CONTRACT NONPERFORMANCE RISK AND AMBIGUITY IN INSURANCE MARKETS

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Insurance contracts may fail to perform, leading to a total or partial default on valid claims. We extend models of such probabilistic insurance to allow for ambiguity in contract nonperformance risk, and derive formally that mean-preserving ambiguity reduces demand. The results of a field lab experiment are consistent with this logic. In particular, we find that a 10 percent contract nonperformance risk reduces insurance demand by 17.1 percentage points even when premiums are adjusted accordingly. Ambiguity about this contract nonperformance probability further decreases demand by 14.5 percentage points. While the demand-reducing effect of ambiguity is more pronounced for high-numeracy and ambiguity-averse individuals, it appears to be little affected by experience. The cause of an insurance contract failing to perform does not significantly influence the strength of these effects, but independently affects demand of low-numeracy and ambiguity-averse individuals. JEL Codes: D03, D81, D83, G22.
I. Introduction

The concept of probabilistic insurance was first introduced by Kahneman and Tversky (1979) as an insurance policy that, in the event of a loss, reimburses policyholders only with some probability, strictly less than one. Various circumstances, such as insolvency, discord about the losses covered, and payment delays, can cause total or partial contract nonperformance. Hence, from an insurance demand perspective, contract nonperformance risk is not restricted to situations where legally valid claims are not settled, but more generally applicable to all rejected claims that are perceived as valid by the policyholders (Doherty and Schlesinger, 1990). In this paper, we extend the probabilistic insurance model to allow for ambiguity in contract nonperformance probabilities. Furthermore, we test theoretical predictions derived from the extended model through a behavioral experiment conducted with rural villagers from the Philippines, focusing on the role of contract nonperformance risk and its ambiguity for insurance demand.


As opposed to contract nonperformance 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. Since Epstein (1999), the presence of an aversion to ambiguity could be identified in the laboratory under different conditions (Chow and Sarin, 2001; Sarin and Weber, 1993; Einhorn and Hogarth, 1986).

While some studies have examined the effect of ambiguous loss probabilities on insurance demand (Bajtelsmit, Coats and Thistle, 2015; Gollier, 2014; Alary, Gollier and Treich, 2013; Huang, Huang and Tzeng, 2013; Hogarth and Kunreuther, 1989) as well as on the demand for self-insurance and self-protection (Snow, 2011), the ambiguity in contract nonperformance risk has so far been neglected in the theoretical and empirical literature. One exception is Bryan (2013), who studies the role of ambiguity aversion in the context of a new index insurance contract. While the setting differs from our paper along some important dimensions, his findings suggest that ambiguous probabilities of insurance payouts are relevant for insurance demand.\(^2\) Our discussion around ambiguous probabilities is also distinct from approaches capturing divergent beliefs about the probability distribution of contract nonperformance risk between insurers and their customers (Cummins and Mahul, 2003). This is because those and other standard economic utility models incorporate only the mean over a probability distribution to affect decisions.

\(^1\)The literature uses different terms to refer to situations where probabilities are known or unknown. The word “risk,” as opposed to “uncertainty,” has been used in Knight (1921). The terms “unambiguous” and “ambiguous” were introduced by Ellsberg (1961). While Savage (1954) uses the terms “precise” and “vague,” Gärdenfors and Sahlin (1982) differentiate between the levels of “epistemic reliability” of a probability estimate to infer the amount of information available on all possible states and outcomes. We rely on the term “ambiguity” because it is common in the literature (Camerer and Weber, 1992).

\(^2\)Bryan (2013) provides a theoretical framework and empirical evidence from Kenya and Malawi, showing that ambiguity-averse clients have a lower propensity to take up a new index insurance product. The setup relates to our case, because basis risk in index insurance (i.e., the probability that the index does not trigger a payout even when the insured faces a loss) might play a role similar to contract nonperformance risk. However, the setting differs from ours in important aspects. Besides the presence of both upside and downside risk, insurance decisions are combined with the adoption of a new production technology. Thus, theoretical predictions of insurance demand differ from ours.
In line with the preceding literature, our model predicts a decrease in insurance demand when introducing contract nonperformance risk, in particular for highly risk-averse individuals. Making the contract nonperformance probability ambiguous further decreases demand for ambiguity-averse individuals. This is because ambiguity aversion essentially makes people more pessimistic about contract nonperformance probabilities. We test these theoretical predictions through a behavioral experiment conducted with rural villagers from the Philippines. In this field lab experiment, we vary the presence of contract nonperformance risk, the existence of ambiguity, and the causes for nonperformance of insurance contracts and evaluate the effects on insurance demand. We find that introducing contract nonperformance risk (i.e., the insurer does not always pay a claim) and making contract nonperformance ambiguous decreases insurance demand. In the former case, we observe a significant 17.1 percentage points decrease in uptake resulting from increasing contract nonperformance risk from 0 to 10 percentage points. Then, relative to a known 10 percent chance of contract nonperformance, ambiguity about contract nonperformance risk leads to a further significant decrease in uptake of 14.5 percentage points. The effects of ambiguity appear little affected by experience and remain stable over time. We also consider the effect of different causes of contract nonperformance on insurance demand. This is because Kunreuther et al. (2002) and Zimmer, Schade and Gründl (2009) suggest that emotions play a role in insurance decisions and we suspect that varying the causes of contract nonperformance risk might in particular evoke different emotions. Low-numeracy and ambiguity-averse sub-samples show substantial and significant effects of framing the cause of contract nonperformance as the insurer’s unwillingness as opposed to the insurer’s inability to pay claims, but overall the effects are insignificant. In addition, framing does not significantly magnify the treatment effects of contract nonperformance and its ambiguity.

Aside from the experimental implementation in the Philippines, the pertinence of our setup extends to insurance markets in developed economies, where signif-
Significant efforts are undertaken to disseminate information on insurers’ reputations for servicing claims (Mahul and Wright, 2004), and consumer complaint statistics suggest that there is good reason to do so.\(^3\) The negative effects of contract non-performance risk on insurance demand are from a developed country perspective. Zimmer, Schade and Gründl (2009), Herrero, Tomás and Villar (2006), Albrecht and Maurer (2000), and Wakker, Thaler and Tversky (1997) examine the effects on hypothetical willingness to pay, and Zimmer et al. (2016) implement an incentive-compatible experiment with real monetary payoffs; these studies further testify to the strong detrimental effects of contract nonperformance risk on insurance demand. Thus, even in an environment with high levels of regulation, customer protection, and access to reliable information, perceived contract nonperformance risk is highly relevant to insurance demand.

Several factors magnify contract nonperformance risk and ambiguity in low-income insurance markets. Individuals face a broad variety of perils that are not easily quantifiable 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) environments. Furthermore, perceptions of high contract nonperformance risk are fueled by limited trust in regulators and legal institutions to enforce contracts and supervise markets. This might explain why, despite significant efforts, insurance demand of low-income consumers remains low, even though the widespread use of risk transfer through insurance solutions holds potentially significant social welfare benefits. Claims considered eligible by the insured but not paid by the insurer emerge as a potential piece of the puzzle explaining the low insurance demand in developing countries. Recently, Liu and Myers (2016) provided theoretical evidence for significant reductions in insurance demand due to perceived insurer default in low-income insurance contexts, and Cole et al. (2013)

\(^3\)Roughly 50 percent of all complaints reported to the U.S. state regulators in 2014 related to denials and delays of claims and unsatisfactory settlements, amounting to over 30,000 cases (National Association of Insurance Commissioners, 2016).
empirically reveal trust as an important market friction constraining demand.

The remainder of this paper proceeds as follows. In Section II, we present our theoretical framework and derive the hypotheses. The experimental design and field implementation, including sample characteristics, are explained in Section III. In Section IV, we discuss our empirical results, and Section V concludes the paper.

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 of Doherty and Schlesinger (1990) for contract nonperformance risk and Alary, Gollier and Treich (2013) and Klibanoff, Marinacci and Mukerji (2005) for ambiguity and attitudes toward ambiguity. Figure 1 describes the process we consider here. We assume that a decision maker with initial wealth \( w \) has a positive probability \( p \) of suffering a loss \( L > 0 \), against which she can purchase insurance that pays \( \varepsilon \), for some premium \( I(\varepsilon) \).\(^4\) In the case that the decision maker buys insurance and the loss does not occur (with probability \( 1 - p \)), she 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 her claim is not reimbursed. In this case, she is left with \( w - I(\varepsilon) - L \); otherwise, the insurer pays the claim and the decision maker gets \( w - I(\varepsilon) - L + \varepsilon \). Thus, any decision maker evaluates the expected utility of the upper branch of the tree (i.e., insurance) against the lower branch (i.e., no insurance) shown in Figure 1.

\(^4\)Note that we remain general in our definition of a premium and do not presume that the insurance is priced as being actuarially fair.
B. Demand for Probabilistic Insurance

Our benchmark probabilistic insurance setting is one with a known probability of contract nonperformance $r$. We use von Neumann–Morgenstern preferences with utility functions $u(.)$ that are continuous, monotonously increasing ($u'(.) > 0$) and twice continuously differentiable. We furthermore restrict our attention to risk averse agents ($u''(.) < 0$). The decision maker’s expected utility under the insurance policy ($EU_r$) is defined as:

\begin{equation}
EU_r = (1 - p)u(w - I(\varepsilon)) + p[(1 - r)u(w - I(\varepsilon) - L + \varepsilon) + ru(w - I(\varepsilon) - L)].
\end{equation}

Our first area of interest is how insurance decisions change when we introduce a positive probability that the insurance fails to perform. Therefore, we compare the benchmark setup, with $r > 0$, to a situation with $r = 0$. Let $I_0(\varepsilon)$ be the premium for non-probabilistic insurance with $r = 0$. Note that when changing $r$ and not adapting the premium accordingly (i.e., $I(\varepsilon) = I_0(\varepsilon)$) we change the
expected payout and, hence, the loading of the insurance policy.\textsuperscript{5} It is obvious that under these circumstances non-probabilistic insurance is always preferred because it features lower risk and a lower loading, ceteris paribus (the proof is presented in Appendix A).

The case becomes less trivial when the premium is discounted by the contract nonperformance probability, thus, keeping the loading factor constant. Let \( I(\varepsilon) \) be the insurance premium for \( r > 0 \), while, again, \( I_0(\varepsilon) \) denotes the premium for \( r = 0 \). Specifying \( I(\varepsilon) = (1 - r)I_0(\varepsilon) \) leads to a constant loading factor. Then, the expected utility derived from probabilistic insurance becomes:

\[
EU_r = (1 - p)u(w - I_0(1 - r)) \\
+ p[(1 - r)u(w - I_0(1 - r) - L + \varepsilon) \\
+ ru(w - I_0(1 - r) - L)],
\]

whereas the expected utility derived from non-probabilistic insurance is:

\[
EU_0 = (1 - p)u(w - I_0) + pu(w - I_0 - L + \varepsilon).
\]

With a constant loading factor, introducing contract nonperformance risk decreases both, premium and expected payout. Whether the decrease in premium or the decrease in expected payout is larger, depends on the loading of the insurance. If it is actuarially unfair (i.e., a positive loading), clients might even profit from contract nonperformance risk in terms of expected wealth. On the other hand, this entails the risk of a default on insurance claims. These advantages and drawbacks are weighted differently by different types of agents and it is not possible to derive

\textsuperscript{5}The loading of the insurance policy is the difference between the premium and the expected payout; the loading factor is the ratio between the two. When there is a positive probability of contract nonperformance, the expected payout decreases, which, ceteris paribus, influences the loading. Thus, if the premium is higher than the expected payout, this implies a positive loading and a loading factor greater than one.
a monotonous relationship between optimal coverage and contract nonperformance risk in general (Doherty and Schlesinger, 1990). To provide more detailed results suited to our empirical setup, we focus on the case of a binary insurance decision with a given coverage level ε. The following lemmas can be shown to hold (see proof in Appendix A):

**Lemma 1.** For sufficiently low loading factors ≥ 1, there must exist agents with sufficiently high risk aversion, such that insurance without contract nonperformance risk is preferred to insurance with contract nonperformance risk. Demand for insurance must (weakly) decrease for those agents when introducing contract nonperformance risk.

**Lemma 2.** For sufficiently high loading factors > 1, there must exist agents with sufficiently low risk aversion, greater than zero, such that insurance with contract nonperformance risk is preferred to insurance without contract nonperformance risk. Demand for insurance must (weakly) increase for those agents when introducing contract nonperformance risk.

In binary uptake decisions, decreasing the utility derived by a product implies (weakly) lower demand and vice versa. The above lemmas hence shed light on the circumstances under which demand reductions can be expected when introducing contract nonperformance risk. For actuarially fair insurance (i.e., a zero loading or a loading factor equal to one), our setting simplifies to a similar case in Doherty and Schlesinger (1990). Here, Lemma 2 is rendered irrelevant, and the condition for Lemma 1 always holds, in the sense that all risk-averse agents prefer non-probabilistic insurance over probabilistic insurance. Therefore, similarly to Doherty and Schlesinger (1990), we expect lower insurance demand for probabilistic insurance. Given actuarially unfair premiums, Lemma 2 presumes a weak demand-increasing effect of contract nonperformance risk for agents with low risk
aversion. However, agents with low risk aversion are more sensitive to loadings, exhibiting a decreasing insurance-demand pattern with increasing loadings (Mossin, 1968; Smith, 1968), and are hence less likely to purchase insurance irrespective of the presence of contract nonperformance risk. Overall effects ultimately hinge on the shape of the utility function. We therefore provide simulations over a range of loading and risk aversion parameters. These simulations clearly predict a decrease in demand when contract nonperformance risk is introduced.\(^6\) Thus, we expect that the share of the population actually switching to buying probabilistic insurance is relatively small and formulate the first hypothesis accordingly:

**Hypothesis 1.** 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 (i.e., \( r \) is unknown). We redefine contract nonperformance risk as the ambiguous probability \( r(\gamma) \), depending on the unknown parameter \( \gamma \). The ambiguity is defined as a probability distribution for \( \gamma \) with discrete support \( \{1, \ldots, n\} \). Let \( q(\gamma) \) denote the subjective probability that the true value of the parameter is \( \gamma \), with \( \sum_{\gamma=1}^{n} q(\gamma) = 1 \). We assume that ambiguity is mean preserving (i.e., \( \sum_{\gamma=1}^{n} q(\gamma)r(\gamma) = r \)). In the case that \( \gamma \) is known to be \( \gamma^* \) (i.e., \( q(\gamma^*) = 1 \)), we define the expected utility derived from probabilistic insurance as follows:

\[
EU_{r(\gamma^*)} = (1 - p)u(w - I(\varepsilon))
+ p[(1 - r(\gamma^*))u(w - I(\varepsilon) - L + \varepsilon)
+ r(\gamma^*)u(w - I(\varepsilon) - L)].
\]

\(^6\)We simulate decision makers exhibiting constant relative risk aversion (CRRA)-type utility functions over a range of loading and risk aversion parameters (see Appendix B for details). The results are clear-cut in that the set of parameter combinations predicted to take up probabilistic insurance is a subset of the parameter combinations predicted to take up non-probabilistic insurance.
Following the smooth ambiguity approach of Klibanoff, Marinacci and Mukerji (2005), we model ambiguity aversion using an increasing and concave valuation function $\Phi$ for the expected utility derived from each state of $\gamma$. Thus, the decision maker’s expected utility derived from ambiguous probabilistic insurance corresponds to:

$$\Phi^{-1}\left(\mathbb{E}_\gamma \Phi(EU_{r(\gamma)})\right) = \Phi^{-1}\left(\sum_{\gamma=1}^{n} q(\gamma) \Phi(EU_{r(\gamma)})\right).$$

An ambiguity-neutral agent uses a linear valuation function, essentially using $EU_r$ from Equation (1) and replacing $r$ with $\mathbb{E}_\gamma r(\gamma)$. Concavity of $\Phi$ expresses ambiguity aversion, that is, an aversion to mean-preserving spreads in the random probability of contract nonperformance $r(\gamma)$. Ambiguity-averse agents assign higher weights to states of $\gamma$ that are associated with low utility. In our case, this would lead to an overweighting of contract nonperformance probabilities. For ambiguity-loving agents, $\Phi$ is convex, and higher weights are assigned to favorable (i.e., high utility) probabilities, leading to an underweighting of contract nonperformance probabilities. Using the above general formula for ambiguity preferences and plugging in the expected utility definition from Equation (1), we can see that individuals maximize the following expression when deciding about insurance uptake:

\begin{equation}
\mathbb{E}_\gamma \Phi(EU_{r(\gamma)}) = \mathbb{E}_\gamma \Phi\left[(1 - p)u(w - I(\varepsilon)) \right. \\
+ \left. p[(1 - r(\gamma))u(w - I(\varepsilon) - L + \varepsilon) + r(\gamma)u(w - I(\varepsilon) - L)]\right].
\end{equation}

Under this setting, the following Lemma holds (see proof in Appendix A):
**Lemma 3.** For ambiguity-averse (-loving) agents, the marginal willingness to pay for additional insurance is strictly lower (higher) at every coverage point after introducing mean-preserving ambiguity over contract nonperformance risk.

This result on the marginal willingness to pay applies to both continuous and binary insurance decisions. It implies that the optimal coverage level decreases (increases) for ambiguity-averse (-loving) individuals once ambiguity with respect to contract nonperformance risk is introduced. It also implies that 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 demand for non-ambiguous probabilistic insurance should be higher for ambiguity-averse agents.

There are arguments as to why the effect of ambiguity-averse, as opposed to ambiguity-neutral or -loving preferences, should dominate. Based on a sample of 30 countries, Vieider et al. (2015) show that individuals seem to be, on average, averse to ambiguity. In addition, risk aversion seems to be positively correlated with ambiguity aversion, and only risk-averse individuals are potential clients, which could be affected by ambiguous contract nonperformance risk. Thus, we state the second hypothesis as follows.

**Hypothesis 2.** Ambiguity about contract nonperformance probabilities reduces insurance demand ($H2$).

It is possible to conduct further comparative statics beyond the introduction of ambiguity. For example, it might be interesting to show the effect of changing the extend of ambiguity or changing ambiguity preferences. In Appendix A, we derive the central condition for the development of marginal willingness to pay when such changes happen. This condition generally holds in our setting of mean-preserving ambiguity and smooth ambiguity aversion as proposed by Klibanoff, Marinacci and
Mukerji (2005). In particular, we derive that any change in ambiguity aversion or the extend of ambiguity leading to an increase in the correlation between \( r(\gamma) \) and \( \Phi'(EU_{r(\gamma)}) \) will decrease the marginal willingness to pay and vice versa. The effect on the marginal willingness to pay directly translates into changes of optimal coverage in both continuous and binary insurance decisions.

III. Experimental Design

A. Insurance Experiment

We implement a field lab experiment where subjects decide whether to purchase probabilistic insurance in a risky environment. Participants received an initial endowment \( W \), and could opt to buy insurance at cost \( I \). Once the insurance decision was made, participants experienced a loss with probability \( p_{\text{Loss}} \). Participants who bought insurance could claim a payment from the insurer, contingent on having experienced a loss. Whether the insurer paid the claim was determined by another random draw, with probability \( p_{\text{Def}} \) for the contract not performing. All random draws are implemented using opaque bags, each containing 10 balls, some of which were orange and the rest white. In the first draw, orange balls represented a loss of \( L \), while in the second draw (i.e., only in the case of an insurance claim), orange balls indicated nonperformance of the insurance contract. Hence, the mixtures of orange and white balls determine the loss probability \( p_{\text{Loss}} \) and the contract nonperformance probability \( p_{\text{Def}} \). Participants were grouped in sessions of six participants. They were not allowed to exchange information or talk amongst themselves during the first round of the experiment. This procedure aims to avoid peer effects on a participant’s initial belief about probabilities. Participants were then allowed to communicate with other members for the remaining rounds, such that they could learn from their peers’ experiences.

An additional lottery choice task was played prior to the insurance experiment in order 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. Here, we use lotteries following Ellsberg (1961), from which we classify individuals as ambiguity averse, ambiguity neutral, or ambiguity loving. Participants earned the average of four randomly drawn gambles, two from the gain domain and two from the loss domain.

B. Treatments

A complete overview of all treatments is presented in Table 1. Every participant was provided with an initial endowment of PHP 210. Under the benchmark control treatment $C$, both the 30 percent probability of losing PHP 150 and the 10 percent probability of experiencing contract nonperformance were known to participants. The variation in contract nonperformance probability introduced in treatment $T_{NoDef}$ (i.e., the elimination of the 10 percent contract nonperformance risk) allows for an inference about hypothesis $H1$. The elimination of contract nonperformance risk is accounted for in terms of a higher premium of PHP 60 for treatment $T_{NoDef}$, as opposed to PHP 50 for all other treatments.

Comparing treatment $T_{Amb}$ with control treatment $C$ allows us to identify the effect of ambiguity on insurance demand and, thus, to test hypothesis $H2$. Here, the contract nonperformance probability was ambiguous to the participants. In order to provide the participants with an initial signal of probabilities, to form their prior beliefs, the balls in the bags of the ambiguous treatments ($T_{Amb}$ and

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

$^8$Because the actual price of an insurance policy is its 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. Given that rounding necessarily leads to different loadings, we made sure that the loading for insurance without contract nonperformance risk was at least as high as that with contract nonperformance risk. This implies that our results are lower bounds of the effect of contract nonperformance risk on insurance demand. In general, insurance premiums commonly include risk and cost loadings, which are often particularly high in low-income insurance markets (Biener, 2013).
Table 1: Experimental Treatments

<table>
<thead>
<tr>
<th>Treatments</th>
<th>C</th>
<th>T_{NoDef}</th>
<th>T_{Amb}</th>
<th>T_{Fr}</th>
<th>T_{Amb~Fr}</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Universal parameters</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Initial endowment (in PHP)</td>
<td>210</td>
<td>210</td>
<td>210</td>
<td>210</td>
<td>210</td>
</tr>
<tr>
<td>Loss (in PHP)</td>
<td>150</td>
<td>150</td>
<td>150</td>
<td>150</td>
<td>150</td>
</tr>
<tr>
<td>$p_{\text{Loss}}$</td>
<td>0.3</td>
<td>0.3</td>
<td>0.3</td>
<td>0.3</td>
<td>0.3</td>
</tr>
<tr>
<td><strong>Panel B: Treatment characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ambiguous contract</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>nonperformance probability</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$p_{\text{Def}}$</td>
<td>0.1</td>
<td>0</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>Framing</td>
<td>Neutral</td>
<td>Neutral</td>
<td>Neutral</td>
<td>Negative</td>
<td>Negative</td>
</tr>
<tr>
<td>Insurance premium (in PHP)</td>
<td>50</td>
<td>60</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td><strong>Panel C: Participants and sessions</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of subjects</td>
<td>144</td>
<td>162</td>
<td>168</td>
<td>174</td>
<td>168</td>
</tr>
<tr>
<td>Number of sessions</td>
<td>24</td>
<td>27</td>
<td>28</td>
<td>29</td>
<td>28</td>
</tr>
</tbody>
</table>

$T_{Amb~Fr}$) were selected blindly from a big bag containing 100 balls, during the instructions by one research assistant. Of the 100 balls in the big bag, 10 were orange and 90 were white. 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 us to analyze the effects over time, which is especially interesting under ambiguity when experience about losses and contract nonperformance can be shared within the peer network. In particular, one might expect ambiguity to decrease over time, once sufficient learning has taken place.

We employ treatments $T_{Fr}$ and $T_{Amb~Fr}$ to make inferences about potential framing effects. The standard framing of contract nonperformance is that the insurer cannot pay the claim. This framing is neutral, and was implemented in the control treatment $C$, as well as in $T_{NoDef}$ and $T_{Amb}$. The negative framing in treatments $T_{Fr}$ and $T_{Amb~Fr}$ presents the source of potential contract nonperformance as the insurer’s unwillingness to pay (e.g., owing to policy exclusions). Thus, not paying claims is at the discretion of the insurer in the negative framing, whereas the insurer has no discretion under the neutral framing.
C. Procedures and Sample Characteristics

We conducted a field lab experiment in the Philippine provinces of Iloilo and Guimaras in October and November 2013. Four treatments and one control setting of this experiment were randomized across four sessions, played in each of a total of 42 villages.\textsuperscript{9} 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. In the first stage, rural villages were selected randomly.\textsuperscript{10} In the second stage, individuals aged between 18 and 65 years were selected randomly from complete household lists, as provided by village officials. The recruitment procedure resulted in 24 participants per village, 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, followed by the lottery choice task to measure risk and ambiguity attitudes. Next, the insurance experiment began with an instructional part. Detailed explanations were provided by one instructor, with the help of visual aids. We ensured participants’ understanding by conducting a test questionnaire. Only when all questions of the test questionnaire could be answered correctly was a participant allowed to continue. Each participant played six rounds of the insurance experiment, and the initial endowment was restored at the start of each round. In order to gather participants’ beliefs about 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, participants provided their beliefs about the number of orange balls in the respective bag, and stated the minimum and maximum numbers of

\textsuperscript{9}One additional treatment, unrelated to ambiguous contract nonperformance risk, was conducted. Thus, six variants were randomized altogether. The omitted treatment is irrelevant to the research questions analyzed in this paper, but more details are available upon request.

\textsuperscript{10}Villages from municipalities with high income (top two income classes out of five) were excluded from the study; income classes are defined by the Department of Finance Republic of the Philippines (2008).
orange balls they believed were in the bag. The first survey at the beginning of round 1 provides participants’ beliefs of the contract nonperformance probabilities in the absence of any peer or network effects.

A post-experimental survey was conducted to gather data on mathematical and numerical capabilities, past real-life loss experiences, insurance ownership, and other beliefs. Finally, participants were paid one of the six rounds played in the insurance experiment, plus the proceeds from the lottery choice task and a show-up fee, in real PHP. The round of the insurance experiment that was paid out was selected randomly by the participant from another opaque bag, with six numbered balls representing the six rounds of the experiment. The average earnings from the experiment were PHP 156.5 in the insurance experiment, and PHP 13.5 in the lottery choice task. Additionally, participants received a show-up fee of PHP 100,\textsuperscript{11} amounting to PHP 270, or approximately USD 6.2—a substantial amount for the average participant.\textsuperscript{12}

In total, we conducted 136 sessions with 816 participants in 42 villages. Table 2 presents the mean values of individual characteristics and equality of means tests by treatment group. The results show that individual characteristics are balanced throughout the treatments (i.e., versus the control treatment $C$) and that few variables exhibit significant differences. Treatments $T_{NoDef}$ and $T_{Fr}$ have slightly higher proportions of female participants. The proportion of employed participants in the $T_{Fr}$ treatment is a bit lower than in the control treatment $C$. The mean risk aversion score is larger under treatment $T_{Amb-Fr}$ than it is in the control treatment $C$. However, overall, it is apparent that the sample is balanced across treatment groups, with only one variable not balanced in treatment $T_{Amb-Fr}$ versus the control treatment $C$, and two variables not balanced in treatments $T_{NoDef}$ and $T_{Fr}$. All

\textsuperscript{11}The show-up fee was increased by PHP 20 if the participant was the head of the household.
\textsuperscript{12}The official exchange rate was PHP 43.3 to USD 1 in early October 2013. Note that the stakes of PHP 210 in the experiment are close to the minimum daily wage of PHP 250 in the agricultural sector in the Iloilo province, as of October 2013 (Republic of the Philippines, 2008), which few participants are able to earn. The median daily earnings of those participants receiving a daily wage (12 percent of total sample) is only PHP 180.
Table 2: Descriptive Statistics

<table>
<thead>
<tr>
<th>Panel A: Socio-demographic characteristics</th>
<th>( C )</th>
<th>( T_{NoDef} )</th>
<th>( T_{Amb} )</th>
<th>( T_{Fr} )</th>
<th>( T_{Amb-\text{Fr}} )</th>
<th>Equality of Means (p-value)(^d)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>39.86</td>
<td>38.80</td>
<td>38.96</td>
<td>38.76</td>
<td>39.86</td>
<td>0.745</td>
</tr>
<tr>
<td>(in years)</td>
<td>(10.50)</td>
<td>(10.08)</td>
<td>(9.966)</td>
<td>(10.94)</td>
<td>(9.755)</td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td>0.741</td>
<td>0.840*</td>
<td>0.810</td>
<td>0.833*</td>
<td>0.786</td>
<td>0.185</td>
</tr>
<tr>
<td>(1 = female)</td>
<td>(0.439)</td>
<td>(0.368)</td>
<td>(0.394)</td>
<td>(0.374)</td>
<td>(0.412)</td>
<td></td>
</tr>
<tr>
<td>Financial responsibility(^a)</td>
<td>0.958</td>
<td>0.994**</td>
<td>0.964</td>
<td>0.977</td>
<td>0.970</td>
<td>0.34</td>
</tr>
<tr>
<td>(1 = yes)</td>
<td>(0.201)</td>
<td>(0.0786)</td>
<td>(0.186)</td>
<td>(0.150)</td>
<td>(0.170)</td>
<td></td>
</tr>
<tr>
<td>Married or in partnership</td>
<td>0.903</td>
<td>0.889</td>
<td>0.869</td>
<td>0.902</td>
<td>0.899</td>
<td>0.848</td>
</tr>
<tr>
<td>(1 = yes)</td>
<td>(0.297)</td>
<td>(0.315)</td>
<td>(0.338)</td>
<td>(0.298)</td>
<td>(0.302)</td>
<td></td>
</tr>
<tr>
<td>(in years)</td>
<td>(2.642)</td>
<td>(2.472)</td>
<td>(2.476)</td>
<td>(2.210)</td>
<td>(2.619)</td>
<td></td>
</tr>
<tr>
<td>Employment status</td>
<td>0.465</td>
<td>0.358</td>
<td>0.387</td>
<td>0.351*</td>
<td>0.429</td>
<td>0.187</td>
</tr>
<tr>
<td>(1 = employed)</td>
<td>(0.501)</td>
<td>(0.481)</td>
<td>(0.488)</td>
<td>(0.479)</td>
<td>(0.496)</td>
<td></td>
</tr>
<tr>
<td>Regular income</td>
<td>0.270</td>
<td>0.295</td>
<td>0.282</td>
<td>0.250</td>
<td>0.275</td>
<td>0.985</td>
</tr>
<tr>
<td>(1 = yes)</td>
<td>(0.447)</td>
<td>(0.460)</td>
<td>(0.453)</td>
<td>(0.436)</td>
<td>(0.449)</td>
<td></td>
</tr>
<tr>
<td>Seasonal income</td>
<td>0.716</td>
<td>0.787</td>
<td>0.732</td>
<td>0.653</td>
<td>0.637</td>
<td>0.3</td>
</tr>
<tr>
<td>(1 = yes)</td>
<td>(0.454)</td>
<td>(0.413)</td>
<td>(0.446)</td>
<td>(0.479)</td>
<td>(0.484)</td>
<td></td>
</tr>
<tr>
<td>Owns land</td>
<td>0.133</td>
<td>0.142</td>
<td>0.113</td>
<td>0.167</td>
<td>0.161</td>
<td>0.635</td>
</tr>
<tr>
<td>(1 = yes)</td>
<td>(0.341)</td>
<td>(0.350)</td>
<td>(0.318)</td>
<td>(0.374)</td>
<td>(0.368)</td>
<td></td>
</tr>
<tr>
<td>Owned dwelling</td>
<td>0.799</td>
<td>0.895*</td>
<td>0.845</td>
<td>0.839</td>
<td>0.851</td>
<td>0.232</td>
</tr>
<tr>
<td>(1 = yes)</td>
<td>(0.402)</td>
<td>(0.307)</td>
<td>(0.363)</td>
<td>(0.369)</td>
<td>(0.357)</td>
<td></td>
</tr>
<tr>
<td>Reduced meals in last month</td>
<td>0.273</td>
<td>0.210</td>
<td>0.214</td>
<td>0.218</td>
<td>0.244</td>
<td>0.666</td>
</tr>
<tr>
<td>(1 = yes)</td>
<td>(0.447)</td>
<td>(0.408)</td>
<td>(0.412)</td>
<td>(0.414)</td>
<td>(0.431)</td>
<td></td>
</tr>
</tbody>
</table>

| Panel B: Mental capabilities, risk and ambiguity aversion |
|---|---|---|---|---|---|---|
| Mathematical ability score | 6.660 | 6.654 | 6.661 | 6.655 | 6.494 | 0.873 |
| (0 min 8 max) | (1.698) | (1.815) | (1.630) | (1.612) | (1.754) | |
| Numerical ability score | 9.236 | 9.142 | 9.119 | 9.040 | 8.994 | 0.961 |
| (0 min 16 max) | (3.084) | (2.988) | (2.999) | (2.930) | (2.958) | |
| Risk aversion\(^b\) | 5.493 | 5.354 | 5.583 | 5.434 | 5.820* | 0.197 |
| (1 min 7 max) | (1.840) | (1.935) | (1.859) | (1.989) | (1.744) | |
| Ambiguity aversion\(^c\) | 1.763 | 1.734 | 1.774 | 1.756 | 1.776 | 0.989 |
| (1 min 3 max) | (0.711) | (0.767) | (0.786) | (0.768) | (0.799) | |

| Panel C: Loss and insurance experience |
|---|---|---|---|---|---|---|
| Insurance ownership | 0.528 | 0.580 | 0.577 | 0.557 | 0.542 | 0.863 |
| (1 = yes) | (0.501) | (0.495) | (0.495) | (0.498) | (0.500) | |
| Illness or accident shocks | 0.625 | 0.627 | 0.631 | 0.590 | 0.563 | 0.654 |
| (1 = yes) | (0.486) | (0.485) | (0.484) | (0.493) | (0.498) | |
| Weather or livestock shocks | 0.451 | 0.391 | 0.423 | 0.439 | 0.425 | 0.861 |
| (1 = yes) | (0.499) | (0.490) | (0.495) | (0.498) | (0.496) | |
| Observations | 144 | 162 | 168 | 174 | 168 | |

Notes: Mean coefficients reported; standard errors in parentheses. \(^a\)Indicator variable in which 1 indicates responsibility for financial decision-making in the household. \(^b\)Scores based on survey measure, “I avoid risky things,” on a seven-point Likert scale: 1-strongly disagree, 7-strongly agree. \(^c\)Ambiguity classification: 1-ambiguity averse, 2-ambiguity neutral, 3-ambiguity loving. \(^d\)p-values for multivariate equality of means test based on Wilks’ lambda test statistics. * p < 0.05, ** p < 0.01, *** p < 0.001 indicate significance levels for equality of means t-tests of all treatments versus the control treatment \( C \).

variables were balanced in treatment \( T_{Amb} \).

As a further balancing check, we implement a multivariate analysis of variance to test for differences between means across treatment groups on each of the variables.
presented in the summary statistics. The last column of Table 2 shows the p-values 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.

IV. Experimental Results

A. Main Results

We show the average uptake across treatments in Figure 2. Appendix Table C1 mirrors the figure using estimates from linear probability and probit models, and shows that the results are robust to the inclusion of control variables. In all our analyses, we account for potential correlation within our unit of randomization (i.e., the experimental session) via clustered standard errors.

The discussion of results is structured along the hypotheses defined in Section II.A. Eliminating contract nonperformance risk in treatment $T_{\text{NoDef}}$, that is, setting $p_{\text{Def}} = 0$ instead of $p_{\text{Def}} = 0.1$, results in a significant increase in insurance uptake of 17.1 ($p=0.007$) percentage points. For all specifications, the treatment dummy is significant at the 1 percent level. Hence, the risk that the insurance contract might not perform is clearly unattractive to participants, on average, even if they are compensated by lower premiums. This is in line with $H1$ as well as the findings of prior studies (Zimmer et al., 2016; Zimmer, Schade and Gründl, 2009; Herrero, Tomás and Villar, 2006; Albrecht and Maurer, 2000; Wakker, Thaler and Tversky, 1997).

Result 1. The presence of contract nonperformance risk in an insurance contract considerably decreases uptake, even when premiums are adjusted for the potential

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13The added covariates are age, gender, financial responsibility, marital status, education, employment, owning a dwelling, owning land, reduced meals in last month, score in mathematical and numerical capabilities, insurance ownership, health or accident shocks, and weather or livestock shocks. We also include round controls and the additional variable Typhoon, which takes a value of one if the subject was exposed to typhoon Haiyan, and zero otherwise. Typhoon Haiyan passed by the Iloilo Province halfway through our experiment, in November 2013. Our main effects are consistent before and after the typhoon.
mean uptake by treatment

Notes: The bars represent the mean proportion of individuals taking up insurance for the different treatment groups. Error bars indicate 95 percent confidence intervals, based on clustered standard errors at the session level.

default on valid claims on an actuarially fair basis.

When introducing ambiguity in the probability of contract nonperformance in treatment $T_{Amb}$, insurance uptake is reduced by 14.5 percentage points ($p=0.062$). For all specifications, the treatment dummy is significant at least at the 10 percent level. The results suggest that the presence of ambiguity in contract nonperformance risk decreases insurance uptake compared to when the nonperformance risk is known. In particular, the magnitude of the effects indicate that the reduction of insurance uptake induced by contract nonperformance risk is almost twice as strong in the presence of ambiguity, thus providing evidence for hypothesis $H2$.

**Result 2.** The reduction in insurance uptake induced by the presence of contract nonperformance risk is amplified significantly if the nonperformance probability of the insurance contract is ambiguous.
Framing the insurer’s contract nonperformance risk negatively rather than neutrally, as represented by treatments $T_{Fr}$, leads to a 12.1 percentage point reduction ($p=0.134$) in insurance uptake. This is almost equal to the effect of ambiguity. Thus, ambiguity about contract nonperformance risk and our negative frame seem to have similar negative effects on insurance uptake. However, the effects are not additive in that introducing ambiguity about contract nonperformance risk to the negatively framed setting in $T_{Amb-Fr}$ does not reduce uptake further with a treatment effect of 10.4 percentage points ($p=0.193$). However, because the treatment effects for $T_{Fr}$ and $T_{Amb-Fr}$ are not statistically significant, we are careful about deriving strong implications from the observed results.

B. Numeracy

Here, we analyze treatment effects, conditional on subjects’ numeracy levels, because a minimum level of numeracy skills might be useful to adequately understanding the experiment and, thus, to reacting 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 the results from the mathematical ability and numeracy scales. The total score ranges from 0 (i.e., no correct answer) to 16 (i.e., 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 3 shows average treatment effects by numeracy level. Columns 1 and 2 show the high-numeracy subsample, and Columns 3 and 4 show the low-numeracy subsample. High numeracy subjects seem to exhibit stronger treatment effects. Eliminating contract nonperformance risk in treatment $T_{NoDef}$ increases insurance demand by 20.8 percentage points ($p=0.003$) for the high-numeracy sample, but only 13.8 percentage points ($p=0.063$) in the low-numeracy sample.

Ambiguity about the probability of contract nonperformance, as implemented in
leads to a reduction of 18.5 percentage points ($p=0.035$) in insurance uptake for the high-numeracy sample, which is 7 percentage points more than that of the low-numeracy sample ($p=0.361$). The significance of the average ambiguity treatment effect disappears in the low-numeracy sample ($p=0.187$).

**Result 4.** Participants with higher numeracy skills exhibit stronger treatment effects and react more to contract nonperformance ambiguity.

### Table 3: Average Treatment Effects by Numeracy

<table>
<thead>
<tr>
<th></th>
<th>High numeracy</th>
<th></th>
<th>Low numeracy</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>$T_{	ext{NoDef}}$</td>
<td>0.208***</td>
<td>0.227***</td>
<td>0.138*</td>
<td>0.145*</td>
</tr>
<tr>
<td></td>
<td>(0.0699)</td>
<td>(0.0696)</td>
<td>(0.0734)</td>
<td>(0.0735)</td>
</tr>
<tr>
<td>$T_{	ext{Amb}}$</td>
<td>-0.185**</td>
<td>-0.166*</td>
<td>-0.113</td>
<td>-0.0982</td>
</tr>
<tr>
<td></td>
<td>(0.0868)</td>
<td>(0.0858)</td>
<td>(0.0851)</td>
<td>(0.0865)</td>
</tr>
<tr>
<td>$T_{	ext{Fr}}$</td>
<td>-0.0978</td>
<td>-0.0889</td>
<td>-0.141</td>
<td>-0.122</td>
</tr>
<tr>
<td></td>
<td>(0.0917)</td>
<td>(0.0872)</td>
<td>(0.0877)</td>
<td>(0.0847)</td>
</tr>
<tr>
<td>$T_{	ext{Amb-Fr}}$</td>
<td>-0.180*</td>
<td>-0.177*</td>
<td>-0.0421</td>
<td>-0.0364</td>
</tr>
<tr>
<td></td>
<td>(0.0958)</td>
<td>(0.0901)</td>
<td>(0.0788)</td>
<td>(0.0788)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.691***</td>
<td>0.658*</td>
<td>0.721***</td>
<td>0.558**</td>
</tr>
<tr>
<td></td>
<td>(0.0670)</td>
<td>(0.394)</td>
<td>(0.0627)</td>
<td>(0.218)</td>
</tr>
<tr>
<td>Observations</td>
<td>2,238</td>
<td>2,232</td>
<td>2,658</td>
<td>2,640</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.096</td>
<td>0.128</td>
<td>0.044</td>
<td>0.070</td>
</tr>
<tr>
<td>F test</td>
<td>21.23</td>
<td>6.892</td>
<td>5.730</td>
<td>2.633</td>
</tr>
<tr>
<td>Covariates</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

*Notes: Linear probability models are used with the dependent variable set to 1 if the subject takes up insurance. Standard errors (reported in parentheses) are corrected for clustering at the session level. Covariates are age, gender, financial responsibility, marital status, education, employment, owning a dwelling, owning land, reduced meals in last month, score in mathematical and numerical capabilities, insurance ownership, health or accident shocks, and weather or livestock shocks. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance levels of 10, 5, and 1 percent, respectively.*

Ambiguity towards the negatively framed probability of contract nonperformance, as implemented in $T_{\text{Amb-Fr}}$, reduces insurance uptake by 18 percentage points for the high-numeracy sample ($p=0.062$). However, in the low-numeracy sample, the reduction is statistically insignificant with an effect size of 4.2 percentage points ($p=0.594$). Our estimates also suggest that framing plays no role in insurance demand for individuals with high numeracy skills. As shown in Table 3, the effects of $T_{\text{Amb}}$ and $T_{\text{Amb-Fr}}$ on subjects with high numeracy are 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. These results make intuitive sense, because framing of the treatment provides no additional information on the probability of contract non-performance, which is the element we expect rational subjects to use when assessing their insurance choices.

C. Ambiguity and Risk Aversion

Following our theoretical model, individual ambiguity aversion should be the major factor explaining the sign and strength of the ambiguity effect. Therefore, we exploit the fact that we can classify participants with respect to ambiguity aversion, given their behavior in the lottery choice task prior to the insurance experiment. In particular, we use two Ellsberg (1961) lottery choices to classify individuals as ambiguity averse, ambiguity neutral, or ambiguity loving.\textsuperscript{14} Table 4 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).

The results for ambiguity-averse subjects are in line with our theoretical predictions. There is a strong reduction in insurance demand when the probability of contract nonperformance is ambiguous, in both the $T_{Amb}$ and the $T_{Amb-Fr}$ treatments. When ambiguity-averse subjects are confronted with the $T_{Amb}$ treatment, insurance demand is reduced by 18.2 percentage points ($p=0.048$), and when the negative framing condition is added to the ambiguous contract nonperformance risk, insurance demand falls by 22 percentage points ($p=0.02$). For ambiguity-neutral and -loving subjects, all effects of contract nonperformance ambiguity are smaller and statistically insignificant. However, even for ambiguity-loving subjects, the effects of ambiguity have a negative sign, even though we would expect

\textsuperscript{14}Those choices are between lotteries with known and unknown content. Participants who chose the known content twice were classified as ambiguity averse, those with one choice for known content were classified as ambiguity neutral, and those choosing unknown content twice were classified as ambiguity loving.


Table 4: Average Treatment Effects by Ambiguity Aversion

<table>
<thead>
<tr>
<th></th>
<th>Ambiguity averse (1)</th>
<th>Ambiguity neutral (3)</th>
<th>Ambiguity loving (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{\text{NoDef}}$</td>
<td>0.166**</td>
<td>0.200**</td>
<td>0.162</td>
</tr>
<tr>
<td></td>
<td>(0.0677)</td>
<td>(0.0921)</td>
<td>(0.131)</td>
</tr>
<tr>
<td>$T_{\text{Amb}}$</td>
<td>-0.182**</td>
<td>-0.155</td>
<td>-0.0861</td>
</tr>
<tr>
<td></td>
<td>(0.0909)</td>
<td>(0.103)</td>
<td>(0.151)</td>
</tr>
<tr>
<td>$T_{\text{Fr}}$</td>
<td>-0.192**</td>
<td>-0.0460</td>
<td>-0.127</td>
</tr>
<tr>
<td></td>
<td>(0.0897)</td>
<td>(0.110)</td>
<td>(0.156)</td>
</tr>
<tr>
<td>$T_{\text{Amb-Fr}}$</td>
<td>-0.220**</td>
<td>-0.0296</td>
<td>-0.0762</td>
</tr>
<tr>
<td></td>
<td>(0.0934)</td>
<td>(0.0851)</td>
<td>(0.156)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.747***</td>
<td>0.658***</td>
<td>0.738***</td>
</tr>
<tr>
<td></td>
<td>(0.0638)</td>
<td>(0.0791)</td>
<td>(0.127)</td>
</tr>
</tbody>
</table>

Observations: 2,004
R-squared: 0.101
F test: 17.48

Notes: Linear probability models are used with the dependent variable set to 1 if the subject takes up insurance. Standard errors (reported in parentheses) are corrected for clustering at the session level. Covariates are age, gender, financial responsibility, marital status, education, employment, owning a dwelling, owning land, reduced meals in last month, score in mathematical and numerical capabilities, insurance ownership, health or accident shocks, and weather or livestock shocks. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance levels of 10, 5, and 1 percent, respectively.

Result 5. The effect of ambiguity in contract nonperformance probabilities on demand tends to be more pronounced among ambiguity-averse individuals than it is among non-ambiguity-averse individuals.

Interestingly, negatively framing known contract nonperformance risk in $T_{\text{Fr}}$ also reduces insurance uptake of ambiguity-averse subjects (-19.2 percentage points, $p=0.034$), while it has no significant effect on ambiguity-neutral and ambiguity-loving subjects (all $p$-values $> 0.4$). One potential explanation is that “framing aversion” is correlated with ambiguity aversion, but that they are independent...
concepts. Another possibility is that mentioning negative motives of the insurer creates a feeling of uncertainty, similarly to making the contract nonperformance probability unknown, particularly for ambiguity-averse participants.

So far, we have focused on the role of ambiguity aversion, because the predictions of its influence on the treatment effect are the most straightforward. However, together with ambiguity aversion, risk aversion also determines decisions in ambiguous (i.e., inherently also risky) environments. Deriving exact predictions on the interplay of risk and ambiguity aversion without further assumptions is difficult. Therefore, we simulate insurance demand under parametric specifications of the utility function (see Appendix B for details). Specifically, we assume constant relative risk aversion (CRRA) and constant relative ambiguity aversion (CRAA); otherwise, we use all parameters as given in our experimental setup. The simulations predict that with contract nonperformance risk, (1) insurance should be taken up primarily by individuals within a range of “moderate” risk aversion parameters, and that (2) the effects for ambiguity-averse subjects should be observed primarily at the boundaries of this “moderate” range. The first prediction is in line with Doherty and Schlesinger (1990), who show a violation of the standard monotonic relationship between risk aversion and optimal insurance demand when contract nonperformance is present. Similarly, Clarke (2016) makes the case for a hump-shaped relationship between risk aversion and optimal insurance demand for index insurance with basis risk, which is similar to the notion of contract nonperformance risk considered here, except that it has both upside and downside risk.\textsuperscript{15}

Therefore, we start by analyzing whether insurance uptake is indeed higher in a certain “moderate” range of risk aversion. The behavior in the lottery choice task prior to the insurance experiment again serves as a basis to classify participants. In particular, we use the percentage of risk-seeking choices made in a set of Holt and Laury (2002) lotteries as a measure of risk aversion, where risk aversion increases

\textsuperscript{15}However, note that the decrease in optimal index insurance demand with basis risk in risk aversion is driven by the downside risk, not by the upside potential. This is equivalent to what we observe here.
with a decreasing share of risk-seeking choices. Figure 3 (a) shows the expected effect of higher insurance uptake by “moderately” risk-averse individuals.

![Figure 3: Average Insurance Uptake and Treatment Effect by Risk Aversion](image)

**Notes:** In this figure we focus on the subsample of participants in Treatments C and \( T_{\text{Amb}} \). The dots in (a) represent the mean proportion of individuals taking up insurance under C and \( T_{\text{Amb}} \), conditional on the percentage of risky choices in the Holt and Laury (2002) lotteries; (b) shows average treatment effects of \( T_{\text{Amb}} \). All estimates are based on third-degree polynomials interacting with \( T_{\text{Amb}} \) for the subsample of ambiguity-averse participants used in Table 4. Error bars indicate 95 percent confidence intervals, based on clustered standard errors at the session level.

A complication when testing the second simulation result is that our measure of risk aversion is noisy and difficult to translate into the parameters used in our simulation. In addition, the “location” of effects is sensitive to the model specifications. However, it is clear that the effects of introducing ambiguity on ambiguity-averse individuals should be driven by those who are risk averse. The reason is that risk-loving subjects should not take up insurance, irrespective of the presence of ambiguity and ambiguity aversion. Thus, we expect that the effects of the \( T_{\text{Amb}} \) treatment should materialize primarily among the risk averse. Figure 3 (b) shows average treatment effects of \( T_{\text{Amb}} \), conditional on our measure of risk aversion. We find that average treatment effects are positively related to risk aversion (i.e., with increasing risk aversion treatment effects increase). These results show that predictions from utility theory are, to some extent, supported by our empirical results. This lends further credibility to our interpretation of the effects.
Ambiguity is essentially due to a lack of information. In our setting, participants lack information about the exact contract nonperformance probability, which is governed by the mixture of orange and white balls in an opaque bag. An interesting question is whether individuals can accumulate information via experience and, hence, decrease the ambiguity over time. Rational individuals should update their beliefs about the unknown stochastic process based on newly available information. As the number of observations increases, the true probability can be estimated more precisely. In terms of our model in Section II, the subjective probability distribution $q(.)$ over the possible probabilities should converge towards a degenerate distribution, with value one, at the true probability. Thus, decreasing ambiguity with experience should be reflected in the participants’ insurance decisions. In particular, the effect of ambiguity in the contract nonperformance probability on insurance demand should converge to zero. Studying dynamic ambiguity is important, because, in reality, individuals collect and share experiences of the outcomes of ex-ante uncertain situations. Whether repeated exposure to such situations (directly or indirectly, via peers) decreases ambiguity effectively has clear implications for the relevance of the results of a static analysis. Therefore, we analyze the trend in ambiguity effects over the six rounds in the experiment.

Figure 4 shows pooled treatment effects for ambiguity treatments $T_{Amb}$ and $T_{Amb-Fr}$, separately, by round for the total sample and for a subsample of ambiguity-averse subjects. If anything, we expect to find a conversion of treatment effects to zero in the ambiguity-averse subsample. However, contrary to the updating hypothesis, the effect of ambiguity exhibits no clear trend, and remains consistent in both the overall sample and the ambiguity-averse subsample. All treatment effects remain negative, irrespective of the experience accumulated, while the effects are more pronounced and more significant in the ambiguity-averse subsample.

16For example, ambiguity measured by the standard error of a simple probability estimate, based on averages, should decrease with the square root of observed realizations.
Figure 4: Average Treatment Effects by Round

Notes: The bars represent the average treatment effects for the pooled treatment groups $T_{Amb}$ and $T_{Amb-Fr}$, by round, for the total sample and for a subsample of ambiguity-averse subjects. The error bars indicate 95 percent confidence intervals, based on clustered standard errors at the session level.

We compare these findings to participants’ beliefs about the contract nonperformance probability. Recall that we elicited beliefs by having participants guess (1) the number of orange balls contained in the bag from which contract nonperformance was drawn, and (2) the minimum and maximum number of orange balls they deemed possible. In addition to observing the “best guess” of participants, we use the spread between the minimum and maximum number of orange balls as a proxy for subjective ambiguity. Finally, the absolute deviation between the best guess and the real number of orange balls serves as an objective measure of uncertainty. Table 5 shows how the best guesses, spread between the minimum and maximum guesses, and error of guesses evolve over rounds for different treatments. For each of these three measures, the averages are presented separately for treatments $T_{Amb}$ and $T_{Amb-Fr}$.

Participants appear to be very pessimistic in treatments $T_{Amb}$ and $T_{Amb-Fr}$, be-
Table 5: Individuals’ Probability Beliefs

<table>
<thead>
<tr>
<th></th>
<th>Mean best guess</th>
<th>Mean subjective spread</th>
<th>Mean absolute error of guess</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$T_{Amb}$</td>
<td>$T_{Amb-Fr}$</td>
<td>$T_{Amb}$</td>
</tr>
<tr>
<td>Round 1</td>
<td>2.589</td>
<td>2.613</td>
<td>1.81</td>
</tr>
<tr>
<td>Round 2</td>
<td>2.673</td>
<td>2.601</td>
<td>1.934</td>
</tr>
<tr>
<td>Round 4</td>
<td>2.542</td>
<td>2.78</td>
<td>1.632</td>
</tr>
<tr>
<td>Round 6</td>
<td>2.655</td>
<td>2.696</td>
<td>1.554</td>
</tr>
<tr>
<td>N</td>
<td>168</td>
<td>168</td>
<td>155</td>
</tr>
</tbody>
</table>

Notes: Guesses were elicited via a short survey in rounds 1, 2, 4, and 6 on the average, minimum, and maximum number of orange balls, from a total of 10 balls (see Section III). The mean subjective spread is computed as the difference between the minimum and maximum number of orange balls stated. The mean absolute error of guesses measures the difference between the guesses and the actual number of orange balls. We restrict the sample for the mean subjective spread and the mean absolute error of guesses to those participants with meaningful statements about the minimum and maximum numbers of orange balls (i.e., minimum $\leq$ maximum).

cause the average guess is substantially above one. If anything, these guesses show a subtle upward tendency away from the real number of orange balls contained in the bags. The spread between the maximum and minimum guesses (Columns 3 and 4) seems to decrease over rounds, suggesting a decrease in the extent of ambiguity. On the other hand, the decrease is very small, and a substantial spread remains. In addition, the difference between the number of orange balls that participants believe are in the bag and the actual number of orange balls (Columns 5 and 6) shows no such downward tendency. Overall, participants do not improve their guesses significantly over the rounds. In summary, there is no clear evidence of a reduction in ambiguity over rounds. This holds for both the $T_{Amb}$ and $T_{Amb-Fr}$ treatments, and is consistent with their persistent negative treatment effects on insurance uptake.

Result 6. The negative impact of contract nonperformance ambiguity on insurance uptake is not eliminated over time by updating beliefs about probabilities.

There might be reasons for the absence of learning that are particular to our experiment. For example, it is possible that participants did not have all the information from other players, in which case they could not properly update on
their signals. Second, participants might have needed more experience in order to reduce ambiguity; that is, updating processes might take longer than the duration of the experiment permits. In order to obtain an intuitive understanding of the potential improvement in agents’ assessments of probabilities, we simulate Bayesian updating under perfect information transmission for all participants. That is, we assume that all participants in one session shared their experiences, and then followed a Bayesian updating rule. The result suggests that for ambiguous contract nonperformance probabilities, agents have access to limited information, because insurance performance can only be observed if there is a loss and insurance had been purchased previously. Hence, ambiguity decreases slowly (see Appendix D).

Even with a longer time horizon, there are good reasons why ambiguity might persist. First, information transmission might be imperfect, thus further increasing the time needed to accumulate the necessary information. Second, consistently updating beliefs is a difficult task, particularly if information is arriving sporadically. Under such circumstances, it is possible that subjective ambiguity remains high, even if sufficient information has eventually been accumulated.

V. Conclusion

We show the detrimental impact of contract nonperformance risk and ambiguity on insurance demand, both theoretically and empirically. Typically, the probability of an insurance contract failing to perform is considered to be known. We extend the theory by allowing contract nonperformance risk to be ambiguous, and show that demand for probabilistic insurance decreases with increasing mean-preserving ambiguity about contract nonperformance risk if agents are ambiguity averse.

Our results from a field lab experiment in the Philippines are consistent with this logic. In particular, we establish empirically that the effects of contract nonperformance risk (a decrease in insurance uptake by 17.1 percentage points) and its ambiguity (a further decrease in insurance uptake by 14.5 percentage points)
are similar in magnitude. These results suggest that the reduction in insurance demand induced by contract nonperformance risk is reinforced by ambiguity. This pattern is strongest among participants classified as ambiguity averse in a separate lottery choice task.

The causes for the failure of insurance contracts also seem to be important, under some circumstances. While they play a smaller role for participants with high numeracy, negatively depicting the insurer as unwilling to pay claims significantly reduces insurance demand for ambiguity-averse subjects. Interestingly, in this subsample, the negative framing seems to have a similar effect to that of introducing ambiguity.

We present additional evidence that the effects of ambiguity are not easily eliminated over time by updating beliefs about probabilities. In reality, learning might be more effective than it is in the lab. However, it seems intuitive that villagers from a low-income setting cannot update their beliefs effectively or compute confidence bounds around their probability guesses, in either the experiment or in reality.

According to our results, ambiguity about contract nonperformance risk clearly influences insurance demand, and has a similar economic relevance to that of contract nonperformance risk. Our results imply that in addition to ensuring low contract nonperformance risk, regulators should have an interest to reduce its ambiguity, for example, by making the repayment practices of insurers transparent. Similar to the case of contract nonperformance risk, such measures might not be in the best interests of individual insurance providers. Here, many potential reasons for contract nonperformance are endogenous to management decisions (e.g., more risky investments, less solvency capital, delaying payments) that benefit the owners of an insurance company. Thus, there is a particular trade-off between the costs and benefits that can be exploited by insurers, which the regulator may want to restrict. Furthermore, in the case of ambiguity, reasons not to create transparency may be endogenous to management decisions. For example, an insurance
provider publishing data about claims payment practices might, at the same time, send an unintended negative signal about claims payment probabilities, or lose the possibility of denying contract nonperformance risk towards clients. These and other strategic reasons might limit the incentives for transparency, even though the insurance market as a whole might profit from reduced ambiguity.

For emerging low-income insurance markets, with limited insurance demand, the effects of contract nonperformance risk and ambiguity are particularly relevant in terms of market development. In line with our results is a call for sound regulatory frameworks. Such frameworks should focus on ensuring low levels of contract nonperformance risk and ambiguity through solvency regulation, contract validation, and market transparency. In particular, there is room for such improvements in low-income insurance markets, because of currently low regulatory oversight, limited customer protection, and low levels of trust. For the management of an insurance company, a strategic focus on sound policies and practices may prove beneficial to gaining a competitive advantage and building trust in an emerging market.

Our conclusions are based on the empirical results presented in this paper, but their interpretation inevitably rests on certain assumptions, because randomizing all potential factors influencing insurance demand under ambiguity is impossible. For example, in our experiment, groups consist of six individuals, and it is not clear how the results would change with larger groups and, thus, more information potentially being available under the ambiguous settings. In addition, varying the contract nonperformance probability is potentially interesting, enabling us to judge the sensitivity of demand with regard to this factor in greater detail. However, prior work suggests that the largest part of the demand-reducing effect of contract nonperformance risk can be attributed to whether this risk is present, and that sensitivity of demand is highest when moving from non-probabilistic insurance to insurance with a non-zero contract nonperformance probability (Zimmer et al., 2016). In a similar vein, further research may investigate the role of the degree of
ambiguity and the way it is introduced, which we did not vary in our experiments. Therefore, in the absence of additional experimental findings across a range of parameters, it is crucial to think about the interpretation of results theoretically in order to judge their plausibility and generalizability. Our main empirical findings are in line with the hypotheses derived from the theoretical model and the corollary findings appear to be sensible: the demand effects of ambiguity are strongest for ambiguity- and risk-averse subjects, and demand seems to follow an inverted U-shape with respect to risk aversion (Doherty and Schlesinger, 1990; Clarke, 2016). These properties suggest that the findings are meaningful, and might hold when moving beyond the restricted parameter set tested here.
REFERENCES


Appendix A: Proofs

A1. Probabilistic Insurance

In this appendix, we prove that introducing contract nonperformance risk, without adjusting premiums, decreases the willingness to pay. This is intuitive, because there is no reason why a contract nonperformance feature should be valued by clients. In the following, we compare the marginal willingness to pay under both scenarios. The marginal willingness to pay when \( r > 0 \) can be obtained from the first-order condition when optimizing Equation (1) with respect to coverage \( \varepsilon \):

\[
\frac{\partial EU_r}{\partial \varepsilon} = (1 - p)u'(w - I(\varepsilon))(-I'(\varepsilon))
\]

\[
+ p[(1 - r)u'(w - I(\varepsilon) - L + \varepsilon)(-I'(\varepsilon) + 1)
+ ru'(w - I(\varepsilon) - L)(-I'(\varepsilon))] = 0.
\]

We solve Equation (A1) for \( I'(\varepsilon) \) and get the following marginal willingness to pay for probabilistic insurance:

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

which can be rewritten as:

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

Then, we set \( r = 0 \) in Equation (A1), and solve for \( I'(\varepsilon) \) to get the following marginal willingness to pay for non-probabilistic insurance:

\[
\frac{pu'(w - I(\varepsilon) - L + \varepsilon)}{(1 - p)u'(w - I(\varepsilon)) + pu'(w - I(\varepsilon) - L + \varepsilon)}
\]

When comparing Equation (A2) and (A3), it follows that the marginal willingness
to pay for probabilistic insurance is lower than it is for the same insurance that settles claims with certainty, irrespective of the coverage point \( \varepsilon \) (i.e., the numerator is the same, but the denominator is larger). This implies a lower overall willingness to pay at all coverage points and, hence, lower demand for insurance with contract nonperformance risk, irrespective of individual risk aversion. This result holds for both binary and continuous insurance decisions.

A2. Lemma 1 and Lemma 2: Premium-Adjusted Probabilistic Insurance

The setting is less trivial once we account for contract nonperformance risk by reducing premiums proportionally (i.e. \( I(\varepsilon) \neq I_0(\varepsilon) \)). In this case, agents face a trade-off between effective coverage and lower premiums. Doherty and Schlesinger (1990) already show that optimal coverage is not necessarily monotonic in nonperformance risk in such a situation. Given this more general result, we focus on the case of a binary insurance decision with a given coverage level \( \varepsilon \) here. This is in line with our empirical setup and should help us to shed further light on reasons for potential non-monotonicities and which direction of the effect is likely to dominate. We hence compare \( EU_r \) and \( EU_0 \), holding coverage \( \varepsilon \) constant. In binary insurance decisions, a lower (higher) utility for policies with contract nonperformance risk implies weakly lower (higher) insurance demand.\(^{19}\) The following equation denotes

\[^{19}\text{In non-binary insurance decisions, a lower (higher) utility for policies with contract nonperformance risk implies that less (more) utility can be derived, even if optimal coverage changes.}
\]

\[^{\text{To see this, let } \varepsilon^* \text{ denote the optimal coverage of agents when } r = 0, \text{ and } \varepsilon^{**} \text{ when } r > 0. \text{ Then:}}
\]

\[
EU_r(\varepsilon) < EU_0(\varepsilon) \implies EU_r(\varepsilon^{**}) < EU_0(\varepsilon^*), \text{ and}
\]

\[
EU_r(\varepsilon) > EU_0(\varepsilon) \implies EU_r(\varepsilon^{**}) > EU_0(\varepsilon^*).
\]

This follows from the fact that \( EU_0(\varepsilon^{**}) < EU_0(\varepsilon^*) \) and \( EU_r(\varepsilon^{**}) > EU_r(\varepsilon^*) \) under the optimal coverage decision. However, the implications for demand are less straightforward, and require additional assumptions.
the difference between $EU_r$ and $EU_0$ at a given level of $\varepsilon$:

$$EU_r - EU_0 = (1 - p)[u(w - I_0(1 - r)) - u(w - I_0)]$$
$$+ p(1 - r)[u(w - I_0(1 - r) - L + \varepsilon) - u(w - I_0 - L + \varepsilon)]$$
$$- pr[u(w - I_0 - L + \varepsilon) - u(w - I_0(1 - r) - L)].$$

If the difference is positive, clients prefer insurance with contract nonperformance risk, and vice versa. As we restrict our attention to risk-averse agents with concave utility functions, it holds that $u'(A) > u'(A + B)$ for $A, B \in \mathbb{R}^+$. We can therefore implement an upper bound approximation, such that $u(A + B) - u(A) < u'(A)B$:

$$EU_r - EU_0 = (1 - p)[u(w - I_0 + rI_0)) - u(w - I_0)]$$
$$+ p(1 - r)[u(w - I_0(1 - r) - L + \varepsilon) - u(w - I_0 - L + \varepsilon)]$$
$$- pr[u(w - I_0 - L + \varepsilon) - u(w - I_0(1 - r) - L)]$$
$$> u'(w - I_0 - L + \varepsilon)I_0$$
$$=(1 - p)u'(w - I_0 - L + \varepsilon)I_0 - \tau_1$$
$$+ p(1 - r)u'(w - I_0 - L + \varepsilon)I_0$$
$$- \tau_2 - pru'(w - I_0 - L + \varepsilon)I_0 - \tau_3$$
$$= (1 - pr)u'(w - I_0 - L + \varepsilon)I_0$$
$$- pru'(w - I_0 - L + \varepsilon)(\varepsilon - rI_0) - \sum_{i=1,2,3} \tau_i,$$

where $\tau_i$ are the approximation errors $(u(A + B) - u(A) - u'(A)B)$, which are zero for risk-neutral agents and strictly increasing in risk aversion.\(^{20}\) Using $I_0 = $

\(^{20}\)This is true, irrespective of the premium loading factor.
(1 + \alpha)\varepsilon p$, where $\alpha$ is the premium loading factor, we get:

$$EU_r - EU_0 = (1 - pr)u'(w - I_0 - L + \varepsilon)r(1 + \alpha)\varepsilon p$$

$$- pr u'(w - I_0 - L + \varepsilon)(\varepsilon - r(1 + \alpha)\varepsilon p) - \sum_{i=1,2,3} \tau_i$$

$$= u'(w - I_0 - L + \varepsilon)pr\varepsilon \alpha - \sum_{i=1,2,3} \tau_i.$$

The above term might be positive or negative, depending on the loading factor and risk aversion. For actuarially fair insurance ($\alpha = 0$) and with risk averse agents, the expression is strictly negative, while for insurance with a positive loading ($\alpha > 0$) and risk neutral agents, the term is strictly positive. As the above expressions are all assumed to be continuous, we can go slightly beyond these extreme cases towards the statements postulated in Lemmas 1 and 2. Lemma 1 states, that for sufficiently low loadings, there must exist agents with sufficiently high risk aversion, such that $EU_r < EU_0$. In binary insurance decisions, this implies that for these agents, the average insurance demand must be weakly lower for insurance with contract nonperformance risk. On the other hand, Lemma 2 states, that for sufficiently high loadings, there must exist agents with sufficiently low risk aversion, above zero, such that $EU_r > EU_0$. This implies weakly higher demand for insurance with contract nonperformance risk for such agents. However, agents with low risk aversion are more sensitive to loadings and tend not to buy insurance that is too expensive (Mossin, 1968; Smith, 1968). Ultimately, the results hinge on the shape of the utility function. Therefore, we implement simulations over a range of parameters to obtain more precise predictions. The simulation results can be found in Appendix B. They strongly suggest that contract nonperformance risk decreases demand.
Lemma 3 can be shown by comparing the marginal willingness to pay when $r$ is known to that when $r$ is ambiguous. The marginal willingness to pay can be obtained from the first-order condition when optimizing Equation (2) with respect to coverage $\varepsilon$:

$$\mathbb{E}_\gamma \Phi'(EU_{r(\gamma)})(1 - p)u'(w - I(\varepsilon))(-I'(\varepsilon)) + p[(1 - r(\gamma))u'(w - I(\varepsilon)) - L + \varepsilon)(-I'(\varepsilon) + 1) + r(\gamma)u'(w - I(\varepsilon) - L)(-I'(\varepsilon))] = 0.$$  

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

$$pu'(w - I(\varepsilon) - L + \varepsilon)$$

where $\hat{r} = \frac{\mathbb{E}_\gamma \Phi'(EU_{r(\gamma)})}{\mathbb{E}_\gamma (1-r(\gamma))\Phi'(EU_{r(\gamma)})}$ and $\tilde{r} = \frac{\mathbb{E}_\gamma r(\gamma)\Phi'(EU_{r(\gamma)})}{\mathbb{E}_\gamma (1-r(\gamma))\Phi'(EU_{r(\gamma)})}$.

We are interested in comparing the above marginal willingness to pay to the marginal willingness to pay for probabilistic insurance with known contract non-performance risk derived in Equation (A2):

$$pu'(w - I(\varepsilon) - L + \varepsilon)$$

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 $\tilde{r}$. If $\hat{r} > \frac{1}{1-r}$ and $\tilde{r} > \frac{r}{1-r}$, it follows that the marginal willingness to pay decreases, and vice versa. We begin by showing that both conditions are equivalent:
The desired result can now be obtained from Equation (A5) by exploiting the shape of $\Phi(\cdot)$. For ambiguity averse agents, $\Phi(\cdot)$ is concave. This means that as $r(\gamma)$ increases (and $EU_{r(\gamma)}$ decreases), $\Phi'(EU_{r(\gamma)})$ increases as well. That is, $r(\gamma)$ and $\Phi'(EU_{r(\gamma)})$ are positively correlated, such that the expectation of their product is greater than the product of their expectation, and Equation (A5) holds. The reverse is true for ambiguity-loving agents. Hence, we have established that for ambiguity-averse (-loving) agents, the willingness to pay for insurance with ambiguous contract nonperformance risk is lower (higher) than it is in the case where it is known.

**A4. Generalizing Lemma 3**

Lemma 3 refers to the introduction of ambiguity regarding contract nonperformance risk. Other comparative statics such as increasing ambiguity aversion or increasing the extend of ambiguity are interesting as well. In the following we show that the development of the marginal willingness to pay boils down to one central property:

$$corr \left( r(\gamma), \Phi'(EU_{r(\gamma)}) \right).$$

If this correlation increases, the marginal willingness to pay decreases and vice
versa. To see this, consider Equation (A4) for two alternative situations with distinct ambiguity in contract nonperformance risk \((r(\gamma_1) \text{ versus } r(\gamma_2))\) and distinct ambiguity preferences \((\Phi_1 \text{ versus } \Phi_2)\). Comparing the marginal willingness to pay between both settings leads to comparing \(\hat{r}_1\) with \(\hat{r}_2\) and \(\bar{r}_1\) with \(\bar{r}_2\). If \(\hat{r}_2 > \hat{r}_1\) and \(\bar{r}_2 > \bar{r}_1\), it follows that the marginal willingness to pay decreases from situation 1 to 2, and vice versa. We again begin by showing that both conditions are equivalent:

\[
\begin{align*}
\hat{r}_2 &> \hat{r}_1 \\
\iff \frac{\mathbb{E}_{\gamma_2} \Phi'_2(EU_{r(\gamma_2)})}{\mathbb{E}_{\gamma_2}(1 - r(\gamma_2)) \Phi'_2(EU_{r(\gamma_2)})} &> \frac{\mathbb{E}_{\gamma_1} \Phi'_1(EU_{r(\gamma_1)})}{\mathbb{E}_{\gamma_1}(1 - r(\gamma_1)) \Phi'_1(EU_{r(\gamma_1)})} \\
\iff 1 - \frac{\mathbb{E}_{\gamma_2} r(\gamma_2) \Phi'_1(EU_{r(\gamma_2)})}{\mathbb{E}_{\gamma_2} \Phi'_2(EU_{r(\gamma_2)})} &> 1 - \frac{\mathbb{E}_{\gamma_1} r(\gamma_1) \Phi'_1(EU_{r(\gamma_1)})}{\mathbb{E}_{\gamma_1} \Phi'_1(EU_{r(\gamma_1)})} \\
\iff \frac{\mathbb{E}_{\gamma_2} r(\gamma_2) \Phi'_2(EU_{r(\gamma_2)})}{\mathbb{E}_{\gamma_2}(1 - r(\gamma_2)) \Phi'_2(EU_{r(\gamma_2)})} &> \frac{\mathbb{E}_{\gamma_1} r(\gamma_1) \Phi'_1(EU_{r(\gamma_1)})}{\mathbb{E}_{\gamma_1}(1 - r(\gamma_1)) \Phi'_1(EU_{r(\gamma_1)})} \\
\iff \bar{r}_2 &> \bar{r}_1.
\end{align*}
\]

(A6)

Note that the expected contract nonperformance probability is assumed to lie in the interval \((0, 1)\) and that \(\Phi'_1(\cdot), \Phi'_2(\cdot) > 0\) such that the direction of inequality holds through all divisions and multiplications. Dividing Equation (A6) by \(r = \mathbb{E}_{\gamma_1} r(\gamma_1) = \mathbb{E}_{\gamma_2} r(\gamma_2)\) and subsequently subtracting one yields the condition:

\[
\begin{align*}
\text{corr} \left( r(\gamma_2), \Phi'_2(EU_{r(\gamma_2)}) \right) &> \text{corr} \left( r(\gamma_1), \Phi'_1(EU_{r(\gamma_1)}) \right).
\end{align*}
\]

(A7)

The evolution of this correlation uniquely determines whether the marginal willingness to pay uniformly decreases (if the inequality holds), remains the same (if equality holds), or increases (if the reverse inequality holds). From here, different
kinds of comparative statics can be derived. Note, for example, that our derivation of Lemma 3 is a special case of the above general statement. Without ambiguity in the initial situation \((r(\gamma_1)\) being a constant), the right hand side of Equation (A7) is necessarily zero. Ambiguity aversion implies that on the left hand side \(r(\gamma_2)\) and 
\[
\Phi'_2(EU_{r(\gamma_2)})
\]
are positively correlated (negatively for ambiguity loving subjects), which proves Lemma 3.

Beyond the result of Lemma 3, it is intuitive that the willingness to pay will decrease when increasing the extend of ambiguity or increasing ambiguity aversion. For this proposition to hold, however, these changes must lead to an increase in the correlation. The above derivation hence delivers a useful criterion which facilitates proving further comparative statics.
APPENDIX B: SIMULATIONS

We have shown that under some circumstances (i.e., high premium loadings and low risk aversion), insurance with contract nonperformance risk might be preferred. Intuitively, some types might value the gain in the expected payoff as being greater than the risk of the contract failing to perform. To assess the extent of this phenomenon, we specify a CRRA utility function of the form $u(A) = \frac{A^{1-\rho}}{1-\rho}$, where $\rho = 0$ indicates risk neutrality, and risk aversion increases in $\rho$. In order to estimate the expected utilities of the different options, we fix the parameters as defined in Table B1 (i.e., following treatments $C$ and $T_{NaDef}$ in our experimental setup).

<table>
<thead>
<tr>
<th>Initial endowment</th>
<th>$C$</th>
<th>$T_{NaDef}$</th>
<th>$T_{Amb}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loss probability</td>
<td>0.3</td>
<td>0.3</td>
<td>0.3</td>
</tr>
<tr>
<td>Loss</td>
<td>150</td>
<td>150</td>
<td>150</td>
</tr>
<tr>
<td>Insurance coverage</td>
<td>150</td>
<td>150</td>
<td>150</td>
</tr>
<tr>
<td>Contract nonperformance probability</td>
<td>0.1</td>
<td>0</td>
<td>0.1</td>
</tr>
<tr>
<td>Contract nonperformance probability ambiguous</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Insurance premium</td>
<td>$I_0(1-\gamma)$</td>
<td>$I_\gamma$</td>
<td>$I_0(1-\gamma)$</td>
</tr>
<tr>
<td>Loading factor</td>
<td>$\alpha$</td>
<td>$\alpha$</td>
<td>$\alpha$</td>
</tr>
</tbody>
</table>

The insurance premium depends on the loading factor because $I = (1 + \alpha)\epsilon p = (1+\alpha)45$. Using the specifications shown in Table B1, we can calculate the expected utility difference $EU_r - EU_0$ for any combination of $\alpha$ and $\gamma$. Figure B1 (a) shows the result of this simulation. As derived theoretically, low risk-aversion types facing insurance policies with high premium loadings might prefer the policy with inherent contract nonperformance risk. However, for high premium loadings, the types preferring insurance with inherent contract nonperformance risk might not opt for insurance anyway. To illustrate this, Figure B1 (b) shows the simulation results for the trade-off between insurance with inherent contract nonperformance risk and no insurance.

Indeed, only those who would not take up insurance anyway prefer insurance with contract nonperformance risk. This implies that demand for insurance not
prone to contract nonperformance risk must be larger, because it is always preferred by those who are sufficiently risk-averse. Figure B1 (c) shows the results of our simulations for the trade-off between insurance without contract nonperformance risk and no insurance.

In summary, our previous analysis of demand is confirmed when comparing Figures B1 (b) and B1 (c); that is, the preference region for insurance with contract nonperformance risk is a subset of the preference region for insurance without contract nonperformance.

When considering the impact of ambiguity on insurance demand in our simulation, we need to make an assumption on the functional form of ambiguity aversion. Therefore, for choices involving ambiguous probabilities, we assume constant rela-
tive ambiguity aversion (CRAA) of the form \( \phi(EU) = \frac{EU^{1-\zeta}}{1-\zeta} \) for \( EU \in \mathbb{R}^+ \) and, thus, for \( \rho < 1 \). For all \( \rho > 1 \), we apply the adapted CRAA function for negative utilities \( \phi(EU) = \frac{-(EU)^{1-\zeta}}{1-\zeta} \) defined in Gollier (2011). For simplicity, we assume loading \( \alpha \) to be the loading defined in our experimental setup for \( T_{Amb} \) (i.e., 25 percent).

The simulation results in Figure B2 clearly suggest that the preference region for insurance with ambiguous contract nonperformance risk in the binary trade-off between insurance and no insurance is a subset of the preference region for insurance with known contract nonperformance risk (i.e., the grey horizontal line at CRRA \( \zeta = 0 \)) for ambiguity-averse individuals (i.e., \( \zeta > 0 \)).\(^{21}\) Thus, we confirm our previous analysis of demand in that the demand for ambiguous probabilistic insurance is always lower than that for non-ambiguous probabilistic insurance, for ambiguity-averse individuals.

\(^{21}\)This result holds irrespective of the premium loading \( \alpha \).
### Appendix C: Linear Probability and Probit Models for Average Treatment Effects

#### Table C1: Average Treatment Effects

<table>
<thead>
<tr>
<th></th>
<th>(1) (OLS)</th>
<th>(2) (OLS)</th>
<th>(3) (OLS)</th>
<th>(4) (Probit*)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{NoDef}$</td>
<td>0.171***</td>
<td>0.172***</td>
<td>0.187***</td>
<td>0.223***</td>
</tr>
<tr>
<td></td>
<td>(0.0626)</td>
<td>(0.0629)</td>
<td>(0.0638)</td>
<td>(0.0718)</td>
</tr>
<tr>
<td>$T_{Amb}$</td>
<td>-0.145*</td>
<td>-0.143*</td>
<td>-0.133*</td>
<td>-0.124*</td>
</tr>
<tr>
<td></td>
<td>(0.0768)</td>
<td>(0.0782)</td>
<td>(0.0763)</td>
<td>(0.0713)</td>
</tr>
<tr>
<td>$T_{Fr}$</td>
<td>-0.121</td>
<td>-0.119</td>
<td>-0.111</td>
<td>-0.103</td>
</tr>
<tr>
<td></td>
<td>(0.0803)</td>
<td>(0.0796)</td>
<td>(0.0771)</td>
<td>(0.0722)</td>
</tr>
<tr>
<td>$T_{Amb-Fr}$</td>
<td>-0.104</td>
<td>-0.101</td>
<td>-0.1</td>
<td>-0.0943</td>
</tr>
<tr>
<td></td>
<td>(0.0795)</td>
<td>(0.0791)</td>
<td>(0.0769)</td>
<td>(0.0725)</td>
</tr>
<tr>
<td>Typhoon</td>
<td>0.038</td>
<td>0.0319</td>
<td>0.0324</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0442)</td>
<td>(0.0430)</td>
<td>(0.0422)</td>
<td></td>
</tr>
<tr>
<td>Round</td>
<td>0.00294</td>
<td>0.00267</td>
<td>0.00309</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00371)</td>
<td>(0.00371)</td>
<td>(0.00376)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.707***</td>
<td>0.678***</td>
<td>0.632***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0580)</td>
<td>(0.0631)</td>
<td>(0.158)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>4,896</td>
<td>4,896</td>
<td>4,872</td>
<td>4,872</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.0612</td>
<td>0.0629</td>
<td>0.0832</td>
<td>0.0709</td>
</tr>
<tr>
<td>F-test</td>
<td>15.02</td>
<td>11.17</td>
<td>4.84</td>
<td></td>
</tr>
<tr>
<td>Covariates</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Notes: Linear probability models are used, with the dependent variable set to 1 if the subject takes up insurance. Standard errors (reported in parentheses) are corrected for clustering at the session level. Covariates are age, gender, financial responsibility, marital status, education, employment, owning a dwelling, owning land, reduced meals in last month, score in mathematical and numerical capabilities, insurance ownership, health or accident shocks, and weather or livestock shocks. * The probit model results are provided in terms of marginal effects. $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance levels of 10, 5, and 1 percent, respectively.
Appendix D: Bayesian Updating

In this appendix, we present the results of simulated Bayesian updating under perfect information transmission, for all participants. This serves as a benchmark for how well rational and well-informed individuals could, in principle, decrease ambiguity over time in our setting. We assume that all participants in a session share their experiences. Then, we follow a Bayesian updating rule to predict the probability that the insurer pays a claim in the case of a loss, and the uncertainty around this probability. In our setup, the number of orange balls ($\#_\gamma$) determines the contract nonperformance probability ($r(\gamma) = \#_\gamma/10$) under the different states of the world $\gamma$. Formally, each participant is assumed to calculate the probability that the state of nature $\gamma = h \in [0, ..., 10]$, given the observation of $K$ orange balls out of $N$ draws, as:

$$P(\gamma = h \mid K \text{ of } N) = \frac{P(K \text{ of } N \mid \gamma = h) \cdot P(\gamma = h)}{\sum_{i} (P(K \text{ of } N \mid \gamma = i) \cdot P(\gamma = i)) \cdot P(K \text{ of } N)},$$

where $P(\gamma = i)$ is the initial prior for the probability of the respective mix in the ambiguous bag. The ambiguous bag is a random subset of a big bag with known content (see Section III.B for more detail). Hence, the initial prior can be calculated using a hypergeometric distribution. In addition, the probability of observing $K$ nonperformance outcomes out of $N$ draws ($P(K \text{ of } N \mid \gamma = i)$) is easy to compute for each of the different possible numbers of orange balls $\#_i$ in the ambiguous bag. Thus, a Bayesian updater can calculate the likelihood for each probability state ($\gamma = h$) based on the history of draws, according to the above formula. In other words, this enables us to calculate the distribution of possible contract nonperformance probabilities based on past experiences, as well as any moment of this distribution.

Table D1 shows two main statistics. The first column describes how the ex-
pected number of orange balls, given the experiment history, deviates from the actual number \(|E[#;K of N] - #|\). This “prediction error” decreases slightly over the rounds. The second statistic describes the “remaining uncertainty” agents face, given the experiment history. This is calculated as the standard deviation of the possible contract nonperformance probabilities \(SD[#;K of N]\); that is, we calculate how much a rational Bayesian updater should expect the real number of orange balls to deviate from the expected value. Consistent with the bias of best guesses, uncertainty also decreases over the rounds. However, this downward trend is very modest, and most of the bias and the uncertainty remain until the end of the experiment. The reason is that, until round six, only 5.2 insurance performances can be observed, on average, which is not sufficient to considerably compress the belief distribution around the correct value.

Table D1: Bayesian Updating Simulation for \(T_{Amb}\) and \(T_{Amb- Fr}\)

<table>
<thead>
<tr>
<th>Round</th>
<th>Mean Deviation</th>
<th>Mean Remaining Uncertainty</th>
</tr>
</thead>
<tbody>
<tr>
<td>Round 1</td>
<td>0.734</td>
<td>0.89</td>
</tr>
<tr>
<td>Round 2</td>
<td>0.725</td>
<td>0.855</td>
</tr>
<tr>
<td>Round 3</td>
<td>0.708</td>
<td>0.824</td>
</tr>
<tr>
<td>Round 4</td>
<td>0.669</td>
<td>0.795</td>
</tr>
<tr>
<td>Round 5</td>
<td>0.621</td>
<td>0.763</td>
</tr>
<tr>
<td>Round 6</td>
<td>0.614</td>
<td>0.733</td>
</tr>
</tbody>
</table>

*Notes:* “Deviation” measures the difference between the expected number of orange balls, given the experiment history, and the actual number of orange balls for the Bayesian updaters. “Remaining Uncertainty” is the standard deviation of orange balls, given the updated probability distribution for the number of orange balls.