG.
[1]Socio-economic control variables include: age (years), female (d), friends in session (share), no. of pot. lenders, concrete house (d), no. of shocks experienced 2014.

Our results provide only partial support for the theoretical model. As proposed by the model, the development of other-regarding preferences depends on the transfer interactions in the risk sharing network. Interactions consisting in a higher level of transfers received lead to an increase in the level of participants' other-regarding preferences towards their network members. Interactions resulting in a lower level of transfers received lead to a decrease in other-regarding preferences. In this regard, however, only the value of transfers received relative to the maximum possible value matters, not the absolute amount. Furthermore, an effect of transfers on other-regarding preferences is only found in particular circumstances: when shocks are collective, i.e. more than one network member is affected at a time, and for one measure of other-regarding preferences, namely trust. No effects are found on altruism or trustworthiness. This can be explained only partially by different model predictions regarding the crowding-out effect of insurance on transfers dependent on the structure of the shocks.

When shocks are individual, i.e. negatively correlated among network members and some of them become insured, absolute and relative transfers received by the non-insured members are not significantly altered. This is valued positively by non-insured network members, who could be expecting to receive lower transfers from the insured network partners and therefore increase trust levels. When shocks are collective, i.e. positively correlated among network members and some of them become insured, non-insured members within those networks receive a higher absolute value of transfers, but a lower value relative to the maximum possible amount. However, we do not find significantly lower trust levels of non-insured network members in that case. Possibly, there exists a threshold level of relative transfers below which trust levels start to decay, and the reduction in transfers found here is not strong enough. This is a matter of further research. Insured subjects, however, decrease their trust towards the other network members in the collective shocks treatment. This might be explained by the following notion: when insured subjects are suffering a loss, even though they are instantly indemnified by the insurance, still may perceive having incurred a loss in terms of utility. In collective shocks treatments, there will be instances in which they are nevertheless asked to provide a transfer to the non-insured. Instead of being asked to provide transfers, in this case they might rather wish to receive transfers, which they cannot. The negative impulse on trust levels of the non-insured network members might therefore be more pronounced compared to the individual shocks treatment, where it could not occur that transfers had to be made from indemnity payments.

Our results illustrate that it is important to take into account heterogeneous effects of introducing insurance to informal risk sharing networks and consider the effect on those left uninsured separately. Moreover, the degree of covariance of the negative income shocks plays a strong role: when formal insurance is introduced, potential negative effects on informal transfers and trust levels are expected to occur especially when shocks are positively correlated, i.e. they affect several members of the network at a time. This is particularly problematic as informal risk sharing is generally efficient in indemnifying negatively correlated, idiosyncratic shocks (Fafchamps and Gubert 2007; Mobarak and Rosenzweig 2013). The potential benefit of formal insurance is especially given when shocks are covariate, or positively correlated across informal risk sharing groups, which may collapse in that case. Special care must then be given to those left uncovered by formal insurance, as they might not only receive less transfers, but possibly also be perceived as less trustworthy by their social networks.

Further research is needed to find optimal insurance designs that increase the complementarities of formal insurance and risk sharing networks, such as group-based index insurance. It was shown that incomplete insurance, when offered to members of a risk sharing group, could complement informal risk sharing and crowd-in risk sharing transfers (Dercon et al. 2014; Dercon et al. 2006; Mobarak and Rosenzweig 2013). This is especially relevant with regard to index-based insurance, where welfare could be increased when idiosyncratic basis risk is shared among the informal network members, while covariate shocks are covered by the insurance. However, when offering group-based insurance to cooperative groups instead of risk sharing networks, demand was found to be low, especially for those farmers that distrusted their fellow cooperative members (McIntosh et al. 2015). This suggests that trust levels within informal networks must be sufficiently high. Apart from that, it is worthwhile to further analyze self-selection into insurance. On the one hand, especially those without well-functioning social networks could benefit from formal insurance. On the other hand, as suggested by Lenel and Steiner (2016), solidarity networks might forego providing transfers to members in need who knowingly decided not to take up formal insurance when they could.

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Annex: Risk sharing model

Proof of Proposition 1

First order condition for an interior solution implies that the optimal transfer $t^*_{ij,t}$ solves:

$$\frac{dL}{dt_{ij,t}} = (1+\lambda)A + B = 0$$

where

$$A = -U'\left(E_{i,t} + w_{i,t} - t^*_{ij,t}\right) + \gamma_{ij,t}V'(E_{j,t} + t^*_{ij,t} + t_{kj,t})$$

and

$$B = \lambda\frac{dEU_{i,t+1}}{dt_{ij,t}} = \lambda q_3\left(U'\left(E_{i,t+1} + t_{ji,t+1} + t_{ki,t+1}\right) - \gamma_{ij,t+1}V'\left(E_{j,t+1} + w_{j,t+1} - t_{ji,t+1}\right)\right)$$
$$+ \lambda q_4\left(\frac{1}{2}U'\left(E_{i,t+1} + \frac{t_{ji,t+1}}{2}\right) - \gamma_{ij,t+1}V'\left(E_{j,t+1} + w_{j,t+1} - t_{ji,t+1}\right)\right)\left(\frac{dt_{ji,t+1}}{d\gamma_{ji,t+1}}\frac{d\gamma_{ji,t+1}}{dt^*_{ij,t}}\right)$$

When the participation constraint in the network is binding, λ > 0, comparative statics imply:

$$\frac{dt_{ij,t}}{d\gamma_{ij,t}} = -\frac{\frac{d^2L}{dt_{ij,t}d\gamma_{ij,t}}}{\frac{d^2L}{dt^2_{ij,t}}} = -\frac{(1+\lambda)V'\left(E_{j,t} + t^*_{ij,t} + t_{kj,t}\right)}{\frac{d^2L}{dt^2_{ij,t}}} > 0$$

$$\frac{dt_{ij,t}}{d\Upsilon_{i,t}} = -\frac{\frac{d^2L}{dt_{ij,t}d\Upsilon_{i,t}}}{\frac{d^2L}{dt^2_{ij,t}}} = -\frac{-(1+\lambda)U'\left(E_{i,t} + w_{i,t} - t^*_{ij,t}\right)}{\frac{d^2L}{dt^2_{ij,t}}} > 0$$

$$\frac{dt_{ij,t}}{dq_3} = -\frac{\frac{d^2L}{dt_{ij,t}dq_3}}{\frac{d^2L}{dt^2_{ij,t}}} = -\frac{\lambda\left(U'\left(E_{i,t+1} + t_{ji,t+1} + t_{ki,t+1}\right) - \gamma_{ij,t+1}V'\left(E_{j,t+1} + w_{j,t+1} - t_{ji,t+1}\right)\right)}{\frac{d^2L}{dt^2_{ij,t}}}\left(\frac{dt_{ji,t+1}}{d\gamma_{ji,t+1}}\frac{d\gamma_{ji,t+1}}{dt^*_{ij,t}}\right) > 0$$

In $t = 2$, the participation constraint is not binding (λ=0), and the first order condition for an interior solution implies,

$$\frac{dL}{dt_{ij,t}} = A = 0$$

$$\frac{dt_{ij,t}}{d\gamma_{ij,t}} = -\frac{\frac{d^2L}{dt_{ij,t}d\gamma_{ij,t}}}{\frac{d^2L}{dt^2{}_{ij,t}}} = -\frac{V'(E_{j,t} + t^*_{ij,t} + t_{kj,t})}{\frac{d^2L}{dt^2{}_{ij,t}}} > 0$$

$$\frac{dt_{ij,t}}{d\Upsilon_{i,t}} = -\frac{\frac{d^2L}{dt_{ij,t}d\Upsilon_{ij,t}}}{\frac{d^2L}{dt^2{}_{ij,t}}} = -\frac{-U''(E_{i,t} + w_{i,t} - t^*_{ij,t})}{\frac{d^2L}{dt^2{}_{ij,t}}} > 0$$

$$\frac{dt_{ij,t}}{dq_3} = -\frac{\frac{d^2L}{dt_{ij,t}d\gamma_{ij,t}}}{\frac{d^2L}{dt^2{}_{ij,t}}} = 0$$

Proof of Proposition 2

Case A: Individual shocks. Non-insured sends transfer to insured participant.

Define the cost of insurance by $c = ph$ (fair premium) and the loss covered as h. Comparative statics for the first order condition imply:

Income effect:

$$\frac{dt_{ij,t}}{dc} = -\frac{\frac{d^2L}{dt_{ij,t}dc}}{\frac{d^2L}{dt^2{}_{ij,t}}} =$$

$$= \frac{-(1+\lambda)\gamma_{ij,t}V''(E_{j,t} + w_{j,t+1} - ph + t_{ijt} + t_{kj,t}) + \lambda\gamma_{ij,t+1}\left((q_3 + q_4)V''(E_{j,t+1} + w_{j,t+1} - ph - t_{ji,t+1})\right)\left(\frac{dt_{ji,t+1}}{d\gamma_{ji,t+1}}\frac{d\gamma_{ji,t+1}}{dt_{ij,t}}\right)}{-\frac{d^2L}{dt^2{}_{ij,t}}}$$

< 0

Substitution effect:

$$\frac{dt_{ij,t}}{dh} = -\frac{\frac{d^2L}{dt_{ij,t}dh}}{\frac{d^2L}{dt^2{}_{ij,t}}} =$$

$$= \frac{-p(1+\lambda)\gamma_{ij,t}V''(E_{j,t} + w_{j,t+1} - ph + t_{ji,t}) + (1-p)\lambda\gamma_{ij,t+1}\left((q_3 + q_4)V''(E_{j,t+1} + (1-p)h - t_{ji,t+1})\right)\left(\frac{dt_{ji,t+1}}{d\gamma_{ji,t+1}}\frac{d\gamma_{ji,t+1}}{dt_{ij,t}}\right)}{-\frac{d^2L}{dt^2{}_{ij,t}}}$$

< 0

Case B. Individual shocks. Insured sends transfer to non-insured participant.

When the sender of transfers i is insured, then $q_3 = q_4 = 0$.

Reduced shocks:

$$\frac{dt_{ij,t}}{dq_3} = -\frac{\frac{d^2L}{dt_{ij,t}dq_3}}{\frac{d^2L}{dt^2{}_{ij,t}}} = \frac{\lambda\left(U'\left(E_{j,t+1} + h + t_{ji,t+1} + t_{ki,t+1}\right) - \gamma_{ij,t+1}V'\left(E_{j,t+1} + w_{j,t+1} - t_{ji,t+1}\right)\right)\left(\frac{dt_{ji,t+1}}{d\gamma_{ji,t+1}}\frac{d\gamma_{ji,t+1}}{dt_{ij,t}}\right)}{-\frac{d^2L}{dt^2{}_{ij,t}}} > 0$$

Income effect:

$$\frac{dt_{ij,t}}{dc} = -\frac{\frac{d^2L}{dt_{ij,t}dc}}{\frac{d^2L}{dt^2{}_{ij,t}}} = \frac{(1+\lambda)U''\left(E_{j,t} + w_{i,t} - ph - t_{ijt}\right)}{-\frac{d^2L}{dt^2{}_{ij,t}}} < 0$$

Case C. Individual shocks. Insured sends transfer to insured participant.

When the sender of transfers i is insured, then $q_3 = q_4 = 0$.

Reduced shocks:

$$\frac{dt_{ij,t}}{dq_3} = -\frac{\frac{d^2L}{dt_{ij,t}dq_3}}{\frac{d^2L}{dt^2{}_{ij,t}}}$$

$$= \frac{\lambda\left(U'\left(E_{i,t+1} + (1-p)h + t_{ji,t+1} + t_{ki,t+1}\right) - \gamma_{ij,t+1}V'\left(E_{j,t+1} + w_{j,t+1} - t_{ji,t+1} - ph\right)\right)\left(\frac{dt_{ji,t+1}}{d\gamma_{ji,t+1}}\frac{d\gamma_{ji,t+1}}{dt_{ij,t}}\right)}{-\frac{d^2L}{dt^2{}_{ij,t}}} > 0$$

Income effect:

$$\frac{dt_{ij,t}}{dc} = -\frac{\frac{d^2L}{dt_{ij,t}dc}}{\frac{d^2L}{dt^2{}_{ij,t}}} = \frac{(1+\lambda)\left(U''\left(E_{j,t} + w_{i,t} + t_{ij,t} - ph\right) - \gamma_{ij,t}V''\left(E_{j,t} + t_{ij,t} + t_{kj,t} + (1-p)h\right)\right)}{-\frac{d^2L}{dt^2{}_{ij,t}}} < 0$$

Substitution effect:

$$\frac{dt_{ij,t}}{dh} = -\frac{\frac{d^2L}{dt_{ij,t}dh}}{\frac{d^2L}{dt^2{}_{ij,t}}} = \frac{(1+\lambda)\left(pU''\left(E_{j,t} + w_{i,t} - t_{ij,t} - ph\right) + (1-p)\gamma_{ij,t}V''\left(E_{j,t} + t_{ij,t} + t_{kj,t} + (1-p)h\right)\right)}{-\frac{d^2L}{dt^2{}_{ij,t}}} < 0$$

Case D. Collective shocks. Non-insured sends transfer to insured participants.

Substitution effect:

$$\frac{dt_{ij,t}}{dh} = -\frac{\frac{d^2L}{dt_{ij,t}dh}}{\frac{d^2L}{dt^2{}_{ij,t}}} =$$

$$= \frac{(1+\lambda)(1-p)\gamma_{ij,t}V''(\cdot) + \lambda[2q_3p\gamma_{ij,t+1}V''(\cdot) + q_4\left(p\gamma_{ij,t+1}V''(\cdot)\right) + \frac{1}{2}(1-p)\gamma_{kj,t+1}V''(\cdot)]\left(\frac{dt_{ji,t+1}}{d\gamma_{ji,t+1}}\frac{d\gamma_{ji,t+1}}{d(\frac{t_{ij,t}}{2})}\right)}{-\frac{d^2L}{dt^2{}_{ij,t}}}$$

$$< 0$$

Income effect:

$$\frac{dt_{ij,t}}{dc} = -\frac{\frac{d^2L}{dt_{ij,t}dc}}{\frac{d^2L}{dt^2{}_{ij,t}}} =$$

$$= \frac{-(1+\lambda)\gamma_{ij,t}V''(\cdot) + \lambda[2q_3\gamma_{ij,t+1}V''(\cdot) + q_4\left(\gamma_{ij,t+1}V''(\cdot)\right) - \frac{1}{2}\gamma_{kj,t+1}V''(\cdot)]\left(\frac{dt_{ji,t+1}}{d\gamma_{ji,t+1}}\frac{d\gamma_{ji,t+1}}{d(\frac{t_{ij,t}}{2})}\right)}{-\frac{d^2L}{dt^2{}_{ij,t}}} < 0$$

if $\lambda\left[2q_3\gamma_{ij,t+1}V''(\cdot) + q_4\left(\gamma_{ij,t+1}V''(\cdot)\right) - \frac{1}{2}\gamma_{kj,t+1}V''(\cdot)\right]\left(\frac{dt_{ji,t+1}}{d\gamma_{ji,t+1}}\frac{d\gamma_{ji,t+1}}{d(t_{ij,t}/2)}\right) < (1+\lambda)\left(\gamma_{ij,t}V''(\cdot)\right)$

Case E. Collective shocks. Insured sends transfer to non-insured participant.

When the sender of transfers i is insured, then $q_3 = q_4 = 0$.

Reduced shocks:

$$\frac{dt_{ij,t}}{dq_4} = -\frac{\frac{d^2L}{dt_{ij,t}dq_4}}{\frac{d^2L}{dt^2{}_{ij,t}}} =$$

$$= \frac{\lambda\left(\frac{1}{2}U'\left(E_{j,t+1} - ph + h + \frac{t_{ji,t+1}}{2}\right) - \gamma_{ij,t+1}V'\left(E_{j,t+1} + w_{j,t+1} - t_{ji,t+1}\right) + \frac{1}{2}\gamma_{kj,t+1}V'\left(E_{k,t+1} + \frac{t_{ji,t+1}}{2}\right)\right)\left(\frac{dt_{ji,t+1}}{d\gamma_{ji,t+1}}\frac{d\gamma_{ji,t+1}}{d(\frac{t_{ij,t}}{2})}\right)}{-\frac{d^2L}{dt^2{}_{ij,t}}}$$

$$> 0$$

Income effect:

$$\frac{dt_{ij,t}}{dc} = -\frac{\frac{d^2L}{dt_{ij,t}dc}}{\frac{d^2L}{dt^2{}_{ij,t}}} = \frac{(1+\lambda)\left(U''\left(E_{i,t} + w_{i,t} + t_{ij,t} - ph\right)\right)}{-\frac{d^2L}{dt^2{}_{ij,t}}} < 0$$

Case F. Collective shocks. Insured sends transfer to insured participant.

When the sender of transfers i is insured, then $q_3 = q_4 = 0$.

Reduced shocks:

$$\frac{dt_{ij,t}}{dq_4} = -\frac{\frac{d^2L}{dt_{ij,t}dq_4}}{\frac{d^2L}{dt^2{}_{ij,t}}} =$$

$$= \frac{\lambda\left(\frac{1}{2}U'\left(E_{j,t+1} - ph + h + \frac{t_{ji,t+1}}{2}\right) - \gamma_{ij,t+1}V'\left(E_{j,t+1} + w_{j,t+1} - ph - t_{ji,t+1}\right) + \gamma_{ik,t+1}\frac{1}{2}V'\left(E_{k,t+1} - ph + h + \frac{t_{ji,t+1}}{2}\right)\right)\left(\frac{dt_{ji,t+1}}{d\gamma_{ji,t+1}}\frac{d\gamma_{ji,t+1}}{d(\frac{t_{ij,t}}{2})}\right)}{-\frac{d^2L}{dt^2{}_{ij,t}}}$$

$$> 0$$

Income effect:

$$\frac{dt_{ij,t}}{dc} = -\frac{\frac{d^2L}{dt_{ij,t}dc}}{\frac{d^2L}{dt^2{}_{ij,t}}} = \frac{(1+\lambda)\left(U''\left(E_{i,t} - ph - t_{ij,t}\right) - \gamma_{ij,t}2V''\left(E_{j,t} + (1-p)h + \frac{t_{ij,t}}{2}\right)\right)}{-\frac{d^2L}{dt^2{}_{ij,t}}} < 0$$

Substitution effect:

$$\frac{dt_{ij,t}}{dh} = -\frac{\frac{d^2L}{dt_{ij,t}dh}}{\frac{d^2L}{dt^2{}_{ij,t}}} = \frac{(1+\lambda)\left(pU''\left(E_{j,t} - ph - t_{ij,t}\right) + (1-p)\gamma_{ij,t}V''\left(E_{j,t} + (1-p)h + \frac{t_{ij,t}}{2}\right)\right)}{-\frac{d^2L}{dt^2{}_{ij,t}}} < 0$$

V Summary and Discussion

The papers presented in this dissertation highlight various aspects related to risk with regards to rural development, and more specifically, to technology adoption and social capital development of rural households. The papers are based on the analysis of farmer surveys and framed field experiments conducted from April to September 2015 with maize farmers in the state of Chiapas in southern Mexico. The study area is a major maize growing region with commercially orientated smallholders that, in majority, live below the poverty line.

The practical relevance of the results and implications of the papers presented here, as well as of any other experimental study, hinge on the assumption of external validity. While internal validity refers to ability of the experimental design to doubtlessly demonstrate a causal relationship, external validity refers to the ability to generalize these found relationships to other persons, times and settings (Roe and Just 2009). A potential lack of external validity is argued to be the main drawback of economic experiments (Loewenstein 1999). In all the presented papers, generalizability towards the group of interest, farmers, is improved by applying framed field experiments with non-standard subjects, namely farmers, as compared to standard lab experiments (Levitt and List 2007). Whether the results apply to farmers in other countries or cultural areas depends on how closely they match the subjects of these papers in terms of relevant observed and unobserved characteristics. The specific aspects and findings addressed in each paper, as well as their external validity, are critically discussed in the following.

The first paper of this dissertation in Chapter II, *"Insurance for Technology Adoption: An Experimental Evaluation of Schemes and Subsidies with Maize Farmers in Mexico"*, analyzes experimentally how bundling the purchase of a risky technology, namely a higher yielding maize seed variety, with different insurance schemes, affects the total take-up of that variety. In this regard, the paper looks at the effects of (1) partial insurance versus full insurance, (2) geographical versus local basis risk, and (3) fair versus below-fair premium. This is the first paper to evaluate insurance schemes with different levels of risk reduction, basis risk and premium subsidies regarding their effect on technology adoption. The results add to the debate on insurance serving as a potential tool for incentivizing agricultural producers to adopt more productive, but more risky technologies, and thereby enabling them to escape poverty (Carter et al. 2016; Fan et al. 2013; Lybbert and Carter 2014; Nicola 2015; World Bank 2013).

The results suggest that insurance at fair and below-fair premiums can be a useful tool for encouraging the adoption of more profitable agricultural technologies, and insurance schemes with different levels of risk reduction and payout forms can serve this purpose. Farmers in our sample responded most to a higher level of risk reduction provided by full indemnity insurance, covering the whole cost of the seed. The partial insurance schemes performed worse in terms of encouraging adoption, but did not significantly differ from each other. In contrast to the predictions, index insurance with local and geographical basis risk did not perform worse than indemnity insurance without geographical basis risk. Furthermore, the results suggest that subsidization of insurance premiums below the fair premium does increase average adoption, however not as strongly as predicted by the risk preferences of our sample. Offering insurance at below-fair premiums had no additional effect on adoption under full or index insurance. This finding challenges the usefulness of insurance subsidies. Nevertheless, the results contribute to the recent debate on the benefits of index insurance, given low demand and basis risk (e.g. Binswanger-Mkhize 2012) and confirm its positive effect on technology adoption. Future studies should focus on increasing benefits of insurance from the perspective of farmers in order to increase their demand also at loaded premiums. Apart from risk considerations, the paper finds that the degree to which farmers perceive the cultivation of their traditional maize varieties to be rooted in their tradition, also affects to what extent they will readily adopt a higher yielding variety. This highlights the general importance of analyzing more thoroughly the interplay between different factors conditioning technology adoption, such as behavioral aspects, traditional institutions, market constraints and profitability (Foster and Rosenzweig 2010).

In addition to using non-standard subjects, this first paper tackles potential issues of external validity by applying an incentivized business simulation game (Musshoff and Hirschauer 2014). Hereby, the generalizability of the experiment is increased through the use of a context that closely resembles the real decision situation of the farmers (Levitt and List 2007), while still allowing for exact causal inference. Hence, in essence, the predictions from the game regarding the effects of insurance are likely to be replicated in a real decision context, given the other assumptions of the game and characteristics of the subjects apply.

The second paper in Chapter III, *"The Relationship between Farmers' Shock Experiences and their Uncertainty Preferences - Experimental Evidence from Mexico"* addresses the relationship between farmers' uncertainty preferences, sociodemographic characteristics and their experience of adverse harvest shocks. Uncertainty preferences refer to a range of preference parameters as derived from Cumulative Prospect Theory (Kahneman and Tversky 1979; Tversky and Kahneman 1992), namely risk aversion, loss aversion and probability weighting, as well as ambiguity aversion (Ellsberg 1961). A series of incentivized lottery games are used to estimate these parameters with the sample of Mexican maize farmers, controlling for (1) sociodemographic characteristics and (2) the severity of experienced maize harvest losses. While there are several field studies examining the effect of shocks on risk preferences with subjects from developing countries, only few look at preferences beyond Expected Utility Theory and take into account Cumulative Prospect Theory, and none has looked at ambiguity aversion. Therefore, this paper sheds light on the role that the experience of adverse random shocks, as well as a range of sociodemographic variables, have in explaining one's uncertainty preferences.

First of all, the results show a strong rejection of Expected Utility Theory in favor of Cumulative Prospect Theory. Furthermore, after correcting for potential endogeneity issues, they provide evidence that having experienced more severe harvest losses leads to more risk aversion and stronger overweighting of small probabilities. No effects of higher loss severity were found on loss aversion or ambiguity aversion. Additionally, the results of this paper suggest that, on average, farmers from richer households display less overweighting of small probabilities, farmers from larger households are more risk and loss averse, and farmers with more diversified incomes are more risk averse. Subjects from indigenous families are more risk and ambiguity averse, while ambiguity aversion is not significantly related to any other sociodemographic variable.

If farmers become more risk averse in the aftermath of harvest 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. This effect could be exacerbated by the farmers' more distorted assessment of small probabilities after experiencing shocks. Such an endogenous change in preferences could lead to "behavioral poverty traps" (Carter and Barrett 2006) and therefore makes the case for policies facilitating risk management through insurance, disaster relief and safety nets in poor rural regions even stronger.

The practical meaningfulness of the found change in uncertainty preferences after experiencing shocks relies on the ability of these parameters to predict real-world decisions of farmers. The predictive power of experimentally elicited risk preferences on risk-related farm decisions, however, has sometimes been challenged. For example, no relationship could be found between risk aversion and insurance take-up or diversification (Hellerstein et al. 2013), and growing of cash crops or market-orientation (Verschoor et al. 2016). However, other studies did find significant relationships between risk and ambiguity aversion and improved seed adoption (Barham et al. 2014; Liu 2013), between risk and loss aversion and pesticide use (Liu and Huang 2013), and between risk aversion and fertilizer use (Verschoor et al. 2016). On a side note, this second paper finds that more diversified farmers are more risk averse, which is in line with predictions from economic theory and suggests a correspondence of the experimental risk measure and field behavior. In order to be able to assess external validity of uncertainty preferences, it is crucial to collect them together with survey data, as done for this dissertation. All in all, it is being argued that in the future, experimental economics will benefit from combining lab data with data from, if possible, representative surveys (Gächter 2009) to exploit complementarities across methods when interpreting research findings.

The third paper in Chapter IV, *"Formal Insurance, Risk Sharing, and the Dynamics of Other-Regarding Preferences"*, analyzes how selectively providing formal insurance to members of a risk sharing network affects informal transfers and, subsequently, the dynamics of other-regarding preferences within that network. Many poor households in developing countries are excluded from formal financial markets and therefore rely on the mutual exchange within informal risk sharing networks to protect themselves against adverse income shocks. Social interactions in the aftermath of such shocks have been found to strengthen the social ties among members of these networks, while formal insurance has been found to crowd-out these transfers. Similarly, this third paper finds that when some members of risk sharing networks become formally insured, it affects the informal exchange of transfers among members, as well as their other-regarding preferences. This is the first study to explore the effect of insurance on other-regarding preferences in that context. In order to do so, an incentivized, three-stage experimental design with a baseline and an ex-post measurement of altruism, trust and trustworthiness through dictator and trust games is implemented with random and anonymous groups of three. Between the baseline and the ex-post measurement, a solidarity game is played with the same anonymous groups as in the ex-post measurement of other-regarding preferences, during which the shock structure and the availability of formal insurance are varied exogenously. The findings suggest that the effect of insurance depends on (1) the covariance structure of shocks and (2) is different for the insured and non-insured members within a network. Insurance either decreases trust levels of the uninsured or increases trust levels of the insured subjects towards the other network members, depending on whether the shocks affects one or more than one network member at a time. Trustworthiness and altruism remain unaffected by insurance. Furthermore, the analysis indicates that the results are driven by a change in the dynamics of the transfer behavior within the network induced by formal insurance. Specifically, there is evidence that subjects increase trust levels towards their network members after receiving higher transfers relative to the maximum possible value from them, but not after receiving higher transfers in absolute terms.

Concerning external validity of the third paper, first of all, it has been criticized that subjects might behave more generously in dictator games where they deal with “windfall gains”, than outside the lab where they deal with their earned money (Cherry et al. 2002). Furthermore, dictator games that were modified from the standard version to put them into an arguably more realistic context show a substantial reduction in giving and thereby challenge its meaningfulness as a measure for altruism. This occurred when the possibility to withdraw money (Bardsley 2008; List 2007), income uncertainty (Andreoni and Bernheim 2009; Dana et al. 2007), or full anonymity (Franzen and Pointner 2012) were introduced. Nevertheless, these studies are themselves contested on grounds of external validity. Differences in experimental protocols and geographic location have also been found to affect outcomes in trust games (Johnson and Mislin 2011). Apart from that, it has been debated whether the trust game actually succeeds in measuring trust, as opposed to other-regarding preferences that are not conditional on the behavior of others (Cox 2004). These issues, however, refer more to internal than to external validity. There are to date relatively few studies examining the external validity of other-regarding preferences elicited in the lab by comparing them to behavior in a natural field setting. However, reviews of the existing evidence find in majority positive correlations of contributions in the dictator and trust game and field behavior (Camerer 2015; Galizzi and Navarro-Martínez 2015). These findings undermine the relevance of the results of the third paper regarding potential effects of formal insurance on other-regarding preferences in communities engaged in informal risk sharing. However, more lab-field research is needed to complement these findings.

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Freudenreich, H. & Musshoff, O. (forthcoming). Insurance for Technology Adoption: An Experimental Evaluation of Schemes and Subsidies with Maize Farmers in Mexico. *Journal of Agricultural Economics,* DOI: 10.1111/1477-9552.12226

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