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Conference Paper

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Beiträge zur Jahrestagung des Vereins für Socialpolitik 2015: Ökonomische Entwicklung - Theorie und Politik - Session: Microinsurance, No. C24-V2

Provided in Cooperation with:

Verein für Socialpolitik / German Economic Association

Suggested Citation: Landmann, Andreas; Biener, Christian; Eling, Martin; Santana, Maria Isabel (2015) : Contract Nonperformance and Ambiguity in Insurance Markets, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2015: Ökonomische Entwicklung - Theorie und Politik - Session: Microinsurance, No. C24-V2, ZBW - Deutsche Zentralbibliothek für Wirtschaftswissenschaften, Leibniz-Informationszentrum Wirtschaft

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Contract Nonperformance and Ambiguity in Insurance Markets

By CHRISTIAN BIENER, MARTIN ELING, ANDREAS LANDMANN, AND MARIA ISABEL SANTANA*

Insurance contract nonperformance relates to situations when valid claims are not paid by the insurer. We extend probabilistic insurance models to allow for such nonperformance risk as well as ambiguity regarding 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 a higher chance of contract nonperformance. In line with our predictions, insurance demand decreases by 17 percentage points in the presence of contract nonperformance risk and is reduced by a further 14 percentage points when contract nonperformance risk is ambiguous. It also seems that 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. 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 contract nonperformance 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 validity of a claim from the policyholder's perspective but not necessarily its legal validity (Doherty and Schlesinger, 1990).

The prospect of potential contract nonperformance of insurance policies is related to the concept of probabilistic insurance, which was first introduced by

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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.

An innovative feature of this research is the incorporation of ambiguity about probabilities for shocks and contract nonperformance, 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 a situation 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 nonperformance². 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 perils arising from geographic settings (e.g., natural disasters), lack of hygiene in 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

¹Different 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).

²Bryan (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.

enforcement) environment. All these risks might be hard to quantify for normal citizens.

Not only does this paper make contributions to understanding contract non-performance 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 be assigned to all possible states of the world by most individuals, which has not been discussed in the literature. For a theoretical analysis we adapt the model 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. Theoretical Framework and Hypotheses

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 loses 0 and is left with $w - I(\varepsilon)$. In the case that the decision maker incurs a loss

³Contract 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.

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

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:

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

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:

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

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

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

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. The

⁵The 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.

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 result with 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 $\{1, \dots, n\}$ 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):

$$(4) \quad U(\gamma) = (1 - p)u(w - I(\varepsilon)) + p[(1 - r(\gamma))u(w - I(\varepsilon) - L + \varepsilon) + r(\gamma)u(w - I(\varepsilon) - L)].$$

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:

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

⁶We 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.

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 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:

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

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 default risk is always preferred by ambiguity averse agents. This in turn implies that uptake should be higher with known default 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 on insurance demand when there is a known risk of contract nonperformance, that is, p is not known with certainty. 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 $\{1, \dots, n\}$. In this case, the decision maker's expected utility can be defined as:

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

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 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 negatively affects insurance demand.

Whereas some theoretical as well as experimental research justifying hypotheses 1, 3, and 4 exist, the theoretical model as well as the experimental results for hypothesis 2 are original and have so far not been discussed in the literature.

III. Experimental Design

We use a field lab experiment that was implemented in the Iloilo and Guimaras provinces of the Republic of the Philippines in October and November 2013. We applied a two-stage randomization procedure where in the first stage rural villages (locally known as Barangays) were randomly selected⁷ and in the second step twelve individuals aged between 18 and 65 years were randomly selected from complete household lists. 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.

Our experimental setup includes five treatment and one control group, randomized across the four groups in each village. 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. A complete overview of all treatments is presented in Table 1.

In total we conducted 166 sessions with 1,008 participants in 42 villages. Subjects played an insurance game where they decided whether to take up insurance or not, facing a probability of loss and a probability of contract nonperformance of the insurance policy. Every participant was provided with an initial endowment

⁷Villages 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)).

TABLE 1—EXPERIMENTAL TREATMENTS

Treatments	<i>Control</i>	<i>TNoDef</i>	<i>TDef</i>	<i>TLoss</i>	<i>C_{Fr}</i>	<i>T_{Def-Fr}</i>
Loss probability:	p_{Loss}	p_{Loss}	p_{Loss}	?	p_{Loss}	p_{Loss}
Default probability:	$p_{Default}$	$p_{Default}$?	$p_{Default}$	$p_{Default}$?
Framing:	-	-	-	-	negative	negative
p_{Loss}	0.3	0.3	0.3	0.3	0.3	0.3
$p_{Default}$	0.1	0	0.1	0.1	0.1	0.1
Insurance cost (PHP)	50	60	50	50	50	50
Number of sessions	24	27	28	30	29	28
Number of subjects	144	162	168	180	174	168

W of PHP 210. Participants could opt to buy insurance at a cost I of PHP 50 (PHP 60 in the case of T_{NoDef})⁸. Each participant played six rounds of the game and the initial endowment was restored at the start of each round.

The experimental procedure for one round was as follows. First, the instructor explained the game to all participants and each participant received an initial endowment in play money. Participants then decided whether they want to buy insurance and paid the required premium. Once the insurance decision was made, participants drew a ball from a bag to determine their shock. An orange ball implied that the participant lost PHP 150. Participants who bought insurance and had a shock could claim a payment from the insurer (except in the treatment T_{NoDef} where the claim was paid with certainty). 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 (i.e., nonperformance of the insurance contract).

Participants in each group of six 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. Participants were paid one of the six rounds played, which was selected randomly by the participant from a third bag with six numbered balls representing the six rounds of the game. 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.

Under the benchmark *Control* setting, both the 30 percent chance of losing

⁸The insurance premium charged for the six treatments has a loading factor of approximately 20% (25% for the T_{NoDef} treatment), with the aim of making the insurance setup more realistic to the Philippine insurance market. Insurance premiums usually have a risk loading and a cost loading. In microinsurance markets high risk loadings for uncertainty in the estimation of expected losses usually need to be added due to data constraints (Biener, 2013).

PHP 150 and the 10 percent chance of 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 chance of contract nonperformance as in the control group, allows us to make inferences about our hypothesis 1. This results in a higher premium for treatment T_{NoDef} with PHP 60.

In treatments T_{Def} and T_{Loss} we focus on the effect of ambiguity to investigate hypotheses 2 and 3. Here, the probability of contract nonperformance (T_{Def}) and the probability of loss (T_{Loss}) were ambiguous to the participants. In order to provide the participants with an initial signal of the probabilities, the balls in the ambiguous bags (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, 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.

In order to gather the participant's beliefs about loss and default 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 probabilities of loss and contract nonperformance without any peer or network effects.

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).

One important addition to the insurance game were the lottery games which we use to classify each participant in terms of risk and ambiguity aversion. In the lottery game, participants were presented 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 time⁹. 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.

⁹Lotteries 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.

The structure of the experimental session was as follows. First, a pre experimental survey was conducted to gather individual and household characteristics data, 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 and a test questionnaire was implemented to assess participant's understanding. 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. Once the insurance game concluded a post experimental survey was conducted to gather data on perception of the experimental insurance product, math capabilities, past shocks, and insurance ownership as well as general experiences and beliefs. Finally, participants were paid their earnings from both games plus a show up fee.

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)¹⁰. 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.

IV. Empirical Identification Strategy and Sample Characteristics

A. Empirical Identification Strategy

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

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

where $d = 1, \dots, 5$ and y_i is the binary insurance decision of participant i . T_1, \dots, 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

¹⁰The 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% 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.

at the group level to correct for intragroup correlation.¹¹

B. Sample Characteristics and Balancing Checks

Table 2 presents the mean values of individual characteristics by treatment group and equality of means test. 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 participants that owned a dwelling they live in is higher in the T_{NoDef} treatment 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 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 final check, we implement a multivariate analysis of variance to test for differences between the 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 the treatments and the *Control* group.

V. Empirical Results

A. Main Results

Table 3 presents the results of our linear probability model as well as results from a probit model, where we estimate the effect of the different treatments on insurance uptake. Standard errors are clustered at the group level to correct for intragroup correlation. The omitted group in our regression is the *Control* group. 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

¹¹Note 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.

TABLE 2—DESCRIPTIVE STATISTICS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	<i>Control</i>	<i>T_{NoDef}</i>	<i>T_{Def}</i>	<i>T_{Loss}</i>	<i>C_{Fr}</i>	<i>T_{Def-Fr}</i>	Equality of Means (p-value) ^c
Insurance Take-up (Round 1)	0.708 (0.456)	0.870*** (0.337)	0.560*** (0.498)	0.761 (0.428)	0.644** (0.480)	0.619* (0.487)	0.000
Age	39.86 (10.50)	38.80 (10.08)	38.96 (9.966)	39.93 (10.98)	38.76 (10.94)	39.86 (9.755)	0.867
Gender (1=female)	0.741 (0.439)	0.840* (0.368)	0.810 (0.394)	0.722 (0.449)	0.833* (0.374)	0.786 (0.412)	0.228
Married or in partnership (1=yes)	0.903 (0.297)	0.889 (0.315)	0.869 (0.338)	0.911 (0.285)	0.902 (0.298)	0.899 (0.302)	0.814
Years of education	9.573 (2.642)	9.580 (2.472)	9.911 (2.476)	9.594 (2.419)	9.552 (2.210)	9.381 (2.619)	0.634
Employment status (1=employed)	0.465 (0.501)	0.358 (0.481)	0.387 (0.488)	0.433 (0.497)	0.351* (0.479)	0.429 (0.496)	0.391
Regular Income (1=yes)	0.270 (0.447)	0.295 (0.460)	0.282 (0.453)	0.270 (0.446)	0.250 (0.436)	0.275 (0.449)	0.769
Seasonal Income (1=yes)	0.716 (0.454)	0.787 (0.413)	0.732 (0.446)	0.663 (0.475)	0.653 (0.479)	0.637 (0.484)	0.297
Owned dwelling (1=yes)	0.799 (0.402)	0.895* (0.307)	0.845 (0.363)	0.856 (0.353)	0.839 (0.369)	0.851 (0.357)	0.435
Reduced meals in last month (1=yes)	0.273 (0.447)	0.210 (0.408)	0.214 (0.412)	0.156** (0.363)	0.218 (0.414)	0.244 (0.431)	0.548
Owns Land (1=yes)	0.133 (0.341)	0.142 (0.350)	0.113 (0.318)	0.139 (0.347)	0.167 (0.374)	0.161 (0.368)	0.885
Math ability score (0 min 8 max)	6.660 (1.698)	6.654 (1.815)	6.661 (1.630)	6.500 (1.851)	6.655 (1.612)	6.494 (1.754)	0.888
Numeracy Score (0 min 16 max)	9.236 (3.084)	9.142 (2.988)	9.119 (2.999)	9.050 (3.143)	9.040 (2.930)	8.994 (2.958)	0.988
Purchasing insurance is risky ^a	5.590 (1.875)	5.385 (2.016)	5.476 (1.917)	5.239* (2.007)	5.341 (1.948)	5.275 (2.050)	0.755
Insurance policy performance ^a	5.306 (2.004)	5.590 (1.745)	5.101 (1.996)	5.217 (1.841)	5.249 (1.944)	5.156 (1.963)	0.236
Insurance ownership	0.528 (0.501)	0.580 (0.495)	0.577 (0.495)	0.594 (0.492)	0.557 (0.498)	0.542 (0.500)	0.881
Illness/accident shock (1=yes)	0.625 (0.486)	0.627 (0.485)	0.631 (0.484)	0.578 (0.495)	0.590 (0.493)	0.563 (0.498)	0.741
Weather/livestock shock (1=yes)	0.451 (0.499)	0.391 (0.490)	0.423 (0.495)	0.450 (0.499)	0.439 (0.498)	0.425 (0.496)	0.91
Avoid risky things ^a	5.493 (1.840)	5.354 (1.935)	5.583 (1.859)	5.583 (1.830)	5.434 (1.989)	5.820* (1.744)	0.326
Ambiguity ^b	1.763 (0.711)	1.734 (0.767)	1.774 (0.786)	1.721 (0.762)	1.756 (0.768)	1.776 (0.799)	0.994
Observations	144	162	168	180	174	168	

Note: Mean coefficients reported; standard errors in parentheses. ^ascores 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.

to typhoon Haiyan¹² and column 3 incorporates additional covariates.¹³

The discussion of results is structured along the hypotheses defined in the previous sections. Eliminating contract nonperformance in treatment T_{NoDef} , that is, setting $p_{def} = 0\%$ instead of $p_{def} = 10\%$ 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 in general show that contract nonperformance risk considerably decreases insurance take up and thus support our hypothesis 1.

TABLE 3—AVERAGE TREATMENT EFFECTS

	(1) (OLS)	(2) (OLS)	(3) (OLS)	(4) (Probit ^a)
T_{NoDef}	0.171*** (0.062)	0.172*** (0.063)	0.182*** (0.064)	0.216*** (0.061)
T_{Def}	-0.144* (.077)	-0.143* (0.078)	-0.126* (0.074)	-0.115* (0.068)
T_{Loss}	0.034 (0.070)	0.037 (0.070)	0.048 (0.067)	0.049 (0.068)
C_{Fr}	-0.121 (0.080)	-0.119 (0.079)	-0.104 (0.075)	-0.096 (0.069)
T_{Def-Fr}	-0.104 (0.079)	-0.101 (0.079)	-0.091 (0.075)	-0.085 (0.070)
Typhoon		0.043 (0.039)	0.045 (0.037)	0.046 (0.036)
Constant	0.707*** (0.058)	0.686*** (0.061)	0.393*** (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 group 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%.

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

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

¹³The 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.

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 2.

Ambiguity about the probability of loss as represented in treatment T_{Loss} increases uptake by 3 percentage points; however, the effect is insignificant in all regression specifications, thus we do not find a significant impact of ambiguity about loss probabilities on insurance uptake and thus our hypothesis 3 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 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 4.

B. Secondary Results

NUMERACY

We also analyze treatment effects by subject’s numeracy levels because a minimum level of numeracy skills might be necessary to adequately understand the game and thus react on the experimental treatments. In order to assess subjects levels of numeracy we use survey questions on mathematical ability and numeracy (Weller et al., 2013). We construct a total score of numeracy by putting together the scores for the mathematical ability with those from the numeracy scale. The total score goes from 0 (no correct answer) to 16 (all answers answered correctly). High numeracy subjects are those with a total score of 10 or more and low numeracy subjects are those with a score of 9 or less. Table 4 shows the results by numeracy level. Columns 1 and 2 show the result for the full sample, columns 3 and 4 present the results for the high numeracy subjects and columns 5 and 6 for 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 levels of numeracy react less to the ambiguity manipulation and seem to exhibit less ambiguity aversion, a finding we elaborate more on in Section V.B.

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*** (0.063)	0.17*** (0.062)	0.21*** (0.070)	0.22*** (0.067)	0.14* (0.073)	0.12* (0.070)
T_{Def}	-0.14* (0.077)	-0.13* (0.076)	-0.18** (0.087)	-0.17** (0.084)	-0.11 (0.085)	-0.10 (0.085)
T_{Loss}	0.034 (0.070)	0.038 (0.067)	0.096 (0.085)	0.10 (0.078)	-0.025 (0.074)	-0.025 (0.071)
C_{Fr}	-0.12 (0.080)	-0.11 (0.076)	-0.098 (0.092)	-0.087 (0.087)	-0.14 (0.088)	-0.14 (0.084)
T_{Def-Fr}	-0.10 (0.079)	-0.094 (0.077)	-0.18* (0.096)	-0.16* (0.089)	-0.042 (0.079)	-0.037 (0.076)
Constant	0.71*** (0.058)	0.43*** (0.15)	0.69*** (0.067)	0.34 (0.39)	0.72*** (0.063)	0.35* (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		Yes		Yes		Yes

Note: Standard errors in parentheses, clustered at the group 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%.

Ambiguity towards the probability of contract nonperformance in combination with a negative framing 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 on the 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 the results of our linear probability model for ambiguity averse, ambiguity neutral, and non-ambiguity averse subjects. Columns 1 and 2 show the result for the ambiguity averse subjects, columns 3 and 4 present the results for the ambiguity neutral, and columns 5 and 6 those for the ambiguity loving. Following our theoretical model, we would expect ambiguity averse subjects to have 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 according to their ambiguity aversion levels, we rely on the results obtained from the lottery games played in the first part of our experimental session, in which we use Ellsberg (1961) lotteries to classify individuals as ambiguity averse, ambiguity neutral, or ambiguity loving.

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** (0.068)	0.15** (0.069)	0.20** (0.092)	0.20** (0.095)	0.16 (0.13)	0.078 (0.13)
T_{Def}	-0.18** (0.091)	-0.16* (0.086)	-0.15 (0.10)	-0.14 (0.100)	-0.086 (0.15)	-0.087 (0.15)
T_{Loss}	0.035 (0.080)	0.022 (0.076)	0.061 (0.097)	0.041 (0.095)	-0.061 (0.14)	-0.065 (0.14)
C_{Fr}	-0.19** (0.090)	-0.17** (0.084)	-0.046 (0.11)	-0.037 (0.10)	-0.13 (0.16)	-0.13 (0.15)
T_{Def-Fr}	-0.22** (0.093)	-0.20** (0.089)	-0.030 (0.099)	-0.028 (0.100)	-0.076 (0.16)	-0.099 (0.15)
Constant	0.75*** (0.064)	0.67*** (0.24)	0.66*** (0.079)	0.38 (0.30)	0.74*** (0.13)	0.53 (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		Yes		Yes		Yes

Note: Standard errors in parentheses, clustered at the group 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%.

Results are in line with our theoretical predictions. Ambiguity averse subjects have 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 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 probability of contract nonperformance 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 the ambiguity averse individuals and for the non-ambiguity averse. Framing the insurer's contract nonperformance risk reduces insurance uptake by 19 percentage points for the ambiguity averse subjects, but has no effect on the 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.

C. Ambiguity over Rounds

Finally, we are interested in analyzing whether there is evidence that ambiguity decreases over the rounds for ambiguity averse individuals. In our experiment - as well as in reality - information about ambiguous probabilities might accumulate through own or peer experience. A rational individual should update beliefs about the unknown stochastic process based on new realizations. With more and more observations arriving, the true probability can be estimated more precisely.¹⁴ In terms of our model from Section II the subjective probability distribution $q(\cdot)$ 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 in loss or nonperformance probabilities should go to zero.

In Table 6, we therefore repeat specification (1) from Table 3 separately by round to assess whether effects of the 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 ambiguity in loss probability (T_{Loss}) is insignificant in all rounds, which is consistent with the pooled results. Also the effect of ambiguity regarding contract nonperformance (T_{Def} , T_{Def-Fr}) is consistent with the pooled results. 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.

As a next step, we compare these findings with participant's beliefs about loss and default probabilities. We elicited beliefs via a guess on the number of orange balls contained in the bags where the shocks (or 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 balls can be used as a proxy for the extent of ambiguity. Table 7 presents how mean guesses and the spread between minimum and maximum guess evolve over rounds for different treatments. Columns 1 to 3 present the mean guesses of how many

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

TABLE 6—AVERAGE TREATMENT EFFECTS PER ROUND FOR AMBIGUITY AVERSE INDIVIDUALS

	(1)	(2)	(3)	(4)	(5)	(6)
	Round 1	Round 2	Round 3	Round 4	Round 5	Round 6
T_{Def}	-0.18* (0.094)	-0.24** (0.10)	-0.17* (0.098)	-0.19** (0.097)	-0.14 (0.10)	-0.17* (0.098)
T_{Loss}	0.11 (0.087)	0.048 (0.089)	0.087 (0.094)	-0.035 (0.094)	0.016 (0.087)	-0.015 (0.081)
T_{Def-Fr}	-0.16 (0.10)	-0.21** (0.10)	-0.24** (0.10)	-0.28*** (0.10)	-0.16 (0.100)	-0.27*** (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 group level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ significance level at 10, 5 and 1%.

balls participants believed were in the bags where the contract non performance shock was drawn for treatments T_{Def} and T_{Def-Fr} and where the loss shock was drawn for treatment T_{Loss} . Columns 4 to 6 illustrate the mean spread between minimum and maximum guess. Additionally, columns 7 to 9 show the mean difference between beliefs and the real number of balls in the bags.

Interestingly, participants appear to be pessimistic in treatments T_{Def} and T_{Def-Fr} , as the average guess is substantially above the 1.0 that would be the average probability. These guesses if anything have a very subtle upward tendency, away from the real value of balls contained in the bags. The spread between maximum and minimum guess (columns 4 to 6) seems to decrease over round, 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 balls (columns 7 to 9) has no such downwards tendency. Hence, overall participants do not significantly improve their guesses over rounds.

TABLE 7—INDIVIDUAL'S BELIEFS ABOUT LOSS AND CONTRACT NON-PERFORMANCE 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 sum, there is no clear evidence of a reduction of ambiguity across rounds.

This in particular holds for the T_{Def} and T_{Def-Fr} treatments where we found 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 of 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 their ambiguity regarding probabilities, i.e. 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 evidence in support of the theoretical prediction of reduced insurance uptake when contract nonperformance risk is present, providing first evidence for this relationship 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 uptake. In contrast, we show that ambiguity does not play a large role when it comes to loss probabilities as found in previous studies.

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 even further by 14 percentage points. The variation of causes for contract nonperformance through different framings of this aspect (i.e., the insurer cannot pay a claim versus the insurer is not willing to pay a claim) does not lead to an obvious result.

The paper presents additional evidence that the effects of ambiguity are not easily eliminated over time by learning about probabilities. While one might argue that learning in reality might take place to a larger extent, it also seems intuitive that random villagers from a low-income setting cannot effectively do 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.

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PROOFS

A1. Positive Probability of Insurance Nonperformance Reduces Willingness to Pay

To show that demand for insurance is lower when there is a positive probability of insurance nonperformance than when the probability is zero, it will suffice to compare the marginal willingness to pay under 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 :

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

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

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

This can be rewritten as:

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

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

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

The marginal willingness to pay is:

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

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 $U_{r>0} > U_{r=0}$:

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

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:

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

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:

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

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 (A8) with respect to coverage ε :

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

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

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

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

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

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

$$(A11) \quad I'(\varepsilon)_{Control} = \frac{pu'(w - I(\varepsilon) - L + \varepsilon)}{(1-p)u'(w - I(\varepsilon)) \cdot \frac{1}{(1-r)} + p[u'(w - I(\varepsilon) - L + \varepsilon) + \frac{r}{(1-r)}u'(w - I(\varepsilon) - L)]}$$

and

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

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} .

$$(A13) \quad \frac{1}{1-r} > \hat{r}$$

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

$$r \cdot E_{\tilde{\gamma}}\Phi'(U(\tilde{\gamma})) > E_{\tilde{\gamma}}r(\tilde{\gamma})\Phi'(U(\tilde{\gamma})).$$

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 the concavity of $\Phi(\cdot)$. Note that as $r(\tilde{\gamma})$ increases, the ambiguity averse agent's utility decreases, and due to the 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 .

$$(A14) \quad \frac{r}{1-r} > \bar{r}$$

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

$$r \cdot E_{\tilde{\gamma}}\Phi'(U(\tilde{\gamma})) > E_{\tilde{\gamma}}r(\tilde{\gamma})\Phi'(U(\tilde{\gamma})).$$

Same argument as presented above applies for equation (A14). Thus, we have that the willingness to pay for the case in which the probability of contract non-performance is known is higher than when 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 unknown to when p is known. The marginal willingness can be obtained with the first-order condition for optimizing (7) with respect to coverage ε :

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

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

and thus we get the marginal willingness to pay:

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

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

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

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

and

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

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

$$(A19) \quad \frac{E_{\tilde{\alpha}}(1-p(\tilde{\alpha}))\Phi'(U(\tilde{\alpha}))}{E_{\tilde{\alpha}}p(\tilde{\alpha})\Phi'(U(\tilde{\alpha}))} < \frac{1-p}{p}$$

$$pE_{\tilde{\alpha}}\Phi'(U(\tilde{\alpha})) - pE_{\tilde{\alpha}}p(\tilde{\alpha})\Phi'(U(\tilde{\alpha})) < E_{\tilde{\alpha}}p(\tilde{\alpha})\Phi'(U(\tilde{\alpha})) - pE_{\tilde{\alpha}}p(\tilde{\alpha})\Phi'(U(\tilde{\alpha}))$$

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

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 side 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:

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

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.

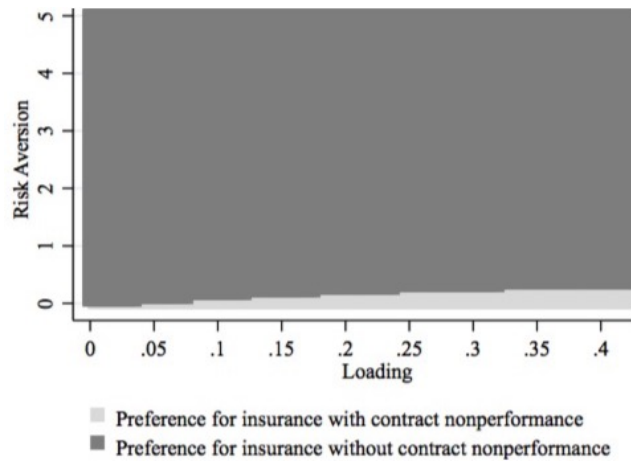


FIGURE B1. PREFERENCE FOR INSURANCE WITH CONTRACT NONPERFORMANCE RISK OR WITHOUT

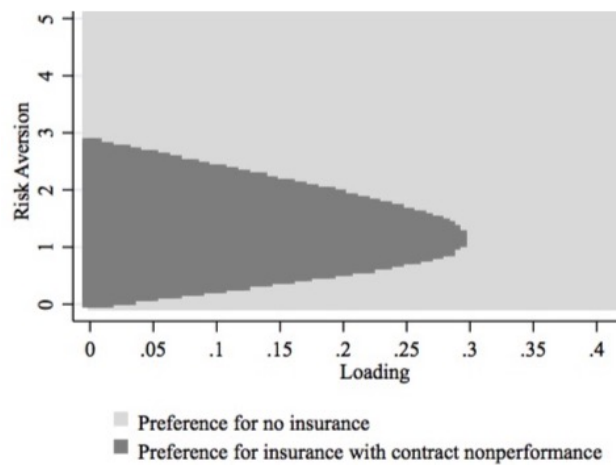


FIGURE B2. INSURANCE UPTAKE WITH CONTRACT NONPERFORMANCE RISK

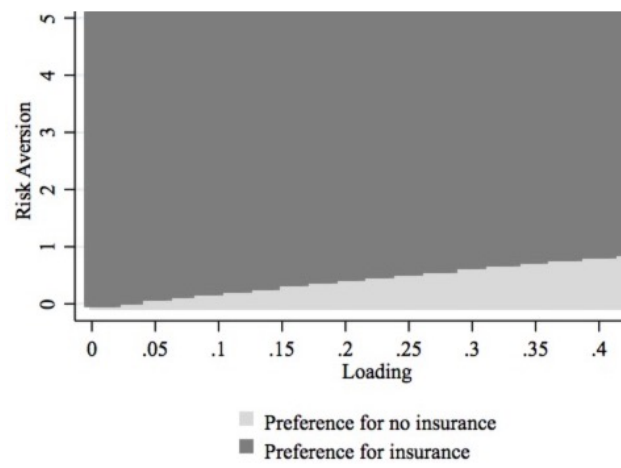


FIGURE B3. INSURANCE UPTAKE WITHOUT CONTRACT NONPERFORMANCE RISK