Contract Nonperformance Risk and Ambiguity in Insurance Markets

By Christian Biener, Martin Eling, Andreas Landmann, and Maria Isabel Santana*

Insurance is referred to as probabilistic when policyholders are exposed to contract nonperformance risk, that is, claims are not reimbursed by the insurer. We extend probabilistic insurance models to allow for ambiguity regarding contract nonperformance and loss probabilities. We empirically test theoretical predictions from our model within a field lab experiment in a low-income setting. This is a persuasive context, since especially in emerging and poorly regulated markets there is significant contract nonperformance risk. In line with our predictions, insurance demand decreases by 17 percentage points in the presence of contract nonperformance risk and by 32 percentage points when contract nonperformance risk is ambiguous. Furthermore, ambiguity does not easily disappear with experience. The results have implications for both industrialized and developing insurance markets.

I. Introduction

Insurance contracts fail to perform when valid insurance claims are not paid or not paid in full by the insurer leading to probabilistic insurance (Kahneman and Tversky, 1979). In this paper, we investigate the role of contract nonperformance risk and ambiguity in the decision to buy insurance. We provide both theoretical as well as empirical contributions to the literature by expanding extant models of probabilistic insurance to account for ambiguity and empirically testing theoretical implications in an experimental field lab within a low-income (i.e., microinsurance) context.

Various circumstances including insolvency, discord about the losses covered, and payment delays can cause contract nonperformance. The concept of claim validity thus signifies the perceived vailidity of a claim from the policyholder's perspective but not necessarily its legal vailidity (Doherty and Schlesinger, 1990).

* Christian Biener (christian.biener@unisg.ch) and Martin Eling (martin.eling@unisg.ch) are with the Institute of Insurance Economics at the University of St. Gallen, Rosenbergstrasse 22, 9000 St. Gallen, Switzerland. Andreas Landmann (andreas.landmann@uni-mannheim.de) and Maria Isabel Santana (maria.santana@gess.uni-mannheim.de) are with the Chair of Econometrics of the University of Mannheim, L7, 3-5, 68131 Mannheim, Germany. We are grateful to the Swiss National Science Foundation (SNSF) and the Chair of Econometrics of the University of Mannheim for funding. Thanks to Pascal Kieslich, Shailee Pradhan and Nikolas Schöll for excellent research assistance. We thank participants of the ZEW/University of Mannheim Experimental Seminar and the Munich Re Foundation Research Workshop on Microinsurance for helpful comments and discussions.

The prospect of potential contract nonperformance of insurance policies is related to the concept of probabilistic insurance, which was first introduced by Kahneman and Tversky (1979) as a novel insurance policy, which, in the event of a loss, reimburses policyholders only with some probability strictly less than one. Wakker, Thaler and Tversky (1997) find that a 20 percent premium discount is demanded for a 1 percent risk of contract nonperformance using an experimental setup. Herrero, Toms and Villar (2006) observe similar results in that agents prefer standard insurance to probabilistic insurance and probabilistic insurance to no insurance.

Doherty and Schlesinger (1990) formalize the setting by providing a model of insurance demand in an insurance market with a given premium and a known probability of insurance default. For an actuarially fair insurance premium they find that risk averse agents will not fully insure in the presence of contract nonperformance risk. Additionally, increasing risk aversion does no longer induce higher optimal insurance coverage. Subsequent empirical work by Zimmer, Schade and Gründl (2009) and Albrecht and Maurer (2000) support the hypothesis of strong detrimental effects of contract nonperformance on insurance demand.

In this paper, we incorporate contract nonperformance and shock ambiguity for which we provide both a theoretical model as well as an empirical test. As opposed to risk, where probabilities can be assigned to all possible outcomes, ambiguity relates to situations where the probabilities of outcomes are unknown (Epstein, 1999).[1] Whereas there has been some research on the role of ambiguous shock probabilities on insurance demand (Alary, Gollier and Treich, 2013; Hogarth and Kunreuther, 1989), neither theoretical nor empirical work we are aware of focuses on ambiguity in the context of contract nonperformance.[2] Standard economic utility models such as expected utility (von Neumann and Morgenstern, 1947) only incorporate the mean over a probability distribution to affect decisions. However, approaches using the complete distribution as in Bayesian analysis are feasible to account for ambiguity (Hogarth and Kunreuther, 1989). Ambiguity is of general relevance to economic decision making because only in very few cases probabilities can be assigned to all possible outcomes. There is an even higher potential relevance for the low-income population context because several factors magnify ambiguity about probabilities. Individuals in developing countries face a broad variety of not easily quantifiable perils arising from geographic settings (e.g., natural disasters), lack of hygiene in public infrastructure (e.g., risk

[1]Different terms to refer to situations where probabilities are known or unknown are used in the literature. "Risk" as opposed to "uncertainty" is already applied in Knight (1921). The terms "unambiguous" and "ambiguous" probabilities have been introduced by Ellsberg (1961). Savage Leonard (1954) uses the terms "precise" and "sharpe," whereas Gärdenfors and Sahlin (1982) differentiate between the level of "epistemic reliability" of a probability estimate to infer about the amount of information available concerning all possible states and outcomes. We rely on the term "ambiguity" as it is common in literature (Camerer and Weber, 1992).

[2]Bryan (2013) provides a theoretical framework and empirical evidence from Kenya and Malawi for an index insurance containing states of the world in which actual yields suggest losses but the index insurance provides no reimbursement. However, this issue rather resembles basis risk inherent in index insurance, which is different from contract nonperformance risk as discussed in this paper.

of diseases due to lack of water provision), and economic (e.g., unemployment), political (e.g., lack of education), and legal (e.g., lack of contract enforcement) environment.

Not only does this paper make contributions to understanding contract nonperformance in low-income insurance and ambiguity about shock probabilities and contract nonperformance separately, but provides a framework to test the interaction of these two aspects. We implement these issues by allowing both the shock probability as well as the contract nonperformance risk to be ambiguous. This setting resembles real-world scenarios where probabilities cannot easily be assigned to all possible states of the world by most individuals, which has not yet been discussed in the literature. For our theoretical model we adapt the approach proposed by Alary, Gollier and Treich (2013) to allow for contract nonperformance risk as defined by Doherty and Schlesinger (1990).

Extant empirical and theoretical evidence suggests that contract nonperformance risk leads to a reduction of insurance demand at least in developed insurance markets. However, no rigorous empirical investigation exists for the low-income insurance context. Several reasons underline the specific relevance of contract nonperformance in low-income insurance. Trust in insurance is a highly sensitive issue in microinsurance, being a significantly determinant for demand (Cole et al., 2013). Claims considered eligible by the insured but not paid by microinsurers may have a severely negative impact on perceptions and trust and thus emerge as a potential piece of the puzzle explaining low microinsurance demand. Only recently, Liu and Myers (2014) provide theoretical evidence for significant reductions in demand for insurance resulting from perceived insurer default in a microinsurance contexts. Perceptions of high contract nonperformance risk are furthermore fueled by limited trust in regulators and legal institutions to enforce contracts and supervise insurance markets. One main contribution of our work is thus an empirical evaluation of contract nonperformance effects in a low-income developing country setting.

Lastly, our work is related to the literature on experimental framing effects. Several experiments on decision-making and insurance have shown that context matters, e.g., Brun and Teigen (1988), Budescu and Wallsten (1985), Hershey and Schoemaker (1980), Johnson et al. (1993), Mano (1994), Kahn and Sarin (1988), and Kahneman and Tversky (1979) and many more. In particular, we are interested in analyzing variations of the source of contract nonperformance and its impact on insurance uptake. We expect that potential low-income customers will not react similarly to different sources of contract nonperformance, that is, different sources will give rise to various emotions and reactions (Kunreuther et al., 2002; Zimmer, Schade and Gründl, 2009) as has been identified for developed insurance markets. For example, individuals are likely to be more upset about a claim not paid due to fraudulent processes (e.g., an insurance policy is not valid because an agent misappropriates insurance premiums) as opposed to situations in which an insurer is insolvent (Churchill and Cohen, 2006; Zimmer, Schade and Gründl, 2009). Just as affect regarding the insured object has an impact on insurance demand as shown by Hsee and Kunreuther (2000) or Slovic et al. (2007), affect regarding the sources of contract nonperformance may matter as well. Indeed, research shows that people are generally less willing to take risks when the source of the risk is another person, which is referred to as "betrayal aversion" (Bohnet et al., 2008).

For our empirical test, we apply an innovative experimental field lab approach on a low-income sample from the Republic of the Philippines. The experimental field labs were implemented with a total of 1,008 participants from 42 rural villages of the Iloilo and Guimaras provinces. We find that eliminating contract nonperformance risk (i.e., the insurer always pays a claim) as well as eliminating the ambiguity about contract nonperformance risk (i.e., the probability of the insurer's contract nonperformance is positive and known) increases insurance uptake. For the former, we observe a significant 17 percentage points increase in uptake resulting from reducing contract nonperformance risk from 10 to 0 percentage points. Relative to a known 10 percent chance of contract nonperformance, ambiguity about the contract nonperformance risk leads to a further significant decrease in uptake by 14 percentage points. We do not find evidence for increased insurance uptake when shock probabilities are ambiguous, which is opposed to previous findings such as those by Hogarth and Kunreuther (1989). Effects of ambiguity appear to be not affected by experience and remain relatively stable over time. We also find no significant effect of a negative frame of contract nonperformance (i.e., inability versus unwillingness to pay) on insurance demand.

The remainder of this paper proceeds as follows. In Section II we present the theoretical framework and the hypotheses. The experimental design as well as the field implementation is explained in Section III. In Section IV we present the empirical identification strategy and an overview of the sample characteristics. The results are discussed in Section V. We conclude in Section VI.

II. Demand for Probabilistic Insurance under Ambiguity

In this section we formalize the characteristics of contract nonperformance risk and ambiguity and relate them to the optimal insurance buying decision. To this end, we rely on the theoretical foundations originating from Doherty and Schlesinger (1990)[3] for contract nonperformance risk and Alary, Gollier and Treich (2013) for ambiguity. We assume that a decision maker with initial wealth w has a positive probability p of suffering a loss $L > 0$. The individual can purchase insurance that pays ε for a premium $I(\varepsilon)$.[4] In the case that the decision maker buys insurance and the loss does not occur (with probability $1 - p$), the agent

[3]Contract nonperformance risk differs from basis risk such as inherent in index-based crop insurance because it is a downside risk only. Theoretical results on the demand for index insurance (Clarke, 2011) as well as empirical evidence (Clarke and Kalani, 2011) are available and suggest that only moderately risk-averse individuals should take up insurance.

[4]Note that in our definition, we do not specify whether the insurance is actuarially fair.

loses 0 and is left with $w - I(\varepsilon)$. In the case that the decision maker incurs a loss of L and has insurance, there is a positive probability r that the insurer does not pay the claim. In this case the decision maker is left with $w - I(\varepsilon) - L$; otherwise the insurer pays and the decision maker gets $w - I(\varepsilon) - L + \varepsilon$. Our benchmark setting is one with known contract nonperformance probability r. The expected utility U for the decision maker is defined as:

$$U = (1-p)u(w - I(\varepsilon)) + p[(1-r)u(w - I(\varepsilon) - L + \varepsilon) + ru(w - I(\varepsilon) - L)], \tag{1}$$

where u is the utility derived from the final payoff. When the insured amount can be freely chosen, the decision maker maximizes U with respect to $I(\varepsilon)$. When the insured amount and premium is fixed, however, utility with insurance is compared to the non-insurance case where ε and $I(\varepsilon)$ are equal to zero. Here, we assume the latter case and assume binary insurance decisions.

Our first area of interest is how insurance decisions change when there is a positive probability that the insurance does not pay. To analyze this question we compare the benchmark setup when $r > 0$ to the situation when $r = 0$. Note that when changing r we also change the expected payout and hence the loading of the insurance policy.[5] It is obvious that insurance without contract nonperformance risk is always preferred by risk-averse agents, because it features lower risk and lower loadings ceteris paribus (see Appendix Proofs). The case is less trivial when the premium amount is discounted by the nonperformance probability, i.e., making the comparison "fair" in terms of the loading factor. Let $I_r(\varepsilon)$ be the insurance premium with default risk $r > 0$, while $I_0(\varepsilon)$ denotes the premium without default risk. Specifying $I_r(\varepsilon) = (1-r)I_0(\varepsilon)$ leads to a constant loading factor. The utility derived from insurance with contract nonperformance risk becomes:

$$U_{r>0} = (1-p)u(w - I_0(1-r)) + p[(1-r)u(w - I_0(1-r) - L + \varepsilon) + ru(w - I_0(1-r) - L)], \tag{2}$$

whereas utility derived from insurance without contract nonperformance risk on the other hand is:

$$U_{r=0} = (1-p)u(w - I_0) + pu(w - I_0 - L + \varepsilon). \tag{3}$$

Introducing contract nonperformance risk increases the expected payoff (if insurance has a positive loading) but entails the risk of a default on insurance claims.

[5]The loading factor of the insurance policy is defined as the ratio between premium amount and expected claims. Expected claims decreases when there is evidence of possible contract nonperformance.

These advantages and drawbacks are weighted differently by different types. The following Lemmas can be shown to hold (see Appendix Proofs).

LEMMA 1: For sufficiently low loadings there must exist agents with sufficiently high risk aversion such that insurance without default risk is preferred.

LEMMA 2: For sufficiently high loadings there must exist agents with sufficiently low risk aversion above zero such that insurance with default risk is preferred.

In reality, agents with low risk aversion are very sensitive to loadings and tend not to buy insurance anyway when it is too expensive. Therefore, there is reason to believe that the share of the population actually switching from no insurance to insurance with default risk is relatively small. Ultimately the results hinge on the exact shape of the utility function. We therefore simulate decision makers exhibiting constant relative risk aversion (CRRA)-type utility functions over a range of loading and risk aversion parameters to obtain more exact predictions.[6] The results are clear-cut in that the set of parameter combinations predicted to take up insurance with contract nonperformance risk is a subset of the parameter combinations predicted to take up insurance without contract nonperformance. Hence, demand can only be lower with contract nonperformance risk. We thus formulate our first hypothesis as follows.

$H1$: ***Contract nonperformance risk reduces insurance demand.***

Next, we focus on the effect of ambiguity of contract nonperformance risk on insurance demand; that is, r is unknown. We redefine contract nonperformance risk as the ambiguous probability $r(\gamma)$, now depending on an unknown parameter γ. The ambiguity is defined as a probability distribution for γ. We consider a discrete support $\{1, \ldots, n\}$ for the random variable $\tilde{\gamma}$. Let $q(\gamma)$ denote the subjective probability that the true value of the parameter is γ, with $\sum_{\gamma=1}^{n} q(\gamma) = 1$.

In the case that γ is known, the expected utility is (similar to Equation 1):

$$
\begin{gathered}
U(\gamma) = (1-p)u(w - I(\varepsilon)) + \\
p[(1 - r(\gamma))u(w - I(\varepsilon) - L + \varepsilon) + r(\gamma)u(w - I(\varepsilon) - L)].
\end{gathered}
\tag{4}
$$

Following Klibanoff, Marinacci and Mukerji (2005) we model ambiguity aversion using an increasing and concave valuation function Φ for the probability of contract nonperformance. The decision maker's expected utility corresponds to:

[6] We set all other parameters such as initial wealth, shock and default probability, etc. according to our game specifications. More details on the simulations can be found in the Appendix.

$$\Phi^{-1}\left(E_{\tilde{\gamma}}\Phi(U(\tilde{\gamma}))\right)=\Phi^{-1}\left(\sum_{\gamma=1}^{n}q(\gamma)\Phi(U(\gamma))\right). \tag{5}$$

Concavity of Φ expresses ambiguity aversion, i.e., an aversion to mean-preserving spreads in the random probability of contract nonperformance $r(\tilde{\gamma})$. An ambiguity neutral agent uses a linear valuation function, essentially evaluating his expected utility with the mean probability of contract nonperformance, which is $E_{\tilde{\gamma}}r(\tilde{\gamma})$. For ambiguity loving agents, Φ is convex. An individual hence maximizes the following expected utility function:

$$\begin{gathered}E_{\tilde{\gamma}}\Phi(U(\tilde{\gamma}))=E_{\tilde{\gamma}}\Phi[(1-p)u(w-I(\varepsilon))+\\ p[(1-r(\tilde{\gamma}))u(w-I(\varepsilon)-L+\varepsilon)+r(\tilde{\gamma})u(w-I(\varepsilon)-L)]].\end{gathered} \tag{6}$$

From this setting the following Lemma can be shown to hold (see Appendix Proofs):

LEMMA 3: For ambiguity averse agents, the marginal willingness to pay for additional insurance is strictly lower at every coverage point when (mean-preserving) ambiguity over contract nonperformance risk is introduced.

This general statement over the marginal willingness to pay implies that also for binary insurance decisions, insurance with known contract nonperformance risk is always preferred by ambiguity averse agents as opposed to insurance with ambiguous contract nonperformance risk. This in turn implies that uptake should be higher for insurance with known contract nonperformance risk for ambiguity-averse agents. We thus derive our second hypothesis as follows.

$H2:$ ***Ambiguity about contract nonperformance probabilities reduces insurance demand.***

Next, we focus on the effect of ambiguous shock probabilities, that is, p is not known with certainty, on insurance demand when there is a known risk of contract nonperformance. Our setting includes both probabilistic insurance with contract nonperformance risk strictly larger than zero and non-probabilistic insurance with zero contract nonperformance risk. We redefine the loss probability as an ambiguous probability $p(\alpha)$, where α is an unknown parameter. The ambiguity is defined as a probability distribution for α. The random variable $\tilde{\alpha}$ has discrete support $\{1,\ldots,n\}$. In this case, the decision maker's expected utility can be defined as:

$$\begin{gathered}E_{\tilde{\alpha}}\Phi(U(\tilde{\alpha}))=E_{\tilde{\alpha}}\Phi[(1-p(\tilde{\alpha}))u(w-I(\varepsilon))+\\ p(\tilde{\alpha})[(1-r)u(w-I(\varepsilon)-L+\varepsilon)+ru(w-I(\varepsilon)-L)]],\end{gathered} \tag{7}$$

where Φ follows the same properties as described above but now represents the decision maker's ambiguity aversion towards loss probabilities. Using a similar approach as before, the following Lemma can be shown to hold (see Appendix Proofs):

LEMMA 4: For ambiguity averse agents, the marginal willingness to pay for additional insurance is strictly higher at every coverage point when (mean-preserving) ambiguity over loss probabilities is introduced.

This general statement over the marginal willingness to pay implies that uptake for insurance (i.e., probabilistic and non-probabilistic) should be higher with ambiguous loss probabilities for ambiguity-averse agents. We thus derive our third hypothesis as follows.

$H3$: ***Ambiguity about loss probabilities increases insurance demand.***

Our fourth hypothesis is motivated by our discussion in Section 1, where we show that several experiments on decision-making and insurance found that context matters. In particular, we expect that potential policyholders will not react similarly to different sources of contract nonperformance, that is, different sources will give rise to various emotions and reactions (Kunreuther et al., 2002; Zimmer, Schade and Gründl, 2009) as has been identified for developed insurance markets. Thus, we state hypothesis four as follows:

$H4$: ***Negatively framing contract nonperformance risk decreases demand for probabilistic insurance.***

Whereas some theoretical as well as experimental research justifying hypotheses $H1$, $H3$, and $H4$ exist, the theoretical model as well as the experimental results for hypothesis $H2$ are original and have so far not been discussed in the literature.

III. Experimental Design

A. *Game*

We model insurance choices exposed to different types of risk in an artefactual field experiment. Risk is introduced in the form of a lottery that involves drawing a ball from an opaque bag containing 10 balls of which a certain number is orange and another white. Orange balls represent a loss; white balls indicate no loss. Every participant was provided with an initial endowment W of PHP 210. Subjects played an insurance game where they decided whether to purchase insurance or not, while facing a risk of loss and a subsequent risk of contract nonperformance if they opted for insurance. Participants could opt to buy insurance at cost I. Once the insurance decision was made, participants drew a ball from a bag to determine their shock. An orange ball implied a loss. Participants who bought insurance and had a shock could claim a payment from the insurer. Whether the insurer paid the claim or not was determined by drawing a ball from a second bag. An orange ball implied that the claim was not to be paid by the insurer, that is, the participant experiences contract nonperformance of the insurance policy. Participants played the game in sessions with six participants. They were not allowed to exchange information or talk among each other during the first round of the game. This procedure aims at avoiding peer effects on the participant's initial belief about probabilities. Participants were then allowed to communicate with other members for the remaining rounds.

An additional lottery game was played prior to the insurance game to classify each participant in terms of risk and ambiguity preferences. Here, participants were presented with pairs of monetary lotteries with one to four outcomes, of which they had to choose one (Glöckner, 2009). The outcome values varied between PHP -250 and PHP 250 and participants played up to 122 lotteries, depending on their response time.[7] We use lotteries following Ellsberg (1961), with which we classify individuals as ambiguity averse, ambiguity neutral, or ambiguity loving. Participants earned the average of four randomly drawn gambles, two from the gain domain and two from the loss domain.

B. *Treatments*

A complete overview of all treatments is presented in Table 1. Under the benchmark *Control* setting, both the 30 percent probability of losing PHP 150 and the 10 percent probability of experiencing contract nonperformance were known to the participants. The variation in contract nonperformance probability introduced in treatment T_{NoDef}, i.e., the elimination of the 10 percent contract nonperformance risk, allows us to make inferences about our hypothesis $H1$. Apparently, the elimination of contract nonperformance risk is accounted for in terms of a higher premium of PHP 60 for treatment T_{NoDef} instead of PHP 50 for all other treatments.[8]

In treatments T_{Def} and T_{Loss} we focus on the effect of ambiguity to investigate hypotheses $H2$ and $H3$. Here, the loss (T_{Loss}) and contract nonperformance (T_{Def}) probabilities were ambiguous to the participants. In order to provide the participants with an initial signal of probabilities to form their prior beliefs, the balls in the bags of the ambiguous treatments – for T_{Loss} the first bag where the shock is drawn from and for T_{Def} and T_{Def-Fr} the second bag where the contract nonperformance is drawn from – were selected blindly from a big bag with 100 balls during the instructions by one research assistant. From the 100

[7] Lotteries were divided in four blocks, and each block had a maximum amount of time the participant could spend on. Once the time was reached, the next block was presented. The lotteries were randomly assigned within each block.

[8] Because the actual price of an insurance policy is it's loading, we added a 20 percent markup to all insurance treatments (25 percent for the T_{NoDef} treatment). Insurance premiums include risk and cost loadings; in microinsurance markets, high risk loadings for uncertainty in the estimation of expected losses due to data constraints often need to be added (Biener, 2013).

Table 1—Experimental Treatments

	Treatments					
	Control	T_{NoDef}	T_{Def}	T_{Loss}	C_{Fr}	T_{Def-Fr}
Panel A: Universal parameters						
Initial endowment (in PHP)			*210*			
Loss (in PHP)			*150*			
p_{Loss}			*0.3*			
Panel B: Treatment characteristics						
Loss probability prior	p_{Loss}	p_{Loss}	p_{Loss}	p_{Loss}	p_{Loss}	p_{Loss}
Ambiguous loss probability	*no*	*no*	*no*	*yes*	*no*	*no*
Default probability prior	p_{Def}	p_{Def}	p_{Def}	p_{Def}	p_{Def}	p_{Def}
Ambiguous default probability	*no*	*no*	*yes*	*no*	*no*	*yes*
p_{Def}	0.1	0	0.1	0.1	0.1	0.1
Framing	neutral	neutral	neutral	neutral	negative	negative
Insurance premium (in PHP)	50	60	50	50	50	50
Panel C: Participants and Sessions						
Number of subjects	144	162	168	180	174	168
Number of sessions	24	27	28	30	29	28

balls in the big bag, 30 were orange and 70 were white for the T_{Loss} treatment and 10 were orange and 90 white for the T_{Def} and T_{Def-Fr} treatments. One of the participants was invited to count the balls in the bag blindly to make sure that 10 balls were placed in the ambiguous bags. Our setting with multiple rounds allows analyzing effects over time, which is especially interesting under ambiguity when experience about losses and nonperformance can be shared within the peer network. In particular, one might expect ambiguity to decrease over time once enough learning has taken place.

We employ treatments C_{Fr} and T_{Def-Fr} to make inferences about potential framing effects. The standard framing of contract nonperformance was that the insurer could not pay the claim. This framing is neutral and was implemented in the *Control* group as well as in T_{NoDef}, T_{Def}, and T_{Loss}. The negative framing in treatments C_{Fr} and T_{Def-Fr} presents the source of potential contract nonperformance as the insurer's unwillingness to pay (e.g., due to policy exclusions or invalid contracts resulting from agent fraud).

C. *Empirical Identification*

To estimate the effect of the treatments on insurance uptake we use a linear probability model with the following specification:

$$y_i = \alpha + \sum_{d=1}^{5} \beta_d T_{d,i} + \gamma X_i + \epsilon_i, \tag{8}$$

where $d = 1, \ldots, 5$ and y_i is the binary insurance decision of participant i. $T_1, \ldots, T_5$ represent the different treatments, whereas the *Control* group is omitted as the reference category. X_i is a vector of covariates including individual characteristics such as age, gender, years of education, employment, owned dwelling/land, marital status, household size, as well as risk aversion, math capabilities, past shock experience, and insurance ownership. In our regression setup we pool the insurance decisions from all rounds and use clustered standard errors at the session level to correct for intragroup correlation.[9]

IV. Procedures and Sample Characteristics

A. Procedures

We used a field lab experiment that was implemented in the Iloilo and Guimaras provinces of the Republic of the Philippines in October and November 2013. The five treatments and one control setting of this experiment were randomized across four sessions played in each of a total of 42 villages. This random assignment was implemented such that distinct treatments were played in each village in order to reduce the likelihood of correlations between village-level covariates and treatment assignment or -order. Furthermore, we applied a two-stage randomization procedure where in the first stage rural villages were randomly selected[10] and in the second stage twelve individuals aged between 18 and 65 years were randomly selected from complete household lists, that were provided by village officials. Each recruited participant was asked to bring one peer to the experimental session. Peers remained together in the game, forming four groups (or sessions) of six participants.

The structure of an experimental session was as follows. First, a pre experimental survey was conducted to gather individual and household characteristics data, which was followed by the lottery game. Subsequent to the lottery game, the insurance game started with an instructional part. Detailed explanations were provided by one instructor with the help of visual aids. We assured participant's understanding by conducting a test questionnaire. Only when all questions of the test questionnaire could be answered correctly was the participant allowed to continue. Otherwise, there was another round of explanation for the subject.

[9]Note that clustering at that level also takes serial correlation of decisions over rounds into account, such that all rounds can be analyzed jointly. Regression results hold for separate estimations by round, as shown later in Section V.

[10]Villages from municipalities with income classes 1 and 2 were excluded from the study (income classes range from 1 to 5 and are defined by the Department of Finance (of the Philippines, 2008)).

Each participant played six rounds of the insurance game and the initial endowment was restored at the start of each round. In order to gather participant's beliefs about loss and contract nonperformance probabilities a brief survey was implemented at the beginning of rounds 1, 2, 4, and 6 (i.e., before the insurance decisions). Here the participants provided guesses about the number of orange balls in the respective bag and also stated the minimum and maximum amount of orange balls they believed were in the bag. The first survey would provide us with the participants' beliefs regarding the loss and contract nonperformance probabilities in the absence of any peer or network effects.

Once the insurance game concluded a post experimental survey was conducted to gather data on perception of the experimental insurance product, math capabilities, past real-life shock experiences, insurance ownership, and general beliefs. Finally, participants were paid one of the six rounds played in the insurance game plus the proceeds from the lottery game and a show-up fee in real PHP. The round of the insurance game that was paid out was selected randomly by the participant from another opaque bag with six numbered balls representing the six rounds of the game. Average earnings from the experiment were PHP 156.5 in the insurance game and PHP 13.5 in the lottery game, amounting to a total of PHP 170, which is approximately equal to 4 U.S. dollars (6 U.S. dollars in PPP).[11] Additionally, each participant received PHP 100 for showing up for the experiment and an additional PHP 20 if the participant was the head of the household.

B. Sample Characteristics

In total we conducted 166 sessions with 1,008 participants in 42 villages. Table 2 presents the mean values of individual characteristics and equality of means tests by treatment group. Results show that individual characteristics are balanced throughout the treatments (i.e., versus the *Control* group) and that few variables exhibit significant differences. Treatments T_{NoDef} and C_{Fr} have slightly higher proportions of female participants. The proportion of employed participants in the C_{Fr} treatment is a bit lower than in the *Control* group. The proportion of individuals that had members of their household reducing meals due to lack of financial resources is lower in T_{Loss} as compared to the *Control* group. The mean score (7 point likert-scale) of individuals that find purchasing insurance risky is lower in T_{Loss}. Finally, the mean score (7 point likert-scale) of individuals that responded to the question "I avoid risky things" is larger under treatment T_{Def-Fr} than in the *Control* group. Overall, it is apparent that the sample is balanced

[11]The official exchange rate was PHP 43.3 per U.S. dollar in early October 2013. The maximum real gain of PHP 210 from the experiment for each participant is approximately 4.8 U.S. dollars (7.5 U.S. dollars in purchasing power parity (PPP) using the latest available PPP conversion factor for private consumption of 28.2 from 2012 (Bank, 2014);and is slightly below the minimum daily wage of PHP 250 in the agricultural sector in the Iloilo province as of October 2013 (of the Philippines, 2008). Note that few people of our target population in fact earn the minimum wage. The median daily earnings of those participants receiving a daily wage (12 percent of total sample) is only PHP 180. In addition, participants were able to earn an additional amount in the lottery games, which are described in the course of this section.

across treatment groups with only one variable not balanced in treatment T_{Def-Fr} versus the *Control* group and two variables not balanced in treatments T_{NoDef}, T_{Loss}, and C_{Fr}. All variables were balanced in treatment T_{Def}.

As a further balancing check, we implement a multivariate analysis of variance to test for differences between means across treatment group on each of the variables presented in the summary statistics. Column 7 of Table 2 shows the p-value associated with the F statistic based on Wilks' Lambda. We do not reject the null hypothesis that the means across the groups are all equal, thus we conclude that the participants' characteristics shown in Table 2 are balanced across treatments and the *Control* group.

V. Experimental Results

A. Main Results

Table 3 presents results of linear probability and probit models, where we estimate the effect of the different treatments on insurance uptake. Standard errors are clustered at the session level to correct for intragroup correlation. The omitted variable and, thus, reference group in our model is the *Control*. Column 1 presents the primary results for the treatment effects, column 2 includes a typhoon variable which takes a value of 1 if the subject was exposed to typhoon Haiyan[12] and column 3 incorporates additional covariates.[13]

The discussion of results is structured along the hypotheses defined in the previous sections. Eliminating contract nonperformance risk in treatment T_{NoDef}, that is, setting $p_{Def} = 0$ instead of $p_{Def} = 0.1$ results in a significant increase in insurance uptake of 17 percentage points and 18 percentage points when covariates are included. For all specifications the treatment dummy is significant at the 1 percent level. The results show that contract nonperformance risk considerably decreases insurance uptake and thus support our hypothesis $H1$. Our finding is furthermore in line with preceding literature (Wakker, Thaler and Tversky, 1997; Albrecht and Maurer, 2000; Herrero, Toms and Villar, 2006; Zimmer, Schade and Gründl, 2009).

The establishment of ambiguity towards the probability of contract nonperformance as represented by treatment T_{Def} reduces insurance uptake by 14 percentage points and by 13 percentage points when covariates are included. For all specifications the treatment dummy is significant at the 10 percent level. The results suggest that ambiguous contract nonperformance probabilities decreases uptake and thus provide evidence for our hypothesis $H2$.

[12]Typhoon Haiyan passed by the Iloilo Province halfway through our experiment, in November 2013. Our main effects are consistent before and after the typhoon Haiyan.

[13]The added covariates are age, gender, years of education, employment, owns dwelling, married (or in partnership), household size, reduced meals in last month, owns lands, responsible for household decisions, score in math capabilities, financial risk, insurer performance risk, experience, risk aversion, insurance ownership, health shocks, weather/livestock shocks.

Table 2—Descriptive Statistics

	(1) *Control*	(2) T_{NoDef}	(3) T_{Def}	(4) T_{Loss}	(5) C_{Fr}	(6) T_{Def-Fr}	Equality of Means (p-value)[c]
Panel A: Sociodemographic characteristics							
Age	39.86	38.80	38.96	39.93	38.76	39.86	0.867
	(10.50)	(10.08)	(9.966)	(10.98)	(10.94)	(9.755)	
Gender (1=female)	0.741	0.840*	0.810	0.722	0.833*	0.786	0.228
	(0.439)	(0.368)	(0.394)	(0.449)	(0.374)	(0.412)	
Married or in partnership (1=yes)	0.903	0.889	0.869	0.911	0.902	0.899	0.814
	(0.297)	(0.315)	(0.338)	(0.285)	(0.298)	(0.302)	
Years of education	9.573	9.580	9.911	9.594	9.552	9.381	0.634
	(2.642)	(2.472)	(2.476)	(2.419)	(2.210)	(2.619)	
Employment status (1=employed)	0.465	0.358	0.387	0.433	0.351*	0.429	0.391
	(0.501)	(0.481)	(0.488)	(0.497)	(0.479)	(0.496)	
Regular Income (1=yes)	0.270	0.295	0.282	0.270	0.250	0.275	0.769
	(0.447)	(0.460)	(0.453)	(0.446)	(0.436)	(0.449)	
Seasonal Income (1=yes)	0.716	0.787	0.732	0.663	0.653	0.637	0.297
	(0.454)	(0.413)	(0.446)	(0.475)	(0.479)	(0.484)	
Owned dwelling (1=yes)	0.799	0.895*	0.845	0.856	0.839	0.851	0.435
	(0.402)	(0.307)	(0.363)	(0.353)	(0.369)	(0.357)	
Reduced meals in last month (1=yes)	0.273	0.210	0.214	0.156**	0.218	0.244	0.548
	(0.447)	(0.408)	(0.412)	(0.363)	(0.414)	(0.431)	
Owns Land (1=yes)	0.133	0.142	0.113	0.139	0.167	0.161	0.885
	(0.341)	(0.350)	(0.318)	(0.347)	(0.374)	(0.368)	
Panel B: Mental capabilities, risk and ambiguity aversion							
Math ability score (0 min 8 max)	6.660	6.654	6.661	6.500	6.655	6.494	0.888
	(1.698)	(1.815)	(1.630)	(1.851)	(1.612)	(1.754)	
Numeracy Score (0 min 16 max)	9.236	9.142	9.119	9.050	9.040	8.994	0.988
	(3.084)	(2.988)	(2.999)	(3.143)	(2.930)	(2.958)	
Avoid risky things[a]	5.493	5.354	5.583	5.583	5.434	5.820*	0.326
	(1.840)	(1.935)	(1.859)	(1.830)	(1.989)	(1.744)	
Ambiguity [b]	1.763	1.734	1.774	1.721	1.756	1.776	0.994
	(0.711)	(0.767)	(0.786)	(0.762)	(0.768)	(0.799)	
Panel C: Loss and insurance experience							
Purchasing insurance is risky[a]	5.590	5.385	5.476	5.239*	5.341	5.275	0.755
	(1.875)	(2.016)	(1.917)	(2.007)	(1.948)	(2.050)	
Insurance ownership	0.528	0.580	0.577	0.594	0.557	0.542	0.881
	(0.501)	(0.495)	(0.495)	(0.492)	(0.498)	(0.500)	
Illness/accident shock (1=yes)	0.625	0.627	0.631	0.578	0.590	0.563	0.741
	(0.486)	(0.485)	(0.484)	(0.495)	(0.493)	(0.498)	
Weather/livestock shock (1=yes)	0.451	0.391	0.423	0.450	0.439	0.425	0.91
	(0.499)	(0.490)	(0.495)	(0.499)	(0.498)	(0.496)	
Observations	144	162	168	180	174	168	

Note: Mean coefficients reported; standard errors in parentheses. [a]scores based on a 7 point likert-scale: 1-strongly disagree, 7-strongly agree.[b] Ambiguity classification: 1-ambiguity averse, 2-ambiguity neutral, 3-ambiguity loving. [c] p-values for multivariate equality of means test based on Wilks' lambda test statistics. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ significance level for equality of means t-test of all treatments versus the *Control* group.

Table 3—Average Treatment Effects

	(1) (OLS)	(2) (OLS)	(3) (OLS)	(4) (Probit[a])
T_{NoDef}	0.171***	0.172***	0.182***	0.216***
	(0.062)	(0.063)	(0.064)	(0.061)
T_{Def}	-0.144*	-0.143*	-0.126*	-0.115*
	(.077)	(0.078)	(0.074)	(0.068)
T_{Loss}	0.034	0.037	0.048	0.049
	(0.070)	(0.070)	(0.067)	(0.068)
C_{Fr}	-0.121	-0.119	-0.104	-0.096
	(0 .080)	(0.079)	(0.075)	(0.069)
T_{Def-Fr}	-0.104	-0.101	-0.091	-0.085
	(0.079)	(0.079)	(0.075)	(0.070)
Typhoon		0.043	0.045	0.046
		(0.039)	(0.037)	(0.036)
Constant	0.707***	0.686***	0.393***	
	(0.058)	(0.061)	(0.144)	
Observations	5,976	5,976	5,952	5,952
R^2	0.055	0.057	0.078	0.079
F	12.09	10.55	3.97	
Covariates	No	No	Yes	Yes

Note: Standard errors in parentheses, clustered at the session level.[a] The probit model results are provided in terms of marginal effects.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ significance level at 10, 5 and 1 percent.

Ambiguity about the probability of loss as represented by treatment T_{Loss} increases uptake by 3 percentage points; however, the effect is insignificant in all regression specifications, thus we cannot conclude on an impact of ambiguous loss probabilities on insurance uptake; thus, our hypothesis $H3$ is not supported. This result is opposed to previous research on the effect of shock ambiguity in the context of non-probabilistic insurance that indicates a positive impact (Hogarth and Kunreuther, 1989). However, our setup deviates from the previous studies by using the probabilistic insurance concept, i.e., there is a probability strictly larger than zero that the insurance does not pay a valid claim. Thus, we only observe the effect of shock ambiguity conditional on the fact that the insurance pays valid claims only with a probability of 90 percent.

Framing the insurer's contract nonperformance risk negatively rather than neutrally as represented by treatments C_{Fr} and T_{Def-Fr} leads to a reduction in insurance uptake that lies between 10 and 12 percentage points. The effect, however, is insignificant independent on whether contract nonperformance risk is ambiguous or not. Thus, we reject hypothesis $H4$.

B. Secondary Results

Numeracy

We analyze treatment effects conditional on subject's numeracy levels because a minimum level of numeracy skills might be necessary to adequately understand the game and thus react to the treatment manipulations. In order to assess subjects' levels of numeracy we use a survey on mathematical ability and numeracy (Weller et al., 2013). We construct a total numeracy score by joining results from the mathematical ability and numeracy scales. The total score goes from 0 (no correct answer) to 16 (all answers correct). High numeracy subjects are those with a total score of 10 or higher and low numeracy subjects are those with a score of 9 or less. Table 4 shows average treatment effects by numeracy level, whereas columns 1 and 2 depict the full sample, columns 3 and 4 the high numeracy subjects, and columns 5 and 6 the low numeracy subjects. Participants with higher numeracy skills in general experience stronger treatment effects. Eliminating contract nonperformance in treatment T_{NoDef} leads to an increase in insurance demand of 21 percentage points for the high numeracy sample compared to 14 percentage points in the low numeracy sample and to 17 percentage points in the total sample.

Ambiguity about the probability of contract nonperformance as implemented in T_{Def} leads to a reduction of 18 percentage points in insurance uptake for the high numeracy sample, 4 points more than the full sample and 7 points more than the low numeracy sample, whereas for the latter the treatment effect is not significant. Thus, subjects with low (high) levels of numeracy react less (more) to the contract nonperformance ambiguity manipulation and seem to exhibit less ambiguity aversion, a finding we elaborate more on in the subsequent section.

Table 4—Average Treatment Effects by Numeracy Level

	Total Sample		High Numeracy		Low Numeracy	
	(1)	(2)	(3)	(4)	(5)	(6)
	(OLS)	(OLS)	(OLS)	(OLS)	(OLS)	(OLS)
T_{NoDef}	0.17***	0.17***	0.21***	0.22***	0.14*	0.12*
	(0.063)	(0.062)	(0.070)	(0.067)	(0.073)	(0.070)
T_{Def}	-0.14*	-0.13*	-0.18**	-0.17**	-0.11	-0.10
	(0.077)	(0.076)	(0.087)	(0.084)	(0.085)	(0.085)
T_{Loss}	0.034	0.038	0.096	0.10	-0.025	-0.025
	(0.070)	(0.067)	(0.085)	(0.078)	(0.074)	(0.071)
C_{Fr}	-0.12	-0.11	-0.098	-0.087	-0.14	-0.14
	(0.080)	(0.076)	(0.092)	(0.087)	(0.088)	(0.084)
T_{Def-Fr}	-0.10	-0.094	-0.18*	-0.16*	-0.042	-0.037
	(0.079)	(0.077)	(0.096)	(0.089)	(0.079)	(0.076)
Constant	0.71***	0.43***	0.69***	0.34	0.72***	0.35*
	(0.058)	(0.15)	(0.067)	(0.39)	(0.063)	(0.18)
Observations	5,976	5,952	2,778	2,772	3,198	3,180
R-squared	0.055	0.089	0.095	0.144	0.037	0.070
Covariates	No	Yes	No	Yes	No	Yes

Note: Standard errors in parentheses, clustered at the session level. Covariates: age, gender, years of education, employment, owns dwelling, married (or in partnership), household size, reduced meals in last month, owns lands, responsible for household decisions, score in math capabilities, financial risk, insurer performance risk, experience, risk aversion, insurance ownership, health shocks, weather/livestock shocks. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ significance level at 10, 5 and 1 percent.

Ambiguity towards the negatively framed probability of contract nonperformance as implemented in T_{Def-Fr} reduces insurance uptake by 18 percentage points for the high numeracy sample, whereas in the low numeracy sample and the total sample the reduction is insignificant with an effect size of 4 percentage points and 10 percentage points respectively. Our estimates show evidence that framing plays no role for insurance demand for individuals with high numeracy skills. As seen in Table 4, the effects of the T_{Def} and T_{Def-Fr} on subjects with high numeracy are very similar, leading to the conclusion that the reduction of insurance uptake for the high numeracy subgroup is driven by the ambiguity towards the probability of contract nonperformance and not by the framing. Results are intuitive since the framing of the treatment provides no additional information to individuals regarding the probability of contract nonperformance or the probability of loss, which are the elements we expect rational subjects would use when assessing their insurance decision. Again, this suggests that a correlation exists between numeracy skills and ambiguity aversion.

Ambiguity Aversion

Table 5 presents average treatment effects for ambiguity averse, ambiguity neutral, and ambiguity loving subjects respectively, whereas columns 1 and 2 show results for the ambiguity averse, columns 3 and 4 for the ambiguity neutral, and columns 5 and 6 for the ambiguity loving subjects. Following our theoretical model, we would expect ambiguity averse subjects to exhibit a strong reduction of insurance demand in the presence of ambiguity towards the probability of contract nonperformance while for non-ambiguity averse subjects there should be no effect.

In order to classify subjects with respect to their ambiguity aversion levels, we rely on the results obtained from the lottery game, in which we use Ellsberg (1961) lotteries to classify individuals as ambiguity averse, ambiguity neutral, or ambiguity loving.

Results are in line with our theoretical predictions. Ambiguity averse subjects exhibit a stronger reduction in insurance demand when the probability of contract nonperformance is ambiguous as is apparent from columns 1 and 2 for the T_{Def} and the T_{Def-Fr} treatments. When ambiguity averse subjects are confronted with the T_{Def} treatment, insurance demand is reduced by 18 percentage points and when negative framing is added to the ambiguous contract nonperformance risk insurance demand falls by 22 percentage points. However, for ambiguity neutral and ambiguity loving subjects there is no significant effect of contract nonperformance ambiguity on insurance demand.

Ambiguity about the probability of loss has a low and insignificant effect on insurance demand for ambiguity averse and non-ambiguity averse subjects likewise. Framing the insurer's non-ambiguous contract nonperformance risk in C_{Fr} reduces insurance uptake by 19 percentage points for ambiguity averse subjects, but has no effect on ambiguity neutral and ambiguity loving subjects. In conclu-

Table 5—Average Treatment Effects by Ambiguity Aversion

	Ambiguity Averse		Ambiguity Neutral		Ambiguity Loving	
	(1)	(2)	(3)	(4)	(5)	(6)
	(OLS)	(OLS)	(OLS)	(OLS)	(OLS)	(OLS)
T_{NoDef}	0.17**	0.15**	0.20**	0.20**	0.16	0.078
	(0.068)	(0.069)	(0.092)	(0.095)	(0.13)	(0.13)
T_{Def}	-0.18**	-0.16*	-0.15	-0.14	-0.086	-0.087
	(0.091)	(0.086)	(0.10)	(0.100)	(0.15)	(0.15)
T_{Loss}	0.035	0.022	0.061	0.041	-0.061	-0.065
	(0.080)	(0.076)	(0.097)	(0.095)	(0.14)	(0.14)
C_{Fr}	-0.19**	-0.17**	-0.046	-0.037	-0.13	-0.13
	(0.090)	(0.084)	(0.11)	(0.10)	(0.16)	(0.15)
T_{Def-Fr}	-0.22**	-0.20**	-0.030	-0.028	-0.076	-0.099
	(0.093)	(0.089)	(0.099)	(0.100)	(0.16)	(0.15)
Constant	0.75***	0.67***	0.66***	0.38	0.74***	0.53
	(0.064)	(0.24)	(0.079)	(0.30)	(0.13)	(0.35)
Observations	2,466	2,448	1,956	1,950	1,104	1,104
R-squared	0.096	0.162	0.051	0.083	0.042	0.158
Covariates	No	Yes	No	Yes	No	Yes

Note: Standard errors in parentheses, clustered at the session level. Covariates: age, gender, years of education, employment, owns dwelling, married (or in partnership), household size, reduced meals in last month, owns lands, responsible for household decisions, score in math capabilities, financial risk, insurer performance risk, experience, risk aversion, insurance ownership, health shocks, weather/livestock shocks. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ significance level at 10, 5 and 1 percent.

sion, the findings indicate that ambiguity averse subjects attach a higher weight to the subjective probability of contract nonperformance and thus are less willing to accept insurance as compared to non-ambiguity averse subjects.

Ambiguity over Rounds

Finally, we are interested in analyzing whether ambiguity decreases over the six game rounds for ambiguity averse individuals. Just as in real-life, information about ambiguous probabilities accumulate through own or peer experience in our experiment. A rational individual should update beliefs about the unknown stochastic process based on newly available information. With more observations arriving, the true probability can be estimated more precisely.[14] In terms of our model from Section II the subjective probability distribution $q(.)$ over the possible probabilities should converge towards a degenerate distribution with value one at the true probability. Decreasing ambiguity with experience should then be reflected in the participant's insurance decision. In particular, effects of ambiguity regarding loss or contract nonperformance probabilities should converge to zero.

In Table 6, we therefore repeat specification (1) from Table 3 separately by round to assess whether effects of ambiguity treatments T_{Def}, T_{Loss}, and T_{Def-Fr} fade away. Contrary to the learning hypothesis, however, effects exhibit no clear

[14]For example, ambiguity measured by the standard error of the probability estimate should decrease with the square root of observed realizations.

trend. The effect of the ambiguous loss probability in T_{Loss} is insignificant for all rounds, which is consistent with the pooled results. Also the effect of ambiguous contract nonperformance risk in T_{Def} and T_{Def-Fr} is consistent with the pooled results, that is, coefficients are all negative and most of them are significant. Variation over time appears to remain within confidence bounds and lacks any clear time trend.

Table 6—Average Treatment Effects per Round for Ambiguity Averse Individuals

	(1) Round 1	(2) Round 2	(3) Round 3	(4) Round 4	(5) Round 5	(6) Round 6
T_{Def}	-0.18*	-0.24**	-0.17*	-0.19**	-0.14	-0.17*
	(0.094)	(0.10)	(0.098)	(0.097)	(0.10)	(0.098)
T_{Loss}	0.11	0.048	0.087	-0.035	0.016	-0.015
	(0.087)	(0.089)	(0.094)	(0.094)	(0.087)	(0.081)
T_{Def-Fr}	-0.16	-0.21**	-0.24**	-0.28***	-0.16	-0.27***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.100)	(0.097)
Observations	411	411	411	411	411	411
R-squared	0.075	0.111	0.136	0.096	0.093	0.092

Note: Standard errors in parentheses, clustered at the session level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ significance level at 10, 5 and 1 percent.

As a next step, we compare these findings with participant's beliefs about loss and contract nonperformance probabilities. We elicited beliefs via having participants guess the number of orange balls contained in the bags from which shocks and contact nonperformance were drawn. Besides a "best guess" we also asked for the minimum and maximum number they deemed possible. The spread between minimum and maximum number of orange balls can be used as a proxy for the extend of ambiguity. Table 7 presents how mean guesses and the spread between minimum and maximum guesses evolve over rounds for different treatments. Columns 1 to 3 present the mean guesses of how many orange balls participants believed were in the bag from which contract nonperformance shocks were drawn for treatments T_{Def} and T_{Def-Fr} and from which loss shocks were drawn for treatment T_{Loss}. Columns 4 to 6 illustrate the mean spread between minimum and maximum guesses. Additionally, columns 7 to 9 show the mean difference between beliefs and the real number of balls in the bags.[15]

Interestingly, participants appear to be pessimistic in treatments T_{Def} and T_{Def-Fr}, as the average guess is substantially above one, that is, the average number of orange balls. These guesses if anything have a very subtle upward tendency, away from the real number of orange balls contained in the bags. The spread between maximum and minimum guess (columns 4 to 6) seems to decrease over rounds, suggesting a decrease in the extend of ambiguity. On the other hand,

[15]Since the actual number of orange and white balls was drawn randomly, it varies between sessions for the ambiguous treatments. Thus, we recorded the actual number of orange and white balls at the end of each session.

the decrease is very limited and a substantial spread remains. Also, the difference between the orange balls that participants believe are in the bag and the real number of orange balls (columns 7 to 9) has no such downwards tendency. Hence, overall participants do not significantly improve their guesses over rounds.

Participants' "best guesses" about ambiguous loss probabilities in T_{Loss}, as opposed to the findings for contract nonperformance risk, appear to be relatively precise. The mean deviation is almost half of that observed with contract nonperformance; however, with a slightly higher mean spread. A potential explanation is the higher frequency with which participants actually observe orange balls for losses themselves and receive signals from their peers, because the average number of orange balls is 3 instead of 1 in the case of contract nonperformance. This is in line with Prospect Theory's overvaluation of small probabilities (Kahneman and Tversky, 1979).

Table 7—Individual's Beliefs About Loss and Contract Nonperformance Probabilities

	Mean Guess			Mean Spread			Mean Deviation		
	T_{Def}	T_{Loss}	T_{Def-Fr}	T_{Def}	T_{Loss}	T_{Def-Fr}	T_{Def}	T_{Loss}	T_{Def-Fr}
Round 1	2.59	2.98	2.61	1.81	2.48	2.07	2.03	1.16	1.69
Round 2	2.67	3.14	2.60	1.93	2.40	1.91	2.17	1.20	1.64
Round 4	2.54	3.10	2.78	1.63	2.23	1.79	2.04	1.22	1.73
Round 6	2.65	3.17	2.70	1.55	2.29	1.83	2.16	1.15	1.63

Note: Guesses elicited via a short survey in rounds 1, 2, 4 and 6 about average, minimum and maximum number of orange balls from a total of ten balls (compare explanation in Section III). Spread computed as difference between minimum and maximum number of balls stated. Deviation measures the difference between guesses and real number of orange balls.

In summary, there is no clear evidence of a reduction in ambiguity over game rounds. In particular, this holds for the T_{Def} and T_{Def-Fr} treatments, for which we find persistent negative treatment effects on insurance uptake. There might be reasons for the absence of learning that are particular to our experiment. It is possible, for example, that participants did not have all the information from other players regarding their shock history, so that they could not properly update on their signal. Second, participants might have needed more experience with the insurance product in order to reduce ambiguity, that is, updating processes might take longer than the duration of the experiment permits. However, it is also possible that ambiguity persists even with better information transmission and a longer time horizon.

VI. Conclusion

This paper finds first empirical evidence in support of the theoretical prediction of reduced insurance uptake in the presence of contract nonperformance risk in a low-income insurance setting. Furthermore, we are the first to analyze the impact of ambiguous contract nonperformance risk for which we find a significant detrimental impact on insurance demand. We further empirically show that ambiguity regarding loss probabilities does not play a role when it comes to demand for probabilistic insurance, which is in contrast to our theoretical model as well as to previous studies on non-probabilistic insurance demand.

In particular, the results from our experimental field lab suggest that contract nonperformance risk decreases insurance uptake by 17 percentage points and that ambiguity about contract nonperformance risk reduces uptake by a further 14 percentage points. The variation of causes for contract nonperformance through different framings, that is, an insurer not able to pay a claim versus an insurer not willing to pay a claim, turns out not to be meaningful for most of our sample population.

The paper presents additional evidence that the effects of ambiguity are not easily eliminated over time by updating beliefs about probabilities. While one might argue that learning in reality might be more effective than it is in the lab, it also seems intuitive that villagers from a low-income setting cannot effectively perform Bayesian updating or compute confidence bounds around their probability guesses – neither in the experiment nor in reality.

The results have implications for all stakeholders with an interest in developing microinsurance markets. In line with our results is a call for introducing sound regulatory frameworks in microinsurance markets, particularly focusing on assuring low levels of contract nonperformance risk as well as limiting ambiguity about this risk through an increase in market transparency. Furthermore, it allows insurers active in this market to focus on sound policies and practices to gain competitive advantage and build trust in the market.

REFERENCES

Alary, David, Christian Gollier, and Nicolas Treich. 2013. "The Effect of Ambiguity Aversion on Insurance and Self-protection." *The Economic Journal*, 123(573): 1188–1202.

Albrecht, Peter, and Raimond Maurer. 2000. "Zur Bedeutung einer Ausfallbedrohtheit von Versicherungskontrakten: ein Beitrag zur Behavioral Insurance." *Zeitschrift für die gesamte Versicherungswissenschaft*, 89(2-3): 339–355.

Bank, World. 2014. "PPP Conversion Factor." World Bank.

Biener, Christian. 2013. "Pricing in Microinsurance Markets." *World Development*, 41(0): 132–144.

Bohnet, Iris, Fiona Greig, Benedikt Herrmann, and Richard Zeckhauser. 2008. "Betrayal Aversion: Evidence from Brazil, China, Oman, Switzerland, Turkey, and the United States." *The American Economic Review*, 98(1): 294–310.

Brun, Wibecke, and Karl Halvor Teigen. 1988. "Verbal probabilities: Ambiguous, context-dependent, or both?" *Organizational Behavior and Human Decision Processes*, 41(3): 390–404.

Bryan, Gharad. 2013. "Ambiguity Aversion Decreases Demand For Partial Insurance: Evidence from African Farmers."

Budescu, David V, and Thomas S. Wallsten. 1985. "Consistency in interpretation of probabilistic phrases." *Organizational Behavior and Human Decision Processes*, 36(3): 391–405.

Camerer, Colin, and Martin Weber. 1992. "Recent developments in modeling preferences: Uncertainty and ambiguity." *Journal of Risk and Uncertainty*, 5(4): 325–370.

Churchill, Craig, and Monique Cohen. 2006. "Protecting the Poor: A Microinsurance Compendium." Chapter 3.2, 174–196. International Labor Organization.

Clarke, Daniel, and Gautam Kalani. 2011. "Microinsurance decisions: evidence from Ethiopia." *Working Paper, University of Oxford.*

Clarke, Daniel J. 2011. *A theory of rational demand for index insurance.* Department of Economics, University of Oxford.

Cole, Shawn, Xavier Gine, Jeremy Tobacman, Petia Topalova, Robert Townsend, and James Vickery. 2013. "Barriers to Household Risk Management: Evidence from India." *American Economic Journal: Applied Economics*, 5(1): 104–35.

Doherty, Neil A., and Harris Schlesinger. 1990. "Rational Insurance Purchasing: Consideration of Contract Nonperformance." *The Quarterly Journal of Economics*, 105(1): 243–53.

Ellsberg, Daniel. 1961. "Risk, Ambiguity, and the Savage Axioms." *The Quarterly Journal of Economics*, 75(4): 643–669.

Epstein, Larry G. 1999. "A Definition of Uncertainty Aversion." *The Review of Economic Studies*, 66(3): 579–608.

Gärdenfors, Peter, and Nils-Eric Sahlin. 1982. "Unreliable probabilities, risk taking, and decision making." *Synthese*, 53(3): 361–386.

Glöckner, Andreas. 2009. "Investigating intuitive and deliberate processes statistically: The Multiple-Measure Maximum Likelihood strategy classification method." *Judgment and Decision Making*, 4(3): 186–199.

Herrero, Carmen, Josefa Toms, and Antonio Villar. 2006. "Decision theories and probabilistic insurance: an experimental test." *Spanish Economic Review*, 8(1): 35–52.

Hershey, John C., and Paul J. H. Schoemaker. 1980. "Risk Taking and Problem Context in the Domain of Losses: An Expected Utility Analysis." *The Journal of Risk and Insurance*, 47(1): 111–132.

Hogarth, Robin M., and Howard Kunreuther. 1989. "Risk, ambiguity, and insurance." *Journal of Risk and Uncertainty*, 2(1): 5–35.

Hsee, Christopher K., and Howard C. Kunreuther. 2000. "The Affection Effect in Insurance Decisions." *Journal of Risk and Uncertainty*, 20(2): 141–159.

Johnson, Eric J., John Hershey, Jacqueline Meszaros, and Howard Kunreuther. 1993. "Framing, probability distortions, and insurance decisions." *Journal of Risk and Uncertainty*, 7(1): 35–51.

Kahn, Barbara E., and Rakesh K. Sarin. 1988. "Modeling Ambiguity in Decisions Under Uncertainty." *Journal of Consumer Research*, 15(2): 265–272.

Kahneman, Daniel, and Amos Tversky. 1979. "Prospect Theory: An Analysis of Decision under Risk." *Econometrica*, 47(2): 263–292.

Klibanoff, Peter, Massimo Marinacci, and Sujoy Mukerji. 2005. "A Smooth Model of Decision Making under Ambiguity." *Econometrica*, 73(6): 1849–1892.

Knight, Frank H. 1921. *Risk, Uncertainty and Profit. Harper Torchbooks*, Houghton Mifflin.

Kunreuther, Howard, Robert Meyer, Richard Zeckhauser, Paul Slovic, Barry Schwartz, Christian Schade, Mary Frances Luce, Steven Lippman, David Krantz, Barbara Kahn, and Robin Hogarth. 2002. "High Stakes Decision Making: Normative, Descriptive and Prescriptive Considerations." *Marketing Letters*, 13(3): 259–268.

Liu, Yanyan, and Robert J. Myers. 2014. "The Dynamics of Microinsurance Demand in Developing Countries Under Liquidity Constraints and Insurer Default Risk." *Journal of Risk and Insurance*, forthcoming.

Mano, Haim. 1994. "Risk-Taking, Framing Effects, and Affect." *Organizational Behavior and Human Decision Processes*, 57(1): 38–58.

of the Philippines, Republic. 2008. "Department Order No. 23-08." Philippine Department of Finance Order 23.

Savage Leonard, J. 1954. *The foundations of statistics.* New York: Wiley.

Slovic, Paul, Melissa L. Finucane, Ellen Peters, and Donald G. MacGregor. 2007. "The affect heuristic." *European Journal of Operational Research*, 177(3): 1333–1352.

von Neumann, J., and O. Morgenstern. 1947. *Theory of games and economic behavior.* . 2nd ed., NJ:Princeton University Press.

Wakker, Peter P, Richard H Thaler, and Amos Tversky. 1997. "Probabilistic Insurance." *Journal of Risk and Uncertainty*, 15(1): 7–28.

Weller, Joshua A., Nathan F. Dieckmann, Martin Tusler, C. K. Mertz, William J. Burns, and Ellen Peters. 2013. "Development and Testing of an Abbreviated Numeracy Scale: A Rasch Analysis Approach." *Journal of Behavioral Decision Making*, 26(2): 198–212.

Zimmer, Anja, Christian Schade, and Helmut Gründl. 2009. "Is default risk acceptable when purchasing insurance? Experimental evidence for different probability representations, reasons for default, and framings." *Journal of Economic Psychology*, 30(1): 11–23.

Proofs

A1. Positive Probability of Insurance Nonperformance Reduces Willingness to Pay

To show that demand for insurance is lower under a positive probability of contract nonperformance as compared to zero contract nonperformance risk, it will suffice to compare the marginal willingness to pay of both scenarios. The marginal willingness to pay when $r > 0$ can be obtained with the first-order condition for optimizing (1) with respect to coverage ε:

$$\frac{\partial U}{\partial \varepsilon} = (1-p)u'(w-I(\varepsilon))(-I'(\varepsilon)) + p[(1-r) u'(w-I(\varepsilon)-L+\varepsilon)(-I'(\varepsilon)+1) + ru'(w-I(\varepsilon)-L)(-I'(\varepsilon))] = 0. \tag{A1}$$

We solve (A1) for $I'(\varepsilon)$ and get:

$$I'(\varepsilon) = \frac{p(1-r)u'(w-I(\varepsilon)-L+\varepsilon)}{(1-p)u'(w-I(\varepsilon)) + p[(1-r)u'(w-I(\varepsilon)-L+\varepsilon) + ru'(w-I(\varepsilon)-L)]}. \tag{A2}$$

This can be rewritten as:

$$I'(\varepsilon) = \frac{pu'(w-I(\varepsilon)-L+\varepsilon)}{(1-p)u'(w-I(\varepsilon)) \cdot \frac{1}{(1-r)} + p[u'(w-I(\varepsilon)-L+\varepsilon) + \frac{r}{(1-r)}u'(w-I(\varepsilon)-L)]}. \tag{A3}$$

The expected utility U for the decision maker when $r = 0$ is defined as:

$$U = (1-p)u(w-I(\varepsilon)) + p(u(w-I(\varepsilon)-L+\varepsilon)). \tag{A4}$$

The marginal willingness to pay is:

$$I'(0) = \frac{pu'(w-L)}{(1-p)u'(w) + pu'(w-L)}. \tag{A5}$$

Comparing equations (A3) and (A5) it is clear that the marginal willingness to pay for insurance when there is a positive probability for contract nonperformance is lower than that of the insurance paying with certainty.

A2. Lemma 1 and Lemma 2

In order to show that LEMMA 1 and LEMMA 2 hold, it will suffice to show that for some agents $U_{r>0} > U_{r=0}$:

$$\begin{aligned} U_{r>0} - U_{r=0} = (1-p)[u(w - I_0(1-r)) - u(w - I_0)] + \\ p(1-r)[u(w - I_0(1-r) - L + \varepsilon) - u(w - I_0 - L + \varepsilon)] - \\ pr[u(w - I_0 - L + \varepsilon) - u(w - I_0(1-r) - L)] \end{aligned} \tag{A6}$$

We restrict our attention to risk averse agents with concave utility functions, as only those would buy insurance. For agents with concave utility functions it holds: $u'(A) > u'(A+B)$. We implement an upper bound approximation such that: $u(A+B) - u(A) < u'(A)$. Hence:

$$\begin{aligned} U_{r>0} - U_{r=0} = (1-p)\underbrace{[u(w - I_0 + rI_0)) - u(w - I_0)]}_{<u'(w-I_0)rI_0 \leq u'(w-I_0-L+\varepsilon)rI_0} + \\ p(1-r)\underbrace{[u(w - I_0(1-r) - L + \varepsilon) - u(w - I_0 - L + \varepsilon)]}_{<u'(w-I_0-L+\varepsilon)rI_0} - \\ pr\underbrace{[u(w - I_0 - L + \varepsilon) - u(w - I_0 - L + rI_0)]}_{>u'(w-I_0-L+\varepsilon)(\varepsilon - rI_0)} \\ = (1-p)u'(w - I_0 - L + \varepsilon)rI_0 - \tau_1 + \\ p(1-r)u'(w - I_0 - L + \varepsilon)rI_0 - \\ \tau_2 - pru'(w - I_0 - L + \varepsilon)rI_0 - \tau_3 \\ = (1-pr)u'(w - I_0 - L + \varepsilon)rI_0 - pru'(w - I_0 - L + \varepsilon)(\varepsilon - rI_0) - \sum_{i=1,2,3} \tau_i, \end{aligned} \tag{A7}$$

where τ_i are the approximation errors which are zero for risk-neutral agents and strictly increasing in risk aversion. Using $I = (1+\alpha)\varepsilon p$ we get:

$$\begin{aligned} U_{r>0} - U_{r=0} = (1-pr)u'(w - I_0 - L + \varepsilon)r(1+\alpha)\varepsilon p - \\ pru'(w - I_0 - L + \varepsilon)(\varepsilon - r(1+\alpha)\varepsilon p) - \sum_{i=1,2,3} \tau_i \\ = u'(w - I_0 - L + \varepsilon)pr\varepsilon\alpha - \sum_{i=1,2,3} \tau_i. \end{aligned} \tag{A8}$$

From this result we know that for sufficiently low loadings there must exist agents with sufficiently high risk aversion such that $U_{r>0} < U_{r=0}$. On the other hand, for sufficiently high loadings there must exist agents with sufficiently low risk aversion above zero such that $U_{r>0} > U_{r=0}$. Yet, agents with low risk aversion are very sensitive to loadings and tend not to buy insurance when it is too expensive. Ultimately the results hinge on the exact shape of the utility function. Therefore, we implement simulations over a range of parameters to obtain more exact predictions. Simulation results can be found in Appendix section A.2.

A3. Lemma 3: Ambiguity of Contract Nonperformance

Lemma 3 can be shown by comparing the marginal willingness to pay when r is unknown to when r is known. The marginal willingness can be obtained with the first-order condition for optimizing (6) with respect to coverage ε:

The first-order condition with respect to coverage ε is:

$$\text{(A9)} \quad E_{\tilde{\gamma}}\Phi'(U(\tilde{\gamma}))[(1-p)u'(w-I(\varepsilon))(-I'(\varepsilon)) + p[(1-r(\tilde{\gamma}))u'(w-I(\varepsilon)- L+\varepsilon)(-I'(\varepsilon)+1) + r(\tilde{\gamma})u'(w-I(\varepsilon)-L)(-I'(\varepsilon))]] = 0.$$

His marginal willingness to pay $I(\varepsilon)$ for a reduction ε in loss is:

(A10)

$$I'(\varepsilon) = \frac{pu'(w-I(\varepsilon)-L+\varepsilon)}{(1-p)u'(w-I(\varepsilon))\hat{r} + p[u'(w-I(\varepsilon)-L+\varepsilon) + \bar{r}u'(w-I(\varepsilon)-L)]},$$

where $\hat{r} = \frac{E_{\tilde{\gamma}}\Phi'(U(\tilde{\gamma}))}{E_{\tilde{\gamma}}(1-r(\tilde{\gamma}))\Phi'(U(\tilde{\gamma}))}$ and $\bar{r} = \frac{E_{\tilde{\gamma}}r(\tilde{\gamma})\Phi'(U(\tilde{\gamma}))}{E_{\tilde{\gamma}}(1-r(\tilde{\gamma}))\Phi'(U(\tilde{\gamma}))}$.

We are interested in comparing the willingness to pay of an individual when there is ambiguity regarding contract nonperformance risk to the case when its probability is known. That would be the same as comparing:

(A11)

$$I'(\varepsilon)_{Control} = \frac{pu'(w-I(\varepsilon)-L+\varepsilon)}{(1-p)u'(w-I(\varepsilon))\cdot\frac{1}{(1-r)} + p[u'(w-I(\varepsilon)-L+\varepsilon) + \frac{r}{(1-r)}u'(w-I(\varepsilon)-L)]}$$

and

$$\text{(A12)} \quad I'(\varepsilon)_{Def} = \frac{pu'(w-I(\varepsilon)-L+\varepsilon)}{(1-p)u'(w-I(\varepsilon))\cdot\hat{r} + p[u'(w-I(\varepsilon)-L+\varepsilon) + \bar{r}u'(w-I(\varepsilon)-L)]}.$$

In order to compare the two equations it will suffice to compare $\frac{1}{1-r}$ to $\hat{r}$ and $\frac{r}{1-r}$ to $\bar{r}$.

(A13)
$$\frac{1}{1-r} > \hat{r}$$
$$\frac{1}{1-r} > \frac{E_{\tilde{\gamma}}\Phi'(U(\tilde{\gamma}))}{E_{\tilde{\gamma}}(1-r(\tilde{\gamma}))\Phi'(U(\tilde{\gamma}))}$$
$$r \cdot E_{\tilde{\gamma}}\Phi'(U(\tilde{\gamma})) > E_{\tilde{\gamma}}r(\tilde{\gamma})\Phi'(U(\tilde{\gamma})).$$

Comparing $\frac{1}{1-r}$ and $\hat{r}$ is the same as comparing the left and right hand size of equation (A13). The desired result follows from concavity of $\Phi(.)$. Note that as $r(\tilde{\gamma})$ increases, the ambiguity averse agent's utility decreases and due to concavity of Φ, $\Phi'(U(\tilde{\gamma}))$ increases as $r(\tilde{\gamma})$ increases. The right hand side of equation (A13) gives higher weight to $\Phi'(U(\tilde{\gamma}))$ for larger values of $r(\tilde{\gamma})$ while the left hand size gives a constant weight to $\Phi'(U(\tilde{\gamma}))$, namely r.

(A14)
$$\frac{r}{1-r} > \bar{r}$$
$$\frac{r}{1-r} > \frac{E_{\tilde{\gamma}}r(\tilde{\gamma})\Phi'(U(\tilde{\gamma}))}{E_{\tilde{\gamma}}(1-r(\tilde{\gamma}))\Phi'(U(\tilde{\gamma}))}$$
$$r \cdot E_{\tilde{\gamma}}\Phi'(U(\tilde{\gamma})) > E_{\tilde{\gamma}}r(\tilde{\gamma})\Phi'(U(\tilde{\gamma})).$$

Same argument as presented above applies for equation (A14). Thus, we have that the willingness to pay for insurance with known contract nonperformance risk is higher as opposed to the case where it is unknown.

A4. Lemma 4: Ambiguity in Shock Probabilities

Lemma 4 can be shown by comparing the marginal willingness to pay when p is ambiguous to when p is known. The marginal willingness to pay can be obtained by the first-order condition for optimizing (7) with respect to coverage ε:

The first-order condition with respect to coverage ε is:

(A15)
$$E_{\tilde{\alpha}}[(1-p(\tilde{\alpha}))u'(w-I(\epsilon))(-I'(\epsilon)) + p(\tilde{\alpha})[(1-r)u'(w-I(\varepsilon)- L+\varepsilon)(-I'(\varepsilon)+1) + ru'(w-I(\varepsilon)-L)(-I'(\varepsilon))]]\Phi'(U(\tilde{\alpha})) = 0,$$

and thus we get the marginal willingness to pay $I'(\varepsilon)_{Loss}$:

(A16)
$$I'(\varepsilon)_{Loss} = \frac{(1-r)u'(w-I(\varepsilon)-L+\varepsilon)}{\bar{p}u'(w-I(\varepsilon)) + (1-r)u'(w-I(\varepsilon)-L+\varepsilon) + ru'(w-I(\varepsilon)-L)},$$

where $\bar{p} = \frac{E_{\tilde{\alpha}}(1-p(\tilde{\alpha}))\Phi'(U(\tilde{\alpha}))}{E_{\tilde{\alpha}}p(\tilde{\alpha})\Phi'(U(\tilde{\alpha}))}$.

We are interested in comparing the willingness to pay of an individual when there is ambiguity regarding loss probabilities to the case when the loss probability is known. We thus compare $I'(\varepsilon)_{Control}$ and $I'(\varepsilon)_{Loss}$:

$$\text{(A17)} \qquad I'(\varepsilon)_{Control} = \frac{(1-r)u'(w-I(\varepsilon)-L+\varepsilon)}{\frac{1-p}{p}u'(w-I(\varepsilon))+(1-r)u'(w-I(\varepsilon)-L+\varepsilon)+ru'(w-I(\varepsilon)-L)}$$

and

$$\text{(A18)} \qquad I'(\varepsilon)_{Loss} = \frac{(1-r)u'(w-I(\varepsilon)-L+\varepsilon)}{\bar{p}u'(w-I(\varepsilon))+(1-r)u'(w-I(\varepsilon)-L+\varepsilon)+ru'(w-I(\varepsilon)-L)}.$$

For Lemma 4 to hold it will suffice to show $\bar{p} = \frac{E_{\tilde{\alpha}}(1-p(\tilde{\alpha}))\Phi'(U(\tilde{\alpha}))}{E_{\tilde{\alpha}}p(\tilde{\alpha})\Phi'(U(\tilde{\alpha}))} < \frac{1-p}{p}$, for which we get:

$$\text{(A19)} \qquad E_{\tilde{\alpha}}p\Phi'(U(\tilde{\alpha})) < E_{\tilde{\alpha}}p(\tilde{\alpha})\Phi'(U(\tilde{\alpha})).$$

As $p(\tilde{\alpha})$ increases, the ambiguity averse agent will have lower levels of utility and due to the concavity of Φ, $\Phi'(U(\tilde{\alpha}))$ increases as $p(\tilde{\alpha})$ increases. The right hand side of (A19) gives higher weight to $\Phi'(U(\tilde{\alpha}))$ as $p(\tilde{\alpha})$ increases while the left hand size gives the constant weight p to $\Phi'(U(\tilde{\alpha}))$. Thus for ambiguous averse agents the willingness to pay when the loss probability is ambiguous is larger than when it is known.

Simulations

We have derived that under some circumstances (i.e., high loading, low risk aversion) the insurance with default risk might be preferred. Intuitively, some might value the gain in expected payoff more than the risk of contract nonperformance. To assess the extent of this phenomenon we specify a CRRA utility function of the following form:

$$u(A) = \frac{A^{1-\gamma}}{1-\gamma}, \tag{B1}$$

where $\gamma = 0$ indicates risk neutrality and risk aversion increases in γ.
We fix the following parameters:

Table B1—Parameters

	Without Nonperformance	With Nonperformance
Initial Endowment	210	210
Shock probability p	0.3	0.3
Loss	150	150
Insurance Payout ε	150	150
Nonperformance risk	0	0.1
Insurance premium	I_0	$I_0(1-r)$
Loading factor	α	α

The insurance premium fully depends on the loading factor because $I = (1+\alpha)\varepsilon p = (1+\alpha)45$. Using the specifications shown in Table B1 we can calculate the utility difference $U_{r>0} - U_{r=0}$ for any combination of (α, γ). Figure B1 shows the result of our simulations.

As shown theoretically before, low risk-aversion types under high loading environment might prefer the nonperformance risk. However, for high loadings the types preferring insurance with default might not opt for insurance anyway. To illustrate this, figure B2 shows our simulation results for insurance uptake for the case of insurance with default.

Indeed, only those who would anyway not take up insurance prefer insurance with nonperformance risk. This implies that demand for the insurance product without nonperformance risk must be larger, because it is always preferred by those risk-averse enough to take up insurance. Figure B3 shows the results of our simulations for the case of insurance without nonperformance risk.

Hence, our prior demand analysis is confirmed when comparing Figures B2 and B3: The region of uptake with contract nonperformance risk is a subset of the uptake region without nonperformance.

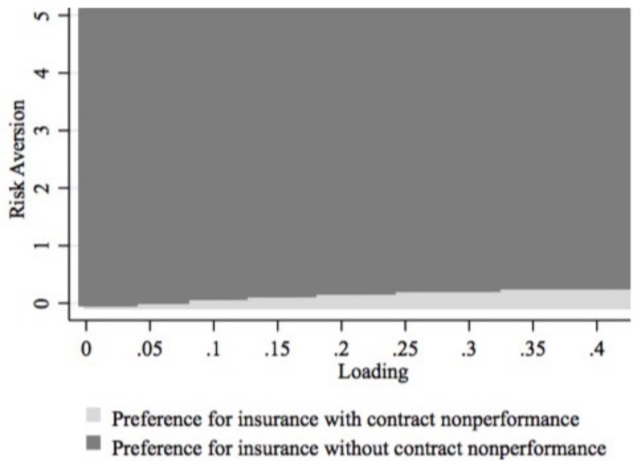

Figure B1. Preference for insurance with contract nonperformance risk or without

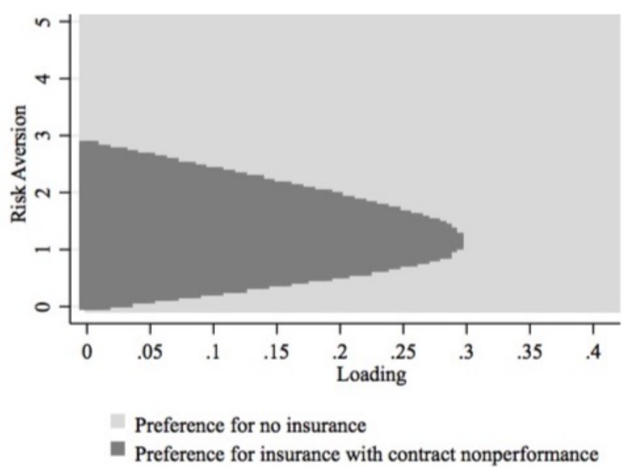

Figure B2. Insurance uptake with contract nonperformance risk

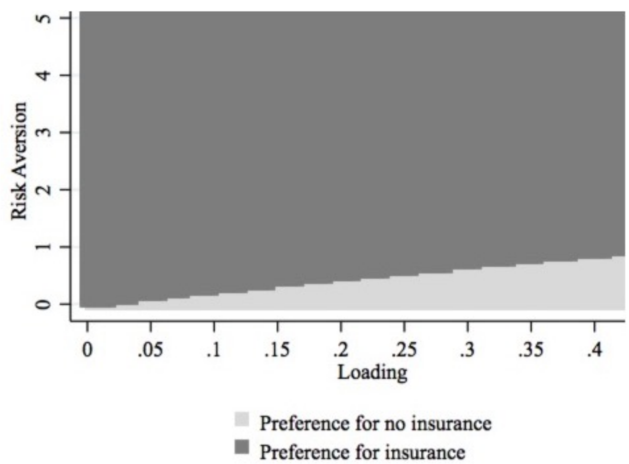

Figure B3. Insurance uptake without contract nonperformance risk