Contract Nonperformance Risk and Ambiguity in Insurance Markets

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Contract nonperformance risk refers to situations when valid claims are not reimbursed by the insurer, which is also known as probabilistic insurance. We extend probabilistic insurance models to allow for ambiguous contract nonperformance and loss probabilities. We experimentally test theoretical predictions from our model using a field lab experiment with a low-income sample. This is a persuasive context, since especially in emerging and poorly regulated economies 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. Also, ambiguity does not easily disappear with experience.

I. Introduction

The concept of probabilistic insurance 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. Various circumstances including insolvency, discord about the losses covered, and payment delays can cause total or partial contract nonperformance. From an insurance demand perspective, contract nonperformance risk is hence not restricted to situations where legally valid claims are not settled, but more generally applicable to all claims rejected, which are perceived as valid by the policyholder (Doherty and Schlesinger, 1990).

Doherty and Schlesinger (1990) show significant implications of contract nonperformance risk for classic results of insurance demand theory. In a nutshell, they

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find that risk averse individuals will not fully insure at actuarially fair prices, that increasing risk aversion and increasing loadings do not generally induce higher optimal insurance demand, and that optimal insurance demand is not generally a monotonic function of contract nonperformance risk. Subsequent empirical work by Zimmer, Schade and Gründl (2009), Herrero, Tomás and Villar (2006), Albrecht and Maurer (2000), and Wakker, Thaler and Tversky (1997) support the hypothesis of strong detrimental effects of contract nonperformance on insurance demand.

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] Ambiguity is of general relevance to economic decision making and resembles real-world scenarios in that probabilities can be assigned to all possible outcomes only in very few cases. 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 theory only incorporate the mean over a probability distribution to affect decisions.

In this paper, we extend probabilistic insurance models to allow for ambiguity regarding contract nonperformance and loss probabilities and provide empirical tests of our theory. 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). We test theoretical predictions derived from this model by conducting a behavioral experiment in the Philippines. In different treatments we vary the presence of nonperformance risk, the existence of ambiguity and the source of ambiguity (either loss or nonperformance probability might be unknown).

Our experimental implementation in a low-income insurance market reflects the particular relevance of (1) identifying factors constraining insurance demand and (2) high exposure to contract nonperformance risk and ambiguity in those settings.[3] Despite significant efforts, low insurance demand by low-income consumers remains a puzzle. Claims considered eligible by the insured but not paid

[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.

[3]We use the term "low-income insurance" for financial arrangements intended to protect low-income populations against specific perils in exchange for regular premium payments proportionate to the likelihood and cost of the risk involved (Churchill, 2007). Another terminology frequently used for such financial arrangements is "micro-insurance."

by the insurer may have a severely negative impact on perceptions and trust (Cole et al., 2013) and thus emerge as a potential piece of the puzzle explaining low insurance demand by low-income consumers. Only recently, Liu and Myers (2014) provide theoretical evidence for significant reductions in demand for insurance resulting from perceived insurer default in a low-income insurance contexts. Several factors magnify contract nonperformance risk and ambiguity in low-income insurance markets. Individuals face a broad variety of not easily quantifiable perils arising from geographic settings (e.g., natural disasters), lack of public infrastructure (e.g., risk 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. Perceptions of high contract nonperformance risk are furthermore fueled by limited trust in regulators and legal institutions to enforce contracts and supervise markets. In highly regulated developed insurance markets, low rates of insurer insolvencies and the existence of guarantee funds indicate that contract nonperformance should not be expected to severely affect insurance demand, but statistics on consumer complaints in the U.S. suggest a potential role for perceived contract nonperformance even in those markets.[4]

We show formally and find empirically that eliminating contract nonperformance risk—i.e. the insurer always pays a claim—as well as eliminating the ambiguity about contract nonperformance risk increases insurance demand. 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 significant evidence for increased uptake of probabilistic insurance when shock probabilities are ambiguous, which is opposed to previous findings for non-probabilistic insurance such as those by Hogarth and Kunreuther (1989). Effects of ambiguity appear to be little affected by experience and remain relatively stable over time.

In our experimental setting, we also control for two framings regarding contract nonperformance. Several experiments on decision-making and insurance have shown that context matters.[5] In particular, we are interested in controlling for 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

[4]In particular, roughly 50 percent of all complaints reported to U.S. state regulators in 2014, 2013, and 2012 relate to denials and delays of claims as well as to unsatisfactory settlements amounting to a total of over 30,000 cases in 2014 (NAIC, 2015).

[5]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) to name only a few.

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). While framing effects are more pronounced in low numeracy and ambiguity averse subsamples, we find no significant effect of negatively framing contract nonperformance (i.e., inability versus unwillingness to pay) on insurance demand overall.

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. Model

A. Preliminaries

Below we formalize the characteristics of contract nonperformance risk and ambiguity and relate them to optimal insurance demand. To this end, we rely on the theoretical foundations originating from Doherty and Schlesinger (1990) for contract nonperformance risk and Alary, Gollier and Treich (2013) for ambiguity. Figure 1 captures the state space we are considering. We assume that a decision maker with initial wealth w has a positive probability p of suffering a loss $L > 0$ against which he or she can purchase insurance that pays ε for some premium $I(\varepsilon)$.[6] In the case that the decision maker buys insurance and the loss does not occur (with probability $1 - p$), the agent is left with $w - I(\varepsilon)$.

In the case that the decision maker buys insurance and incurs a loss of L, 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 $w - I(\varepsilon) - L + \varepsilon$. A decision maker, thus, evaluates expected utility of the upper tree branch (i.e., insurance) against the lower tree branch (i.e., no insurance) of Figure 1.

[6]Note that we remain very general in our premium definition and do not presume that the insurance is priced actuarially fair.

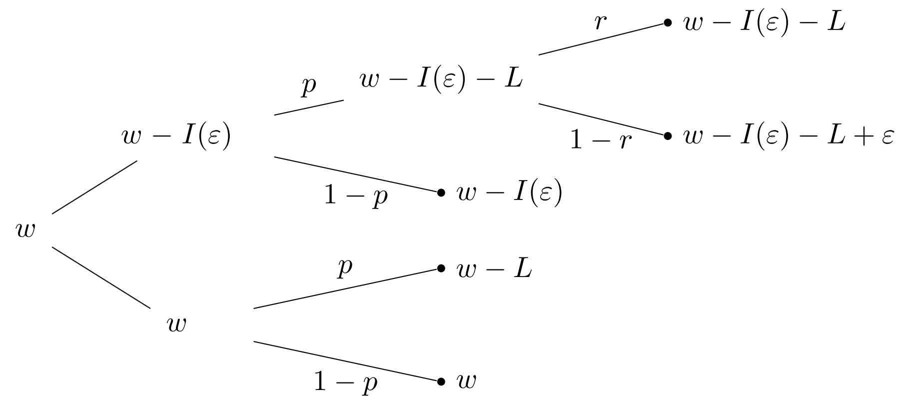

Figure 1. : State space

B. Demand for Probabilistic Insurance

Our benchmark setting is one with known contract nonperformance probability r. The expected utility for known contract nonperformance probability 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, expected utility with insurance is compared to the no 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 and not adapting the premium accordingly we change the expected payout and hence the loading of the insurance policy.[7] 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 A: Proofs). The case is less trivial when the premium amount is discounted by the nonperformance probability, i.e., making the comparison "fair" in

[7]The loading factor of the insurance policy is defined as the ratio between premium amount and expected payout. Expected payout decreases when there is a positive probability of contract nonperformance.

terms of the loading factor. Let $I_r(\varepsilon)$ be the insurance premium with nonperformance risk $r > 0$, while $I_0(\varepsilon)$ denotes the premium without nonperformance risk. Specifying $I_r(\varepsilon) = (1-r)I_0(\varepsilon)$ leads to a constant loading factor. The expected 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 expected 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. These advantages and drawbacks are weighted differently by different types of agents. The following Lemmas can be shown to hold (see Appendix A: Proofs).

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

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

For fair insurance with zero loading, the case simplifies to a case similar to the one in Doherty and Schlesinger (1990) with fair premiums. Here, our LEMMA 2 becomes irrelevant and the condition for LEMMA 1 always holds, in a sense that all risk-averse agents prefer insurance without contract nonperformance. Similar to Doherty and Schlesinger (1990) we would therefore predict lower insurance uptake with nonperformance. In general, 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 contract nonperformance 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 (see Appendix B: Simulations). 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: contract nonperformance risk reduces insurance demand ($H1$).

C. Demand for Ambiguous Probabilistic Insurance

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 utility derived from each state of γ. The decision maker's expected utility corresponds to:

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

An ambiguity neutral agent uses a linear valuation function, essentially using U from Equation 1 and replacing r with $E_{\tilde{\gamma}} r(\tilde{\gamma})$. Concavity of Φ expresses ambiguity aversion, i.e., an aversion to mean-preserving spreads in the random probability of contract nonperformance $r(\tilde{\gamma})$. Ambiguity averse agents give higher weight to states of γ that are associated with unfavorable (low utility) probabilities. In our case this would lead to an overweighting of loss and nonperformance probabilities. For ambiguity loving agents, Φ is convex and higher weights are given for favorable (high utility) probabilities, leading to an underweighting of loss and nonperformance probabilities. 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 A:

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.

There are arguments why the effect of ambiguity-averse agent should dominate. Vieider et al. (2015) show over a range of 30 countries that individuals seem to be, on average, averse to ambiguity. Also, risk aversion seems to correlate positively with ambiguity aversion and only risk-averse individuals are potential clients which could be affected by ambiguous nonperformance risk. We thus derive our second hypothesis as follows: ambiguity about contract nonperformance probabilities reduces insurance demand ($H2$).

D. Demand for Probabilistic Insurance Under Ambiguous Shocks

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:

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

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 A: 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. Similar to our argument for hypothesis H2, we expect ambiguity aversion to dominate, especially for potential insurance clients. We thus derive our third hypothesis as follows: ambiguity about loss probabilities increases insurance demand ($H3$).

III. Testing the Model

A. Experimental Design

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 randomly drawing a ball from a bag containing 10 balls of which a certain number is orange and another white. Orange balls represent a loss of L, while white balls indicate no loss. Losses are paid from an initial endowment W. 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 randomly drew a ball with probability p_{Loss} of experiencing a shock. Participants who bought insurance could claim a payment from the insurer contingent on having experienced a shock. Whether the insurer paid the claim or not was determined by drawing a ball from a second bag with probability p_{Def} of drawing an orange ball. An orange ball implied that the claim was not to be paid by the insurer, that is, the participant experiences contract nonperformance. Participants played the game in sessions with six participants. They were not allowed to exchange information or talk amongst 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 -250 and 250 Philippine pesos (PHP) and participants played up to 122 lotteries, depending on their response time.[8] We use lotteries following Ellsberg (1961), with which we classify individuals as ambiguity averse, ambiguity

[8]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.

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						
Ambiguous loss probability	*No*	*No*	*No*	*Yes*	*No*	*No*
Ambiguous contract nonperformance 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

neutral, or ambiguity loving. Participants earned the average of four randomly drawn gambles, two from the gain domain and two from the loss domain.

Treatments. — A complete overview of all treatments is presented in Table 1. Every participant was provided with an initial endowment of PHP 210. 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.[9]

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

[9]Because the actual price of an insurance policy is it's loading, we added a 30 percent markup to all insurance treatments. To make the resulting premium values manageable in our experimental setting using artificial PHP bills, we rounded premium values to even amounts resulting in actual loadings of 25 percent and 33 percent for the T_{NoDef} treatment. Insurance premiums include risk and cost loadings; in low-income insurance markets, high risk loadings for uncertainty in the estimation of expected losses due to data constraints often need to be added (Biener, 2013).

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 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). Thus, not paying claims is at the discretion of the insurer in the negative framing, whereas the insurer has no scope of discretion under the neutral framing.

Procedures and Sample Characteristics. — 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

[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).

the test questionnaire could be answered correctly was the participant allowed to continue. 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.

A post experimental survey was conducted to gather data on perception of the experimental insurance product, mathematical and numerical 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.

In total we conducted 166 sessions with 996 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 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 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

[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.

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
(*in years*)	(10.50)	(10.08)	(9.966)	(10.98)	(10.94)	(9.755)	
Gender	0.741	0.840*	0.810	0.722	0.833*	0.786	0.228
($1 = female$)	(0.439)	(0.368)	(0.394)	(0.449)	(0.374)	(0.412)	
Married or in partnership	0.903	0.889	0.869	0.911	0.902	0.899	0.814
($1 = yes$)	(0.297)	(0.315)	(0.338)	(0.285)	(0.298)	(0.302)	
Education	9.573	9.580	9.911	9.594	9.552	9.381	0.634
(*in years*)	(2.642)	(2.472)	(2.476)	(2.419)	(2.210)	(2.619)	
Employment status	0.465	0.358	0.387	0.433	0.351*	0.429	0.391
($1 = employed$)	(0.501)	(0.481)	(0.488)	(0.497)	(0.479)	(0.496)	
Regular income	0.270	0.295	0.282	0.270	0.250	0.275	0.769
($1 = yes$)	(0.447)	(0.460)	(0.453)	(0.446)	(0.436)	(0.449)	
Seasonal income	0.716	0.787	0.732	0.663	0.653	0.637	0.297
($1 = yes$)	(0.454)	(0.413)	(0.446)	(0.475)	(0.479)	(0.484)	
Owned dwelling	0.799	0.895*	0.845	0.856	0.839	0.851	0.435
($1 = yes$)	(0.402)	(0.307)	(0.363)	(0.353)	(0.369)	(0.357)	
Reduced meals in last month	0.273	0.210	0.214	0.156**	0.218	0.244	0.548
($1 = yes$)	(0.447)	(0.408)	(0.412)	(0.363)	(0.414)	(0.431)	
Owns land	0.133	0.142	0.113	0.139	0.167	0.161	0.885
($1 = yes$)	(0.341)	(0.350)	(0.318)	(0.347)	(0.374)	(0.368)	
Panel B: Mental capabilities, risk and ambiguity aversion							
Mathematical ability score	6.660	6.654	6.661	6.500	6.655	6.494	0.888
(0 *min* 8 *max*)	(1.698)	(1.815)	(1.630)	(1.851)	(1.612)	(1.754)	
Numerical ability score	9.236	9.142	9.119	9.050	9.040	8.994	0.988
(0 *min* 16 *max*)	(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 *min* 7 *max*)	(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
(1 *min* 3 *max*)	(0.711)	(0.767)	(0.786)	(0.762)	(0.768)	(0.799)	
Panel C: Loss and insurance experience							
Insurance ownership	0.528	0.580	0.577	0.594	0.557	0.542	0.881
($1 = yes$)	(0.501)	(0.495)	(0.495)	(0.492)	(0.498)	(0.500)	
Illness or accident shock	0.625	0.627	0.631	0.578	0.590	0.563	0.741
($1 = yes$)	(0.486)	(0.485)	(0.484)	(0.495)	(0.493)	(0.498)	
Weather or livestock shock	0.451	0.391	0.423	0.450	0.439	0.425	0.91
($1 = yes$)	(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.

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.

IV. 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 in line with preceding literature (Wakker, Thaler and Tversky, 1997; Albrecht and Maurer, 2000; Herrero, Tomás 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 $H2$.

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

[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, marital status, education, household size, responsible for household decisions, employment, income (seasonal, regular), owning a dwelling, owning land, reduced meals in last month, score in mathematical and numerical capabilities, risk and ambiguity aversion, insurance ownership, health or accident shocks, and weather or livestock shocks.

Table 3—: Average Treatment Effects

	(1) (OLS)	(2) (OLS)	(3) (OLS)	(4) (Probit[a])
T_{NoDef}	0.171***	0.172***	0.184***	0.219***
	(0.0626)	(0.0630)	(0.0638)	(0.0707)
T_{Def}	-0.145*	-0.143*	-0.132*	-0.121*
	(0.0768)	(0.0783)	(0.0765)	(0.0708)
T_{Loss}	0.0345	0.0373	0.0394	0.0403
	(0.0703)	(0.0705)	(0.0699)	(0.0706)
C_{Fr}	-0.121	-0.119	-0.110	-0.101
	(0.0802)	(0.0795)	(0.0773)	(0.0717)
T_{Def-Fr}	-0.104	-0.101	-0.102	-0.0949
	(0.0795)	(0.0791)	(0.0774)	(0.0723)
Typhoon		0.0426	0.0385	0.0393
		(0.0389)	(0.0381)	(0.0376)
Round		0.00267	0.00245	0.00279
		(0.00337)	(0.00337)	(0.00339)
Constant	0.707***	0.677***	0.551***	
	(0.0580)	(0.0621)	(0.148)	
Observations	5,976	5,976	5,952	5,952
R-squared	0.055	0.057	0.078	0.070
F test	12.09	9.648	4.329	
Covariates	No	No	Yes	Yes

Note: Standard errors in parentheses, clustered at the session level. Covariates: age, gender, marital status, education, household size, responsible for household decisions, employment, income (seasonal, regular), owning a dwelling, owning land, reduced meals in last month, score in mathematical and numerical capabilities, risk and ambiguity aversion, insurance ownership, health or accident shocks, and weather or livestock shocks. [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.

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.

B. Secondary Results

Numeracy. — We analyze treatment effects conditional on subject's numeracy levels because a minimum level of numeracy skills might be useful 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 seem to exhibit stronger treatment effects. Eliminating contract nonperformance in treatment T_{NoDef} increases insurance demand by 21 percentage points for the high numeracy sample compared to a 14 percentage point increase in the low numeracy sample and a 17 percentage point increase 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 percentage points more than the full sample and 7 percentage 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, marital status, education, household size, responsible for household decisions, employment, income (seasonal, regular), owning a dwelling, owning land, reduced meals in last month, score in mathematical and numerical capabilities, risk and ambiguity aversion, insurance ownership, health or accident shocks, and weather or 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 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 (Columns 1 and 2), ambiguity neutral (Columns 3 and 4), and ambiguity loving subjects (Columns 5 and 6) respectively. 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.

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, marital status, education, household size, responsible for household decisions, employment, income (seasonal, regular), owning a dwelling, owning land, reduced meals in last month, score in mathematical and numerical capabilities, risk and ambiguity aversion, insurance ownership, health or accident shocks, and weather or livestock shocks. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ significance level at 10, 5 and 1 percent.

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 seemingly stronger reduction in insurance demand when the probability of contract nonperformance is ambiguous as is apparent from Columns 1 and 2 of Table 5 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 the negative framing condition 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 conclusion, 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 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.

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

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, 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

[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.

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.

V. 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 low-income insurance markets. In line with our results is a call for sound regulatory frameworks in those markets, particularly focusing on assuring low levels of contract nonperformance risk as well as limiting ambiguity about this risk through sound solvency regulation and contract validation as well as an increase in market transparency. Regulation is generally considered beneficial to policyholders and costly to the insurance industry. Our results, however, show that insurance companies and regulators have a common interest in regulating contract nonperformance risk because it increases insurance demand. Furthermore, insurers active in this market segment focussing on sound policies and practices have the opportunity to gain competitive advantage and build trust in the market.

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Appendix A: Proofs

A1. Positive Probability of Insurance Nonperformance Reduces Willingness to Pay

In this appendix section we proof that introducing nonperformance risk without adjusting premiums decreases the willingness to pay. This is quite intuitive, as there is no reason why a nonperformance feature should be valued by clients. In the following, we will 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:

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

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

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

This can be rewritten as:

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

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

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

The marginal willingness to pay is:

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

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, irrespective of the coverage point ε (numerator is the same, denominator is larger). This implies a lower overall willingness to pay and hence, lower demand for insurance with nonperformance risk.

A2. Lemma 1 and Lemma 2: Effects of nonperformance risk when adjusting the premium

The setting is less trivial when together with increasing nonperformance risk, premiums are decreased. Agents in this case will face a tradeoff between effective coverage and premiums. In order to show that LEMMA 1 and LEMMA 2 hold, we will focus on comparing $U_{r>0}$ and $U_{r=0}$:

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

If the difference is positive, clients will prefer insurance with nonperformance risk and vice versa. 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: $u(A+B) - u(A) < u'(A)B$. Hence:

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

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:

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

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 B.

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:

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

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

$$I'(\varepsilon) = \frac{pu'(w - I(\varepsilon) - L + \varepsilon)}{(1-p)u'(w - I(\varepsilon))\hat{r} + p[u'(w - I(\varepsilon) - L + \varepsilon) + \bar{r}u'(w - I(\varepsilon) - L)]}, \tag{A10}$$

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

(A12)

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

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 expected 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:

(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 $I'(\varepsilon)_{Loss}$:

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

and

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

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:

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

As $p(\tilde{\alpha})$ increases, the ambiguity averse agent will have lower levels of expected 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 ambiguity averse agents the willingness to pay when the loss probability is ambiguous is larger than when it is known.

Appendix B: Simulations

We have derived that under some circumstances (i.e., high premium loadings and low risk aversion) the insurance with contract nonperformance 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

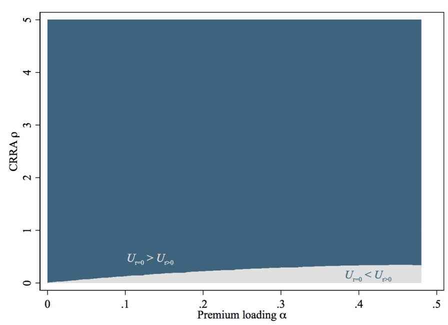
	Without contract nonperformance	With contract nonperformance
Initial Endowment	210	210
Shock probability p	0.3	0.3
Loss	150	150
Insurance Payout ε	150	150
Nonperformance risk	0	0.1
Insurance premium	I_0	$I_0(1-r)$
Loading factor	α	α

The insurance premium 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 expected utility difference $U_{r>0} - U_{r=0}$ for any combination of (α, γ). Figure B1a shows the result of our simulations.

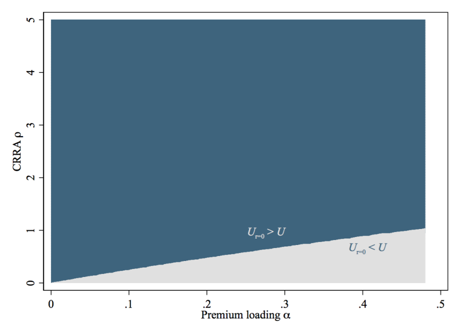
As shown theoretically before, low risk-aversion types facing insurance policies with high premium loadings might prefer the policy with contract nonperformance risk. However, for high premium loadings the types preferring insurance with contract nonperformance risk might not opt for insurance anyway. To illustrate this, Figure B1c shows simulation results for the case of insurance with contract nonperformance risk.

Indeed, only those who would anyway not take up insurance prefer insurance with contract nonperformance risk. This implies that demand for the insurance policy without contract nonperformance risk must be larger, because it is always preferred by those sufficiently risk-averse. Figure B1b shows the results of our simulations for the case of insurance without contract nonperformance risk.

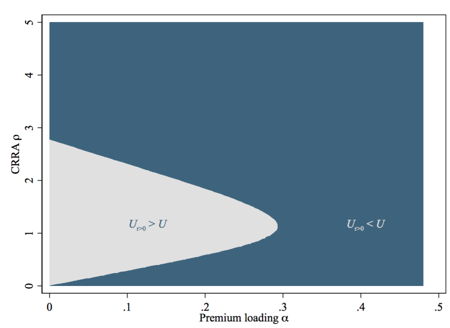
Hence, our prior demand analysis is confirmed when comparing Figures B1b and B1c—i.e., the preference region for insurance with contract nonperformance risk is a subset of the preference region for insurance without contract nonperformance.



(a) $U_{r>0}$ versus $U_{r=0}$



(b) $U_{r=0}$ versus U



(c) $U_{r>0}$ versus U

Figure B1. : Insurance preference patterns for (α, γ)