

# CONTRACT NONPERFORMANCE RISK AND UNCERTAINTY IN INSURANCE MARKETS

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*Insurance contracts may fail to perform, leading to a default on valid claims. We relax the standard assumption of known probabilities for such defaults by allowing for uncertainty. Within a large behavioral experiment, we show that introducing risk and uncertainty each leads to significant reductions in insurance demand and that the effects are comparable in magnitude (17.1 and 14.5 percentage points). Furthermore, risk- and ambiguity-averse participants are affected most. These findings are in line with models incorporating ambiguity attitudes or, alternatively, pessimistic beliefs. An analysis of the belief and decision dynamics suggests persistent pessimistic priors and disregard of peer experiences, leading to a stable uncertainty effect.*

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## I. Introduction

When economists think about insurance, they usually consider policies that pay claims conditional on the losses incurred. However, in reality, claims are not always reimbursed, and there is a very limited understanding of how various circumstances, such as insolvency, discord about coverage, payment delays, or the basis risk inherent in index insurance, contribute to the probability of an insurance contract not to perform. While there is a literature on such so-called probabilistic insurance contracts (Kahneman and Tversky, 1979; Doherty and Schlesinger, 1990), a central assumption here is that the contract nonperformance probability is known to all parties. This assumption could easily be violated in reality; for example, when insurance clients have limited experience with providers and cannot judge their reliability. Such uncertainty regarding probabilities attached to economic outcomes has been shown to be undesirable for many individuals and should therefore also influence the perceived value of probabilistic insurance.<sup>1</sup> So whenever there is limited transparency regarding the reliability of providers, it is relevant to know how uncertainty affects insurance demand and whether these effects persist with increasing experience.

In this paper, we assess the effect of both contract nonperformance risk and uncertainty on insurance demand within a large behavioral experiment. We find that increasing contract nonperformance risk from 0 to 10 percent significantly decreases insurance demand by 17.1 percentage points. Uncertainty regarding contract nonperformance risk leads to a further significant decrease in uptake of 14.5 percentage points. The effects of uncertainty are particularly pronounced for ambiguity-

<sup>1</sup>The literature uses different terms to refer to situations in which 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 the “epistemic reliability” of a probability estimate to infer the amount of information available on all possible states and outcomes. We use the term “uncertainty” in general and “ambiguity” specifically when we employ models of ambiguity aversion. The presence of an aversion to ambiguity was established in the laboratory under different conditions (Einhorn and Hogarth, 1986; Sarin and Weber, 1993; Epstein, 1999; Chow and Sarin, 2001) and in field settings (Dimmock, Kouwenberg and Wakker, 2016).

and risk-averse agents. These results are supported by a theoretical framework in which we extend probabilistic insurance models to allow for uncertainty in contract nonperformance probabilities and by corresponding simulations calibrated to our setup. The predictions of our model are driven by the presence of ambiguity-averse individuals (Klibanoff, Marinacci and Mukerji, 2005), but we show that pessimistic beliefs (Savage, 1954) under uncertainty could equivalently explain these results. As uncertainty is essentially a lack of information, we also study dynamics over time. We find that individuals take some experience into account, but they seem unable to form more precise beliefs using the information they accumulate. In particular, own experiences affect beliefs, but pessimistic priors and disregard of peer experiences hinder optimal updating. Consistent with this, the effects of uncertainty are little affected by experience and remain stable over time. We also test different framings regarding the insurer’s influence on the decision not to pay claims. While we cannot rule out that framing plays a role for some participants, it does not seem to change the effect of uncertainty.

The literature on contract nonperformance in insurance markets so far mainly studies risky environments, i.e., those with known probabilities. Doherty and Schlesinger (1990) show that contract nonperformance risk reduces insurance demand in theory.<sup>2</sup> Subsequent empirical works confirm the strong detrimental effects of contract nonperformance risk on insurance demand.<sup>3</sup> Uncertainty regarding contract nonperformance risk has been neglected in both the theoretical and empirical literature.<sup>4</sup> Exceptions are Bryan (2018) and Peter and Ying (2017). In a very

<sup>2</sup>Generalizations and further theoretical explanations of these results are provided by Hau (1999) and Mahul and Wright (2004, 2007). Cummins and Mahul (2003) capture divergent beliefs about the probability of contract nonperformance risk between insurers and their customers. In such a setting, however, none of the contracting parties perceives uncertainty, and hence ambiguity aversion plays no role.

<sup>3</sup>Wakker, Thaler and Tversky (1997), Albrecht and Maurer (2000), Herrero, Tomás and Villar (2006), and Zimmer, Schade and Gründl (2009) examine the effects of such risk on hypothetical willingness to pay. Zimmer et al. (2016) implement an incentive-compatible experiment with real monetary payoffs. All studies find a negative effect of contract nonperformance risk on insurance demand. Harrison and Ng (2018) further analyze the welfare consequences of probabilistic insurance, taking into account violations of the reduction of compound lotteries axiom.

<sup>4</sup>Studies including uncertainty in the context of insurance have so far focused on the effect of uncertain loss probabilities on insurance demand (Hogarth and Kunreuther, 1989; Alary, Gollier

complementary approach, Bryan (2018) uses data from a field setting to show that uncertainty reduces demand for an index insurance contract featuring contract nonperformance probability. While this paper clearly suggests the relevance of uncertain contract nonperformance for insurance demand in a real-world setting, the identification is relatively complicated and essentially relies on comparing ambiguity-averse and non-ambiguity-averse individuals in a double difference approach. In contrast to Bryan (2018), we exogenously vary uncertainty, permitting us to assess cleanly its effect on insurance decisions.<sup>5</sup> We also give full theoretical consideration to the problem, including modeling heterogeneous attitudes towards risk and uncertainty, and provide simulations suited to our experimental setup. Furthermore, we can exploit random variation in contract nonperformance experience generated in our experiment and analyze dynamics under the presence of both one’s own and peer signals. Our detailed and targeted analysis thus neatly complements the field evidence Bryan (2018) provides on the uncertainty effect, effect heterogeneity by risk aversion, and stability of effects over time. Peter and Ying (2017) follow the theoretical idea of our paper and indicate that the implications of our model are robust to some extensions and variations.

Perceived contract nonperformance risk seems to be relevant to insurance demand, even in an environment with high levels of regulation, customer protection, and access to reliable information. In such markets, significant efforts have been made to disseminate information on insurers’ reputations for servicing claims (Mahul and Wright, 2004).<sup>6</sup> Our empirical setup, in contrast, is based on a behavioral experiment conducted with participants from the Philippines, the leading emerging insurance market in terms of coverage around the world (Munich Re Foun-

and Treich, 2013; Huang, Huang and Tzeng, 2013; Gollier, 2014; Bajtelsmit, Coats and Thistle, 2015) and self-insurance as well as self-protection (Snow, 2011).

<sup>5</sup>In Bryan (2018), uncertainty enters through a new production technology combined with insurance, such that the identification requires more assumptions and it is harder to model the problem in a standard way, resulting in a somewhat less straightforward theory.

<sup>6</sup>Roughly 50 percent of all complaints reported to the US state regulators in 2014 are related to denials and delays of claims and unsatisfactory settlements, amounting to over 30,000 cases (National Association of Insurance Commissioners, 2016).

dation, 2014). This setting ensures participant familiarity with insurance, while at the same time many recent market entries limit the information about insurance provider reliability, and lower income levels of participants exacerbate the consequences of an insurance policy default. Additionally, low levels of regulation and customer protection in many emerging markets are likely to generate higher levels of contract nonperformance risk, whereas limited access to reliable information and limited trust in regulators and legal institutions may fuel perceptions of high uncertainty. Thus, the topic of our research is particularly salient in this context.

Contract nonperformance risk and uncertainty emerge as a potential piece of the puzzle explaining the low demand for insurance with potentially significant social welfare benefits in emerging markets.<sup>7</sup> Our results are consistent with these findings, and our extension from risky to uncertain nonperformance of insurance contracts offers a novel and economically relevant perspective on the factors restricting insurance demand. In a broader sense, this novel perspective has explicit policy implications. While regulations to restrict contract nonperformance risk (i.e., solvency and market conduct) are obvious candidates to stimulate demand, making individual providers' contract nonperformance risk transparent can reinforce (or even enable in the first place) the regulatory stimulus by reducing uncertainty. There is a particular value to increasing transparency in emerging markets where many new insurers with unknown reliability operate.

The remainder of this paper proceeds as follows. In Section II, we present our theoretical framework as well as the corresponding simulations 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.

<sup>7</sup>Motivated by a low-income setup with liquidity constraints, Liu and Myers (2016) provide theoretical evidence for reductions in insurance demand due to possible insurer default (similar to Doherty and Schlesinger (1990)), and Cole et al. (2013) empirically reveal trust as an important market friction constraining demand.

## II. Model Predictions and Simulations

### A. Preliminaries

In this section, we formalize the characteristics of contract nonperformance risk and uncertainty, provide a theoretical intuition on how insurance demand should behave, and provide simulations calibrated to our setup in order to derive more specific predictions. 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  $I(\varepsilon)$ .<sup>8</sup> 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  $w - I(\varepsilon) - L + \varepsilon$ . Table 1 summarizes the parameters and the specific values of our experimental setup, which are also used for the corresponding simulations.

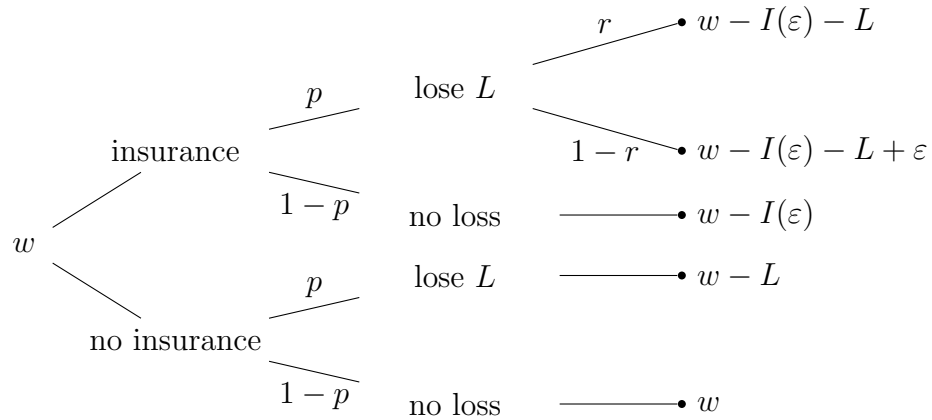


Figure 1: Decision Tree

In our theoretical framework, any decision maker evaluates the expected utility

<sup>8</sup>We remain general in our definition of a premium and do not presume that the insurance is priced as being actuarially fair.

Table 1: Simulation Parameters

Name	Parameter	Value
Initial wealth	$w$	210
Loss	$L$	150
Insurance coverage	$\varepsilon$	150
Insurance premium	$I(\varepsilon)$	50
Loss probability	$p$	0.3
Contract nonperformance probability	$r$	0.1

of the upper branch of the tree (i.e., insurance) against the lower branch (i.e., no insurance) shown in Figure 1. This is a binary setup, which is different from insurance decisions under continuous coverage. While our theory provides results which are relevant to both setups, we are mostly interested in deriving predictions for the binary decision described here. Whereas we remain more general in our theory (see Appendix A1 and A2), we employ a constant relative risk aversion (CRRA) utility function  $u(x) = x^{1-\rho}/(1-\rho)$ <sup>9</sup> and the parameters presented in Table 1 in our simulations.<sup>10</sup>

### B. Demand for Probabilistic Insurance

As our empirical application also includes testing the role of contract nonperformance (i.e.,  $r > 0$  versus  $r = 0$ ) in the standard probabilistic insurance setting, we provide some theoretical intuition at this point. Doherty and Schlesinger (1990) show that, with actuarially fair premiums, the introduction of contract nonperformance risk leads to a decrease in optimal insurance demand. Because this theoretical literature only provides conclusive results for actuarially fair premiums, we also discuss the case of unfair premiums. The following aspect makes predictions more

<sup>9</sup> $\rho = 0$  indicates risk neutrality, and risk aversion increases with  $\rho$ .

<sup>10</sup>Under decreasing absolute risk aversion (DARA), which is implied by CRRA, heterogeneity in asset integration could in principle bias empirical results if it correlates with ambiguity preferences or subjective beliefs. To probe the stability of our simulation results, we substituted the CRRA utility function with an exponential utility function exhibiting constant absolute risk aversion (CARA)  $u(x) = 1 - e^{-ax}$ , where  $a = 0$  indicates risk neutrality, and risk aversion increases with  $a$ . The results are qualitatively equivalent. Note also, that our theory (see Appendix A1 and A2) shows that the results derived from the simulations hold independent of assumptions about the particular shape of the preference functional.

complicated under actuarially unfair premiums: when introducing contract nonperformance risk and adjusting the premium correspondingly, absolute loadings may decrease, which certain individuals might perceive as beneficial.<sup>11</sup> In particular, for mildly risk-averse individuals the utility loss generated by increased contract nonperformance risk is lower than the utility gains from a reduction in absolute loadings. Reductions in absolute loadings should be only sizable, however, if overall loadings are large—a condition which usually deters mildly risk-averse individuals from purchasing any insurance at all. The simulation results presented in Figure 2 are in line with this argument and show that, for any loading factor  $\alpha$ , the demand for insurance without contract nonperformance risk dominates demand for probabilistic insurance. Thus, we formulate the first hypothesis accordingly.

**Hypothesis 1.** Introducing contract nonperformance risk reduces insurance demand.

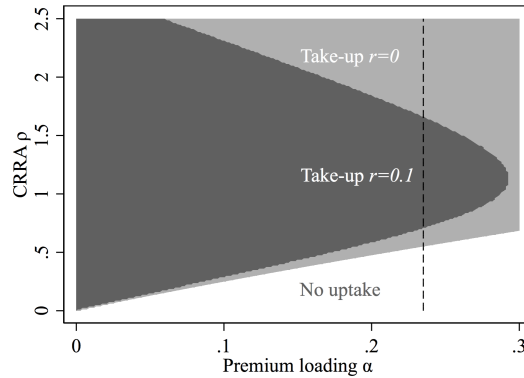


Figure 2: Demand for Insurance with Known Contract Nonperformance Risk

*Notes:* The colored areas represent the preference regions of the respective insurance policy over no insurance coverage. In particular, the dark (light) grey area indicates that the expected utility from insurance with known (without) contract nonperformance is preferred to no insurance coverage. The dashed line indicates the actual loading factor of 23.5 percent applied in the experimental setup for the insurance contract with  $r = 0.1$ .

<sup>11</sup>We define corresponding premiums for different levels of contract nonperformance risk as  $I_r(\varepsilon) = (1 - r)I_0(\varepsilon)$ , where  $I_0(\varepsilon)$  is the premium with  $r = 0$ .



### C. Demand for Uncertain Probabilistic Insurance

We now focus on our main area of interest, the effect of uncertainty with respect to contract nonperformance risk on insurance demand (i.e.,  $r$  is unknown). This situation gives rise to two major streams of decision models: subjective expected utility (SEU), suggested by Savage (1954), and expected utility models incorporating ambiguity attitudes. These types of models differ, because agents following SEU may simply hold optimistic or pessimistic beliefs, while ambiguity-averse expected utility individuals genuinely adjust their utility when exact probabilities are unknown. This might lead ambiguity-averse (or -loving) agents to behave in ways which cannot be rationalized by subjective beliefs, as shown in the seminal work of Ellsberg (1961). In our setup, we can show that both types of behavioral models lead to very similar predictions. More precisely, it is possible to show that, in an expected utility model with smooth ambiguity aversion (Klibanoff, Marinacci and Mukerji, 2005), ambiguity-averse (-loving) agents act *as if* they hold pessimistic (optimistic) beliefs under SEU (the proof is presented in Appendix A3). As both explanations are behaviorally equivalent, we are to some extent agnostic about which of the channels exactly explains the results. Even though we employ a model of ambiguity aversion for our theoretical results, we consider ambiguity preferences and subjective beliefs under SEU to be two related interpretations leading to an equivalent effect.

To incorporate uncertainty, we define contract nonperformance risk as the ambiguous probability  $r(\gamma)$ , depending on the unknown parameter  $\gamma$ . Ambiguity is defined as a probability distribution for  $\gamma$  with discrete support  $\{1, \dots, n\}$ . 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.,  $\sum_{\gamma=1}^n q(\gamma)r(\gamma) = r$ ). Following the smooth ambiguity approach of Klibanoff, Marinacci and Mukerji (2005), we model ambiguity aversion using an increasing valuation function for the expected utility derived from each state of  $\gamma$ . Ambiguity-neutral agents use a linear valuation function, while concavity expresses ambigui-

ity aversion and convexity mirrors ambiguity-loving preferences. We show that, for ambiguity-averse (-loving) agents, marginal willingness to pay for insurance is strictly lower (higher) when ambiguity over contract nonperformance risk is introduced, and therefore also demand should decrease (increase) (see Appendix A1). This Lemma can be generalized to situations in which the extent of ambiguity or ambiguity aversion changes (see Appendix A2).<sup>12</sup> These results are in line with Mukerji and Tallon (2001), who show that risk-sharing opportunities on financial markets that involve ambiguity can be less attractive to ambiguity-averse agents.

The rationale for our theoretical result is that ambiguity-averse agents assign higher weights to states of  $\gamma$  that are associated with low utility. In our case, this is equivalent to giving higher weight to high contract nonperformance probabilities. The reverse is true for ambiguity-loving agents. We show that, given risk aversion, there is a monotonic one-to-one mapping between ambiguity aversion  $\zeta$  and subjective contract nonperformance probability  $r_{sub}$ , leading to exactly the same behavioral predictions (see Appendix A3). The slope of the mapping changes with risk aversion, but the monotonic nature always holds.

Figure 3 shows the result of simulating insurance demand with uncertainty, where the contract nonperformance probability on average should be 0.1 but can be in the range between 0 to 1 (as in our empirical setup). Dark shading indicates predicted insurance uptake. In the left panel, we assume constant relative ambiguity aversion (CRAA) of the form  $\phi(EU) = \frac{EU^{1-\zeta}}{1-\zeta}$  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). In the right panel, we simulate insurance choices for a range of subjective probabilities  $r_{sub}$ .

Demand for insurance with a known contract nonperformance probability is shown at  $\zeta = 0$  or equivalently  $r_{sub} = 0.1$ . Relative to this benchmark, it is clearly

<sup>12</sup>We derive the central condition for the development of marginal willingness to pay, which involves the covariance between  $r(\gamma)$  and  $\Phi'(EU_{r(\gamma)})$ . This condition generally holds in our setting of mean-preserving ambiguity and smooth ambiguity aversion as proposed by Klibanoff, Marinacci and Mukerji (2005). The effect on the marginal willingness to pay directly translates into changes of optimal coverage in both continuous and binary insurance decisions.

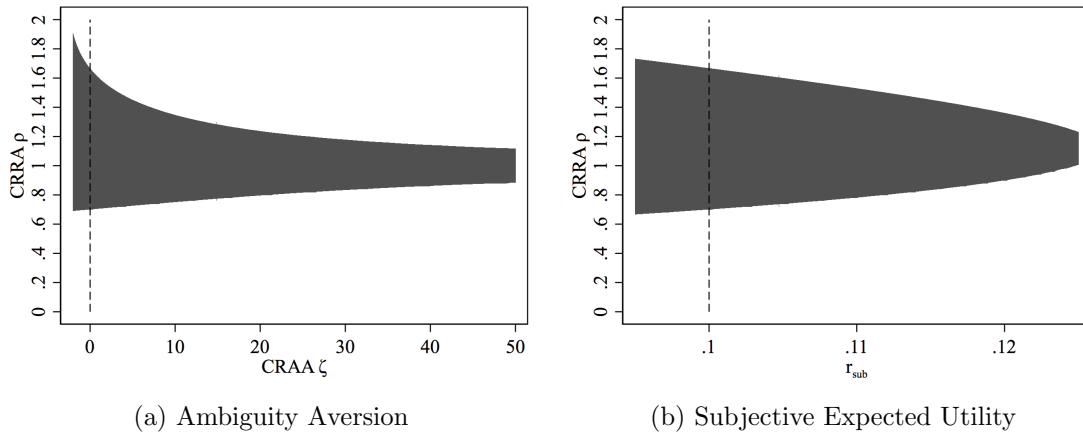


Figure 3: Demand for Insurance with Uncertain Contract Nonperformance Risk

*Notes:* The dark grey areas represent the preference regions of the insurance with inherent contract nonperformance uncertainty over no insurance coverage. While predictions in part (a) are based on simulations of our ambiguity model, part (b) provides estimates of areas of take-up based on our subjective expected utility model. The horizontal axes in (a) and (b) map comparable regions based on the translation of ambiguity aversion parameter  $\zeta$  into subjective probabilities  $r_{sub}$  which we provide in Appendix A3.

apparent that the range of predicted uptake shrinks with increasing  $\zeta$  or  $r_{sub}$ , and vice versa. The effect of introducing uncertainty therefore depends on the degree of ambiguity aversion (or pessimism) and on the joint distribution of risk and ambiguity aversion (or pessimism). However, there are arguments regarding 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. The group of potential insurance clients should therefore have a strong tendency towards ambiguity aversion. In addition to the overall effect, our theory also clearly predicts differential effects by ambiguity aversion or pessimism. Thus, we state the second and third hypotheses as follows.

**Hypothesis 2.** Uncertainty about contract nonperformance probabilities reduces insurance demand compared to when contract nonperformance risk is known.

**Hypothesis 3.** Uncertainty about contract nonperformance probabilities reduces insurance demand more strongly for ambiguity-averse (pessimistic) individuals.

We now turn to an analysis conditional on risk aversion. Based on our simulation results presented in Figures 2 and 3, we should only expect uptake for insurance with inherent contract nonperformance risk in the area of mildly risk-averse individuals.<sup>13</sup> Predictions of the uncertainty effect conditional on risk aversion are slightly more complicated, because they are at the same time conditional on ambiguity aversion or pessimism. Simulations of the treatment effects of uncertainty for different levels of ambiguity aversion while continuously varying risk aversion suggest that we should expect the strongest uncertainty treatment effects among the risk-averse (see Appendix B). We therefore formulate the following hypothesis.

**Hypothesis 4.** Uncertainty about contract nonperformance probabilities reduces insurance demand, particularly for strongly risk-averse individuals.

### III. Experimental Design

We implement a field lab experiment in which subjects decide whether to purchase probabilistic insurance in a risky environment. The experiment was explained with reference to real insurance policies, a concept which is well known to our sample, given the prevalence of insurance products in the Philippines (Munich Re Foundation, 2014).

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  $p$ . Participants who bought insurance could claim a payment from the insurer, contingent on having experienced a loss. Whether the insurer

<sup>13</sup>The exact range varies by ambiguity aversion or pessimism. Individuals who are ambiguity neutral or hold unbiased beliefs should take up insurance in a range of risk aversion  $\rho \in (0.7, 1.7)$ ; the range becomes smaller (larger) for more (less) ambiguity averse or pessimistic (optimistic) individuals.

paid the claim was determined by another random draw, with probability  $r$  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  $p$  and the contract nonperformance probability  $r$ . Participants were grouped into sessions of six participants. They were not allowed to exchange information or talk amongst themselves during the first round of the experiment. This procedure aimed to prevent peer effects on the participants' initial beliefs about probabilities. Participants were then allowed to communicate with other members for the remaining five 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. At this stage, participants were presented with pairs of two-outcome monetary lotteries, of which they had to choose one (Glöckner, 2009). We use incentivized lottery choices involving uncertainty and risk (Holt and Laury, 2002), from which we infer ambiguity and risk preferences (details in Appendix E2).<sup>14</sup> The lottery choices we use in this study were part of a larger choice experiment for which participants played up to 122 lotteries and earned the average of four randomly drawn gambles. To avoid potential wealth effects, participants only learned about the gambles drawn and their respective outcomes at the very end of the experiment. Protocols for the insurance experiment and the lottery choice task are provided in Appendices E1 and E2.

<sup>14</sup>For inferring ambiguity preferences, we rely on two easy-to-understand lottery choices with equally likely outcomes and equal expected value. Trautmann, Vieider and Wakker (2011) stress the importance of using choice-based measures of ambiguity aversion as opposed to those relying on willingness to pay, which tend to overestimate the degree of ambiguity aversion.

Table 2: Experimental Treatments

	<i>Treatments</i>				
	<i>C</i>	<i>T<sub>NoDef</sub></i>	<i>T<sub>Unc</sub></i>	<i>T<sub>Fr</sub></i>	<i>T<sub>Unc-Fr</sub></i>
<i>Panel A: Universal parameters</i>					
Initial endowment (in PHP)	210	210	210	210	210
Loss (in PHP)	150	150	150	150	150
Loss probability $p$	0.3	0.3	0.3	0.3	0.3
<i>Panel B: Treatment characteristics</i>					
Contract nonperformance probability $r$	0.1	0	0.1	0.1	0.1
Uncertainty of $r$	<i>No</i>	<i>No</i>	<i>Yes</i>	<i>No</i>	<i>Yes</i>
Framing	Neutral	Neutral	Neutral	Negative	Negative
Insurance premium (in PHP)	50	60	50	50	50
<i>Panel C: Participants and sessions</i>					
Number of subjects	144	162	168	174	168
Number of sessions	24	27	28	29	28

### A. Treatments

A complete overview of all treatments is presented in Table 2. 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 1. 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.<sup>15</sup>

Comparing treatment  $T_{Unc}$  with control treatment  $C$  allows us to identify the effect of uncertainty on insurance demand and, thus, to test Hypothesis 2. Here,

<sup>15</sup>Because the actual price of an insurance policy is its loading, we targeted a 30 percent markup on all insurance treatments. This target resulted from simulations that suggested sufficient variation across 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 23.5 percent and 33.3 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 high in low-income insurance markets (Biener, 2013).

the contract nonperformance probability was uncertain to the participants. In order to provide the participants with an initial signal of probabilities by which to form their prior beliefs, the balls in the bags of the uncertain treatments ( $T_{Unc}$  and  $T_{Unc-Fr}$ ) were selected blindly by one research assistant from a big bag containing 100 balls during the instructions. 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 uncertain bags. Our setting with multiple rounds allows us to analyze the effects over time, which is especially interesting under uncertainty, when experience about losses and contract nonperformance can be shared within the peer network. In particular, one might expect uncertainty to decrease over time once sufficient learning has taken place.

We also test the role of different framings regarding the insurer’s influence on the decision not to pay claims in treatments  $T_{Fr}$  and  $T_{Unc-Fr}$ . In these treatments, we describe contract nonperformance as a case in which the insurer does not want to pay a valid claim, providing examples such as fraud or scam. All other treatments include a neutral statement (“the specific type of loss is not covered by the insurance”). We expect that the negative framing might lead to a more pessimistic evaluation of insurance, leading to an overweighting of contract nonperformance probabilities. There should be more scope for subjective weighting when probabilities are unknown, and we thus suspect a stronger reduction in insurance demand when contract nonperformance risk is uncertain. To test this conjecture, our experiment includes a two-by-two factorial design to test uncertainty, negative framing, and their combination.

### *B. 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, implemented in each

of a total of 42 villages.<sup>16</sup> This random assignment was implemented such that distinct treatments were executed 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.<sup>17</sup> 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 instructions. Detailed explanations were provided by one instructor, with the help of visual aids. We ensured the participants' understanding by conducting a test questionnaire. Only when all questions of the test could be answered correctly was a participant allowed to continue, whereas we allowed for one re-explanation.<sup>18</sup> 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 the 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 orange balls they believed were in the bag. The first survey at the beginning of round 1 inquired about participants' beliefs regarding the contract nonperformance probabilities in the absence of any peer or network

<sup>16</sup>One additional treatment, unrelated to uncertain contract nonperformance risk, was conducted. Thus, six variants were randomized altogether. The omitted treatment is irrelevant to the research questions analyzed in this paper. Details are available upon request.

<sup>17</sup>Villages from municipalities with high income (i.e., the 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).

<sup>18</sup>The share of correctly answered questions in the first attempt was higher than 90 percentage points in all treatments on average. A sample of the test questionnaire implemented for  $T_{Unc}$  and  $T_{Unc-Fr}$  is provided in Appendix E3.



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 the proceeds from 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,<sup>19</sup> amounting to PHP 270, or approximately USD 6.2—a substantial amount for the average participant.<sup>20</sup>

In total, we conducted 136 sessions with 816 participants in 42 villages. Table 3 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. Treatment  $T_{NoDef}$  exhibits a slightly higher share of participants being responsible in household financial decision making. The proportion of employed participants in the  $T_{NoDef}$  and  $T_{Fr}$  treatments is a bit lower than in the control treatment  $C$ . Finally, the share of participants owning a dwelling is higher under treatment  $T_{NoDef}$ . However, overall, it is apparent that the sample is balanced across treatment groups.

As a further balancing check, we implement a multivariate analysis of variance to

<sup>19</sup>The show-up fee was increased by PHP 20 if the participant was the head of his or her household. We wanted to make sure that the sample is representative of members of the household who are involved in financial decision-making at the household level, which holds true for almost all of our participants.

<sup>20</sup>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 3: Descriptive Statistics

	$C$	$T_{NoDef}$	$T_{Unc}$	$T_{Fr}$	$T_{Unc-Fr}$	Equality of Means (p-value) <sup>d</sup>
<i>Panel A: Socio-demographic characteristics</i>						
Age	39.86	38.80	38.96	38.76	39.86	0.838
(in years)	(10.50)	(10.08)	(9.966)	(10.94)	(9.755)	
Gender	0.741	0.840*	0.810	0.833*	0.786	0.464
(1 = female)	(0.439)	(0.368)	(0.394)	(0.374)	(0.412)	
Financial responsibility <sup>a</sup>	0.958	0.994*	0.964	0.977	0.970	0.324
(1 = yes)	(0.201)	(0.0786)	(0.186)	(0.150)	(0.170)	
Married or in partnership	0.903	0.889	0.869	0.902	0.899	0.812
(1 = yes)	(0.297)	(0.315)	(0.338)	(0.298)	(0.302)	
Education	9.573	9.580	9.911	9.552	9.381	0.467
(in years)	(2.642)	(2.472)	(2.476)	(2.210)	(2.619)	
Employment status	0.465	0.358*	0.387	0.351*	0.429	0.329
(1 = employed)	(0.501)	(0.481)	(0.488)	(0.479)	(0.496)	
Regular income	0.270	0.295	0.282	0.250	0.275	0.627
(1 = yes)	(0.447)	(0.460)	(0.453)	(0.436)	(0.449)	
Seasonal income	0.716	0.787	0.732	0.653	0.637	0.234
(1 = yes)	(0.454)	(0.413)	(0.446)	(0.479)	(0.484)	
Land ownership	0.133	0.142	0.113	0.167	0.161	0.793
(1 = yes)	(0.341)	(0.350)	(0.318)	(0.374)	(0.368)	
Dwelling ownership	0.799	0.895**	0.845	0.839	0.851	0.318
(1 = yes)	(0.402)	(0.307)	(0.363)	(0.369)	(0.357)	
Reduced meals within last month	0.273	0.210	0.214	0.218	0.244	0.869
(1 = yes)	(0.447)	(0.408)	(0.412)	(0.414)	(0.431)	
<i>Panel B: Mental capabilities, risk and ambiguity aversion</i>						
Mathematical ability score	6.660	6.654	6.661	6.655	6.494	0.901
(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	0.968
(0 min 16 max)	(3.084)	(2.988)	(2.999)	(2.930)	(2.958)	
Risk aversion <sup>b</sup>	0.480	0.451	0.479	0.482	0.498	0.689
(0 min 1 max)	(0.297)	(0.281)	(0.295)	(0.272)	(0.287)	
Ambiguity averse <sup>c</sup>	0.397	0.461	0.445	0.445	0.454	0.91
(1 = yes)	(0.491)	(0.5)	(0.499)	(0.499)	(0.5)	
<i>Panel C: Loss and insurance experience</i>						
Insurance ownership	0.528	0.580	0.577	0.557	0.542	0.884
(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	0.682
(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	0.874
(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. <sup>a</sup>Indicator variable in which 1 indicates responsibility for financial decision-making in the household. <sup>b</sup>Percentage of risk-seeking choices made in a set of Holt and Laury (2002) lotteries. <sup>c</sup>Ambiguity classification: 1 indicates ambiguity aversion, while 0 indicates no aversion to ambiguity. <sup>d</sup>p-values for multivariate equality of means test based on Wilks' lambda test statistics. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  indicate significance levels for equality of means t-tests of all treatments versus the control treatment  $C$ .

test for differences between means across treatment groups on each of the variables presented in the summary statistics. The last column of Table 3 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 3 are balanced across treatments.

## IV. Experimental Results

### A. Main Results

The discussion of results is structured along the hypotheses defined in Section II. We show the average uptake across treatments in Figure 4. 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.<sup>21</sup> In all of our analyses, we account for the potential correlation within our unit of randomization (i.e., the experimental session) via clustered standard errors.<sup>22</sup>

*Hypothesis 1*—Eliminating contract nonperformance risk in treatment  $T_{NoDef}$ , that is, setting  $r = 0$  instead of  $r = 0.1$ , 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. In line with Hypothesis 1 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

<sup>21</sup>The added covariates are age, gender, financial responsibility, marital status, education, employment, dwelling ownership, land ownership, reduced meals within the last month, score on 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.

<sup>22</sup>We assured that wealth effects cannot play a role in the repeated game by restoring the initial endowment at the start of each round. While learning could theoretically explain average treatment effects observed for all rounds, our results also hold when considering first-round decisions only.

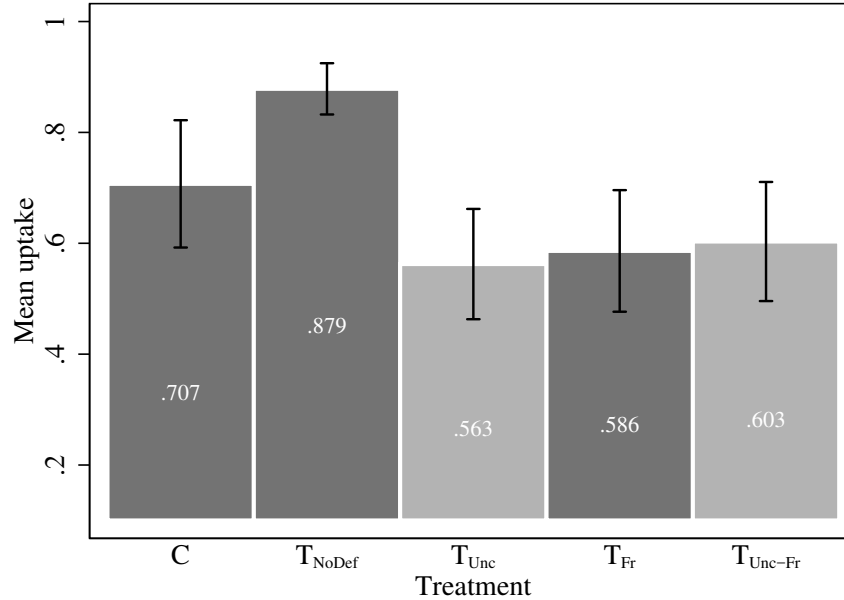


Figure 4: Average Insurance Uptake by Treatment

*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.

Tversky, 1997), we thus conjecture that the presence of contract nonperformance risk in an insurance contract considerably decreases uptake, even when premiums are adjusted for the potential default on valid claims on an actuarially fair basis.

*Hypothesis 2*—When introducing uncertainty in the probability of contract nonperformance in treatment  $T_{Unc}$ , insurance uptake is reduced by 14.5 percentage points ( $p=0.062$ ) relative to  $C$ . The result suggests that the presence of uncertainty in the contract nonperformance probability decreases insurance uptake compared to when contract nonperformance risk is known. In particular, the magnitude of the effects indicates that the reduction of insurance uptake induced by contract nonperformance risk is almost twice as strong in the presence of uncertainty. In line with Hypothesis 2, we conjecture that 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 uncertain.

*Hypothesis 3*—Following our theoretical model, individual ambiguity aversion could be a major factor explaining the sign and strength of the uncertainty 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 lottery choices involving uncertainty to classify individuals as ambiguity averse or non-ambiguity averse.<sup>23</sup> Figure 5 presents average treatment effects for ambiguity-averse and non-ambiguity-averse subjects.<sup>24</sup>

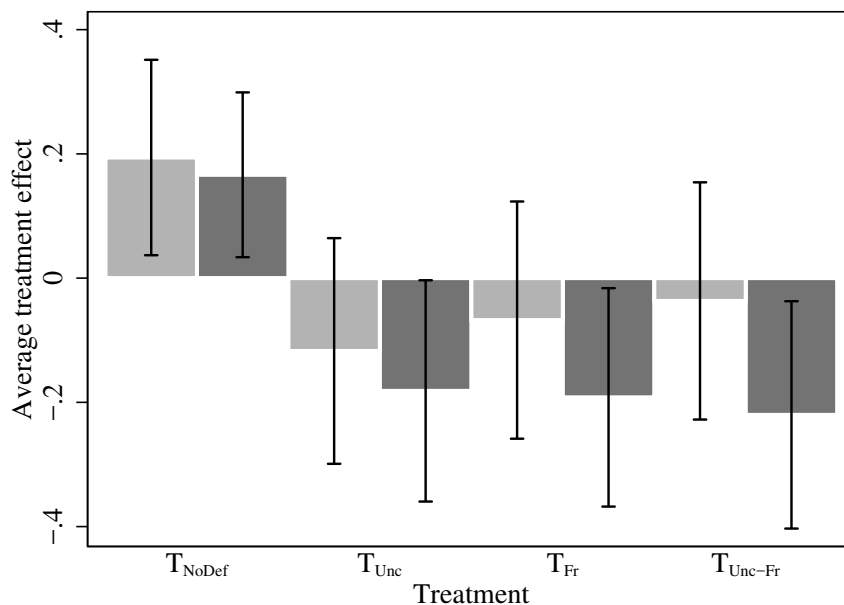


Figure 5: Average Treatment Effects by Treatment and Ambiguity Aversion

*Notes:* The bars represent the average treatment effects relative to control treatment  $C$  for the two subsamples of ambiguity-averse (dark grey) and non-ambiguity-averse (light grey) individuals. Error bars indicate 95 percent confidence intervals, based on clustered standard errors at the session level.

The results for ambiguity-averse subjects are in line with our theoretical predic-

<sup>23</sup>Those choices are between lotteries with known and unknown content. Participants who chose the known content twice were classified as ambiguity averse, and those with one or two choices for known content were classified as non-ambiguity averse. The protocol for this task is available in Appendix D2.

<sup>24</sup>In Appendix Table C2 we provide the respective regression results. The result that a large share of participants exhibits ambiguity aversion is in line with the empirical literature (Trautmann and van de Kuilen, 2015).

tions. There is a strong reduction in insurance demand when the probability of contract nonperformance is uncertain. When ambiguity-averse subjects are confronted with the  $T_{Unc}$  and  $T_{Unc-Fr}$  treatments, insurance demand is reduced by 18.2 percentage points ( $p=0.048$ ) and 22.0 percentage points ( $p=0.02$ ), respectively. For non-ambiguity-averse subjects, all effects of contract nonperformance uncertainty are smaller, but this difference is only significant for  $T_{Unc-Fr}$  ( $p=0.0499$ ).<sup>25</sup> One reason the differences are not more pronounced might be the imprecise classification of participants, leading to a negative point estimate, even for non-ambiguity-averse subjects.<sup>26</sup> Note that we cannot take these latter results as evidence against our theory, as we cannot reject that these effects are, in fact, positive. Overall, the more pronounced uncertainty effect among ambiguity-averse individuals is in line with our theoretical predictions, but these results should be carefully interpreted given the imprecise differences between subsamples and the risk of multiple hypothesis testing involved in subsample regressions.

*Hypothesis 4*—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 uncertain (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 Section II for details). Specifically, we assume CRRA and 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 (see Figure 2), and that (2) the effects for ambiguity-averse subjects should be observed primarily at the boundaries of this “moderate” range

<sup>25</sup>We test the difference between the two subsamples using seemingly unrelated regressions, which consistently follow our earlier specifications.

<sup>26</sup>A possible explanation for this could be that measures of ambiguity aversion are subject to high levels of noise (see l’Haridon et al. (2018)).

(see Figure 3). Our 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.<sup>27</sup>

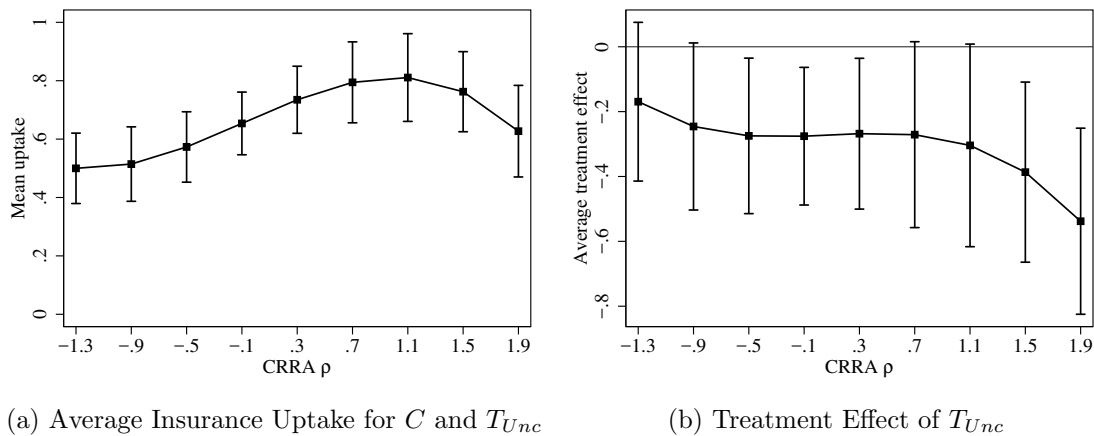


Figure 6: Average Insurance Uptake and Treatment Effect by Risk Aversion

*Notes:* In parts (a) and (b) of this figure, we focus on the subsample of participants in Treatments  $C$  and  $T_{Unc}$ . The dots in (a) represent the mean proportion of individuals taking up insurance under  $C$  and  $T_{Unc}$ , conditional on the percentage of risky choices in the Holt and Laury (2002) lotteries; (b) shows average treatment effects of  $T_{Unc}$ . All estimates are based on third-degree polynomials interacting with  $T_{Unc}$  for the subsample of ambiguity-averse participants used in Table C2. Error bars indicate 95 percent confidence intervals, based on clustered standard errors at the session level.

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 that we translate into their implied midpoints of CRRA parameter intervals. Figure 6 (a) shows the expected

<sup>27</sup>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.

effect of higher insurance uptake among “moderately” risk-averse individuals.<sup>28</sup>

From our simulation, we expect that the effects of the  $T_{Unc}$  treatment should materialize primarily among the risk-averse up until a certain level of risk aversion at which differences between  $C$  and  $T_{Unc}$  no longer matter, because insurance is anyway forgone (i.e.,  $\rho > 1.9$ ). Testing this prediction empirically is not straightforward, because 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, the results presented in Figure 6 (b) mirror the predictions from our model presented in Figure B1, showing that predictions from utility theory are, to some extent, supported by our empirical results. This lends further credibility to our interpretation of the effects.

### B. Belief Formation

Uncertainty is essentially a lack of information. Studying the *dynamics* of decisions under uncertainty is important, because individuals might collect information over time. If such experience (directly, or indirectly via peers) affects the degree of uncertainty, static analyses are insufficient. In our setting, participants lack information about the contract nonperformance probability, which is governed by the mixture of orange and white balls in an opaque bag. We study the dynamics of subjective beliefs about the mixture of balls in this section and thereby shed some light on how individuals update beliefs as well as how they adapt insurance decisions.

A standard economic principle for updating beliefs is based on Bayes’ rule that considers beliefs about an unknown stochastic process in the context of newly available information. As the number of observations increases, the true probability can be estimated more and more precisely. For a perfectly rational Bayesian updater, the subjective probability distribution  $q(\cdot)$  over the possible contract non-

<sup>28</sup>We expect the hump-shape for the  $C$  as well as the  $T_{Unc}$  treatment and Figure 6 (a) shows average patterns accordingly. Note that the patterns within each treatment are in line with our predictions as well.



performance probabilities should converge towards a degenerate distribution with a value of one at the true probability. Such decreasing uncertainty with experience should be reflected in a more positive evaluation of the insurance contract and thus uptake under models of ambiguity. Also under SEU, the level of individuals' prior beliefs and the speed of updating jointly determine posterior probability beliefs, which are the key determinants for uptake. However, consistently updating beliefs is a difficult task. A number of experimental studies suggest that the Bayes' rule is usually not applied correctly, and several cognitively less demanding heuristics have been proposed to explain updating behavior (Tversky and Kahneman, 1971, 1973; Kahneman and Tversky, 1972; Grether, 1980, 1992; Ouwensloot, Nijkamp and Rietveld, 1998; Zizzo et al., 2000; Charness and Levin, 2005). This has particular bearing in our setting, as the experimental subjects stem from a rural low-income population with lower levels of education and (potentially) lower numeracy than populations considered previously.

Irrespective of the exact heuristic that participants use to update beliefs, it is interesting to see whether the incoming information is used. We therefore elicited participants' beliefs about the contract nonperformance probability by having them guess (1) the number of orange balls contained in the bag from which contract nonperformance was drawn (best guess), and (2) the minimum and maximum number of orange balls they deemed possible (as described on the experimental design section). The spread between the minimum and maximum guess of orange balls can be used as a proxy for subjective uncertainty.

Figure 7(a) shows pooled treatment effects for uncertainty treatments  $T_{Unc}$  and  $T_{Unc-Fr}$  as well as beliefs, separately by round. Contrary to the rational updating hypothesis, the treatment effect of uncertainty exhibits no clear trend. At the same time, Figure 7(b) shows that participants are highly pessimistic in terms of subjective contract nonperformance probability. Their best guess is around 2.5, which is 150 percent above the true average contract nonperformance probability. This bias does not decrease over time (Appendix D shows that it should under

Bayesian updating, even when starting out with a pessimistic prior). The minimum and maximum guesses are also high (about 1.6 and 3.5). Only the maximum guess exhibits a downward tendency ( $p=0.003$ ), which also implies a decreasing trend for the subjective spread, our proxy for uncertainty ( $p=0.001$ ).

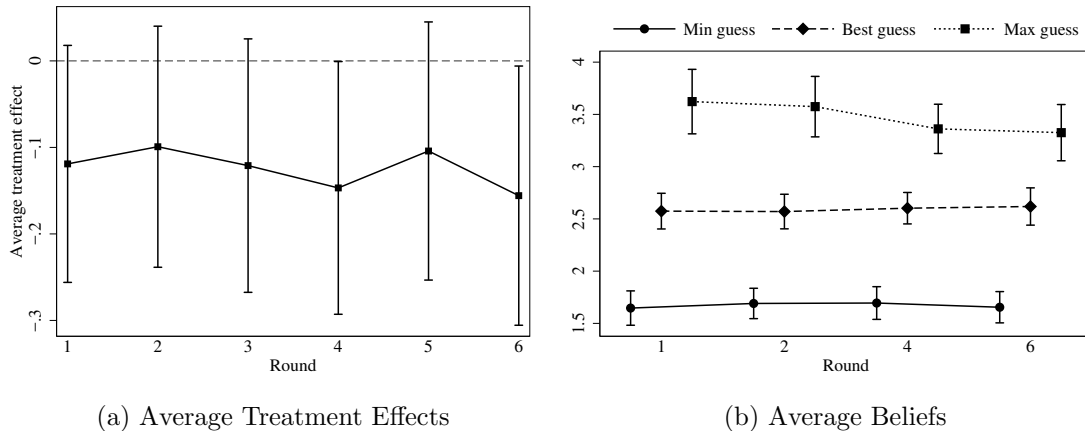


Figure 7: Average Treatment Effects and Beliefs by Round

*Notes:* (a) shows average treatment effects for the pooled treatment groups  $T_{Unc}$  and  $T_{Unc-Fr}$ , and (b) shows average beliefs about the number of orange balls, from a total of 10 balls, in terms of the mean minimum, mean best, and mean maximum guess, by round. Guesses were elicited via a short survey in rounds 1, 2, 4, and 6 (see Section III). We restrict the sample to those participants which always made meaningful statements (i.e., minimum  $\leq$  best guess  $\leq$  maximum, no extreme outliers). The error bars indicate 95 percent confidence intervals, based on clustered standard errors at the session level.

Overall, it seems that the changes in beliefs do not affect demand on average. These aggregate trends might mask interesting dynamics at the individual level. We will therefore pursue the following questions in greater detail: do beliefs play a role in insurance demand? How do realizations of contract nonperformance (own and peer experiences) affect beliefs and insurance uptake? While these questions are important plausibility checks for our theoretical framework, they are difficult to answer, as causality runs multiple ways. Participants' experiences not only influence beliefs and uptake, but also vice versa. For example, without insurance uptake, no realizations of contract nonperformance can be experienced. Additionally, peer effects through communication within the experiment create even more possible causal chains and feedback loops (similar to learning in reality). We can,

however, exploit some features of our experimental setup to avoid identification problems.

First, we did not allow communication in the initial round of the experiment to eliminate peer effects during this period. We can therefore use beliefs, which were always elicited before the corresponding insurance decision, to explain insurance uptake in the first round. Table 4 provides the result of a simple probit regression of insurance uptake on minimum guess, best guess, and maximum guess. The only significant finding is the negative correlation between uptake and the maximum guess ( $p=0.008$ ). The other estimates are imprecise relative to their effect size. Controlling for a number of covariates does not change these results. The results, however, also indicate that perceived uncertainty (i.e., difference between minimum and maximum guess) correlates negatively with insurance uptake, as predicted by the theory. This correlation is significant when replacing the minimum and maximum guess with their difference in the regression ( $p=0.046$ ).

Table 4: Impact of Beliefs on Insurance Uptake

	(1)	(2)
Best guess	0.0466 (0.0373)	0.0421 (0.0363)
Min guess	-0.0016 (0.0554)	-0.0096 (0.0522)
Max guess	-0.0505*** (0.0191)	-0.0520** (0.0206)
Observations	249	249
Covariates	No	Yes

*Notes:* Probit models are used (marginal effects shown) with the dependent variable set to 1 if the subject takes up insurance in the first round. We restrict the sample to those participants which always made meaningful statements (i.e., minimum  $\leq$  best guess  $\leq$  maximum, no extreme outliers). Standard errors (reported in parentheses) are corrected for clustering at the session level. Covariates are age, gender, financial responsibility, marital status, education, employment, dwelling ownership, land ownership, reduced meals within the last month, score on mathematical and numerical capabilities, insurance ownership, health or accident shocks, and weather or livestock shocks. An alternative linear probability specification leads to the same conclusions. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  indicate significance levels of 10, 5, and 1 percent, respectively.

Second, we can use random draws during the experiment for causal inference. In particular, we exploit the random contract nonperformance realizations to identify causal effects of experiences on future beliefs and behavior. It is important to

note that contract nonperformance is only truly exogenous if conditioning on prior insurance uptake *and* experiencing a loss. Our data features 683 such situations (323 in treatments with uncertainty), which represents a sufficiently large set for quantitative analysis. Depending on the contract nonperformance realization, we can compare subsequent reactions in terms of beliefs and insurance uptake.

Figure 8 shows simple OLS regression coefficients of two outcomes—(a) change in maximum guesses and (b) insurance demand—on contract nonperformance.<sup>29</sup> To illustrate effect dynamics over time, we compute lagged outcome variables by ordering outcomes according to game play order, i.e., orders 0 and 6 correspond to outcomes for the participant and the remaining are peer outcomes. We run separate regressions for each lagged outcome on contract nonperformance, whereas the latter takes a value of 1 if contract nonperformance is realized, and 0 otherwise. As contract nonperformance is always the last experience of an individual in each round, no causal effects should exist up to order 0. Only when the subsequent peer (i.e., order 1) makes decisions and states beliefs, can effects start to materialize. An important focal point is order 6, in which the individual experiencing the contract nonperformance takes part in the next round of the experiment. Effects indeed seem strongest, most significant, and most intuitive at order 6, at which there is a significant upwards trend in maximum guesses and a negative, though insignificant, effect on future insurance uptake. Peer effects all seem to fluctuate around zero, even though estimates are too imprecise for drawing firm conclusions. Reassuringly, the "placebo effects" (i.e., decisions up to order 0) do not suggest a violation of our identifying assumptions.

Given that we do not find evidence of peer effects, we now focus on the effects of own experience in the next round (i.e., order 6) for all relevant outcomes. Instead of focusing only on the difference between nonperformance and performance of the contract (as in Figure 8), we consider the effect of each signal separately

<sup>29</sup>We focus on the maximum guesses in particular, because they seem to play the largest role for demand in the previous regression.

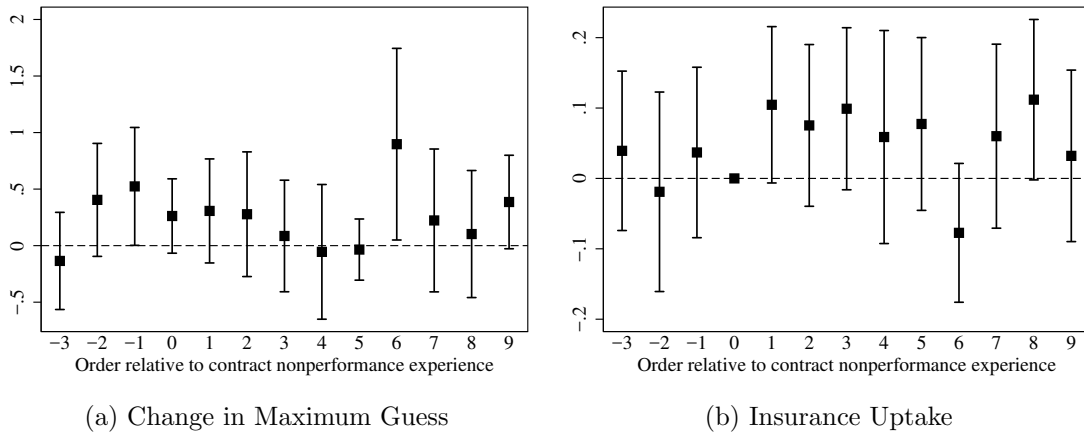


Figure 8: Dynamic Contract Nonperformance Effects

*Notes:* The figures show simple OLS regression coefficients of the two outcomes on contract nonperformance. We compute lagged outcome variables by ordering outcomes according to game play order. Separate regressions are run for each lagged outcome. The sample excludes the treatment without contract nonperformance probability  $T_{NoDef}$  and is restricted to those taking up insurance and facing a loss. The change in maximum guess in part (a) is calculated as the change of the next available maximum guess of the respective participant relative to the last available guess at the time of the event. For guesses, we restrict observations to those participants who always made meaningful statements (i.e., minimum  $\leq$  best guess  $\leq$  maximum, no extreme outliers). Figure (b) shows lagged insurance uptake. The error bars indicate 95 percent confidence intervals, based on clustered standard errors at the session level.

at this point. The reason is that each of the two signals should lead participants to update their beliefs in different directions, relative to receiving no signal. If there is contract nonperformance, chances are that the contract nonperformance probability is higher, and vice versa. We therefore regress future guesses as well as uptake on two dummies: one indicating a loss with subsequent payout and one indicating a loss with subsequent contract nonperformance. As both the contract nonperformance experience and the arrival of losses are fully exogenous and independent events (given insurance uptake), these coefficients are unbiased estimates of the corresponding causal effects.

Table 5 shows the effects of the two possible signals. In almost all cases, effects point in the expected direction: with an insurance payout, guesses tend to decrease (except for the best guess) and uptake increases, while guesses increase and uptake decreases with contract nonperformance. Even though precision of the estimates is limited, we find several significant effects: a positive contract performance effect on

insurance uptake, a positive contract nonperformance effect on minimum as well as maximum guesses, and effect differences between the two signals with respect to minimum and maximum guesses.

Table 5: Impact of Experimental Experience on Beliefs and Uptake

	Best guess	Min guess	Max guess	Uptake
Loss and performance	0.0492 (0.0840)	-0.0228 (0.0574)	-0.147 (0.130)	0.0401** (0.0157)
Loss and nonperformance	0.162 (0.114)	0.396*** (0.0939)	0.750* (0.439)	-0.0372 (0.0486)
p-value $\text{Loss}_{\text{perf}} = \text{Loss}_{\text{nonperf}}$	0.3247	0.0003***	0.0379**	0.1358
Observations	695	695	695	1710

*Notes:* The sample excludes the treatment without nonperformance probability  $T_{NoDef}$  and is restricted to those taking up insurance. For guesses, we restrict the sample to those participants who always made meaningful statements (i.e., minimum  $\leq$  best guess  $\leq$  maximum, no extreme outliers). Standard errors (reported in parentheses) are corrected for clustering at the session level. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  indicate significance levels of 10, 5, and 1 percent, respectively.

These results point to individual updating behavior, which is in line with the theoretical framework to some extent. Several restricting factors stand out. First, participants hold very pessimistic initial priors, and the individual dynamics do not add up to reduced pessimism over time. Second, peer experiences do not seem to influence updating behavior, or at least not as strongly as own experiences. This might be one reason why updating is too slow to affect aggregate demand. We cannot rule out, however, that pessimism and uncertainty also persist in the longer run. At least, the issue does not seem to disappear easily.

### C. Framing

Insurance clients have been shown to be sensitive to the insurer's influence on the decision not to pay claims (Kunreuther et al., 2002; Zimmer, Schade and Gründl, 2009), and we are interested in whether these framing effects are relevant in our uncertain contract nonperformance setting. We consider two main channels by which framing could impact insurance demand. The first channel relates to a framing impact on the perceived uncertainty of contract nonperformance risk. Here we would expect framing to induce a more pessimistic evaluation of insurance that

implies an overweighting of contract nonperformance probabilities. As there should be more scope for subjective weighting when probabilities are unknown, we suspect that the negative framing and the uncertainty treatment should be complementary, jointly inducing a stronger reduction in insurance demand. The second channel presumes a direct impact of framing on utility, independent of perceived uncertainty and subjective probabilities. A utility loss driven by negative framing could, for example, be rationalized by betrayal aversion (Bohnet and Zeckhauser, 2004). In this scenario, framing effects should be independent of the presence of uncertainty.

Figure 4 shows average insurance uptake under all combinations of framing and uncertainty. The treatment effect of introducing negative framing without uncertainty in  $T_{Fr}$  is a 12.1 percentage point reduction in insurance uptake, which is statistically insignificant ( $p=0.134$ ). In contrast to our initial hypothesis, the framing effect does not become larger but even seemingly smaller under uncertainty; the average uptake in treatments featuring uncertainty ( $T_{Unc}$ ), framing ( $T_{Fr}$ ), and their combination ( $T_{Unc-Fr}$ ) is very similar. We cannot reject the hypothesis that the effects of these treatments relative to the control ( $C$ ) are equal ( $p=0.858$ ), suggesting that they are not complementary but substitute each other. This interpretation is substantiated further by the fact that the subjective beliefs about contract nonperformance probabilities measured within our experiment in treatments  $T_{Unc}$  and  $T_{Unc-Fr}$  are very similar.<sup>30</sup>

A remaining question is whether framing and uncertainty are substitutes, as they influence the same belief-related channel, or whether framing works in a distinct way, directly reducing the utility derived by insurance (e.g., through betrayal aversion). Some evidence can be obtained when looking at heterogeneous treatment effects by ambiguity aversion. Ambiguity aversion should only play a role in the belief-related channel, while it would be harder to argue why it should drive the strength of the direct utility loss. Revisiting Figure 5, similar heterogeneity pat-

<sup>30</sup>When testing for differences induced by framing, p-values are large:  $p=0.44$  for maximum guess,  $p=0.91$  for minimum guess, and  $p=0.833$  for mean guess.

terns emerge for all treatments  $T_{Unc}$ ,  $T_{Fr}$ , and  $T_{Unc-Fr}$ . Irrespective of whether uncertainty or negative framing is present, effects are similarly more pronounced for ambiguity-averse participants. While these point estimates suggest that both uncertainty and the framing effect work through a similar mental channel, limited precision prevents us from drawing firm conclusions.

## V. Conclusion

We show the detrimental impact of contract nonperformance risk and uncertainty on insurance demand in a large behavioral experiment and develop a theoretical model that rationalizes the observed effects. Our setup relaxes the standard assumption of known probabilities for insurance contracts failing to perform by allowing for uncertainty. We establish empirically that the demand for insurance significantly decreases when introducing risk and uncertainty, respectively, and that the effects are comparable in magnitude (17.1 and 14.5 percentage points). Along the lines of our theoretical framework, we analyze effect heterogeneity by risk and ambiguity preferences and show that the group of risk- and ambiguity-averse participants is affected most. These results suggest that the reduction in insurance demand induced by contract nonperformance risk that has been identified in the literature is significantly reinforced by uncertainty.

Though the strong uncertainty effect on ambiguity-averse participants is in line with models incorporating ambiguity attitudes (Klibanoff, Marinacci and Mukerji, 2005), we show that pessimistic beliefs within a subjective expected utility framework (Savage, 1954) lead to behaviorally equivalent predictions. In particular, we show that ambiguity-averse (-loving) agents act *as if* they hold pessimistic (optimistic) beliefs under subjective expected utility. In other words, both modes of judgment under uncertainty might equivalently explain results, and we are to some extent agnostic about which of the two is more likely to drive choices.

Uncertainty essentially results from insufficient information about the contract nonperformance probability and should be reduced with experience over time fol-



lowing Bayes' rule. We find that individual updating behavior is to some extent in line with this framework, as own experiences affect beliefs and demand in a meaningful way. However, very pessimistic initial priors and the disregard of peer experiences impede optimal updating, potentially explaining why updating is too slow to affect aggregate demand in our experiment. High subjective uncertainty might well persist also outside the experiment, because information transmission is potentially less effective when information arrives sporadically over longer time periods (Gallagher, 2014).

We also study framing effects regarding the insurer's influence on the decision not to pay claims. While previous studies show that the reason for contract nonperformance is important for demand under probabilistic insurance (Kunreuther et al., 2002; Zimmer, Schade and Gründl, 2009), such framing effects might be even larger under uncertainty. The substance of this conjecture depends very much on whether agents simply dislike unreliable insurers framed as such (as a direct component of their utility) or whether this aspect is related to subjectively overweighting the contract nonperformance probability. In the latter case, there should be a much greater scope for overweighting under uncertainty. Our results, however, do not support this hypothesis. While we cannot rule out that framing plays a role for some participants, it does not seem to change the effect of uncertainty. Results even suggest that both the uncertainty and the framing effect work in a similar way, as they create similar heterogenous treatment effects by ambiguity preferences.

Our findings imply that ensuring low contract nonperformance risk and reducing its uncertainty should both be primary policy objectives. Consequential policy interventions might not be in the best interests of individual insurance providers, because they limit the range of valuable management decisions that benefit the owners of an insurance company. For example, contract nonperformance risk is endogenous to increases in investment risk, decreases in solvency capital, or delays of claims payments. 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 through solvency and market conduct regulation. Similarly, in the case of uncertainty, reasons not to create transparency may be endogenous to management decisions. For example, an insurance provider publishing data about claims payment practices might send an unintended negative signal or lose the option of denying contract nonperformance risk towards clients altogether. These and other strategic factors might limit the incentives for transparency, even though the insurance market as a whole might profit from reduced uncertainty.

There is particular room for improvement in emerging insurance markets with currently low regulatory oversight, limited customer protection, and low levels of trust. Contract nonperformance risk and uncertainty might explain why insurance demand is limited in these settings, and our results show that the effects from reducing contract nonperformance risk and uncertainty can be sizeable among such a low-income population, providing a potential tool to improve market development. From the perspective of an insurance company, a strategic focus on sound policies and practices may prove beneficial in order to gain a competitive advantage and build 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 uncertainty 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 uncertain 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

uncertainty 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 our theoretical model, and the corollary findings appear to be sensible: the demand effects of uncertainty are strongest for ambiguity-averse or pessimistic 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.

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## APPENDIX A: PROOFS

In this appendix we analyze the effects of uncertain contract nonperformance risk, compared to the benchmark setting with a known probability of contract nonperformance. Alary, Gollier and Treich (2013) show that ambiguity aversion raises both marginal willingness to pay and optimal insurance for self-insurance if *loss probabilities* are uncertain.<sup>31</sup> Their intuition is that ambiguity aversion increases the distorted probability of the state to insure, thus also increasing demand for insurance (a special case of self-insurance). We proceed in a very similar way, but in our case uncertainty about contract nonperformance risk leads ambiguity-averse agents to overweight states with positive nonperformance probabilities and thus makes them less willing to insure. This aspect can be observed best when focusing on willingness to pay, and we therefore devote most of our attention to it. We nevertheless show the implications for optimal demand as well.

*A1. Introducing Uncertainty in Probabilistic Insurance*

We assume a decision maker with von Neumann–Morgenstern preferences with utility function  $u(\cdot)$  that is continuous, monotonically increasing ( $u'(\cdot) > 0$ ), and two times continuously differentiable. We furthermore restrict our attention to risk-averse agents ( $u''(\cdot) < 0$ ). Without uncertainty, agents maximize expected utility  $EU_r$ :

$$\begin{aligned}
 (A1) \quad EU_r = & (1 - p)u(w - I(\varepsilon)) \\
 & + p[(1 - r)u(w - I(\varepsilon) - L + \varepsilon) \\
 & + ru(w - I(\varepsilon) - L)].
 \end{aligned}$$

Under uncertainty, we define the ambiguous contract nonperformance probability  $r(\gamma)$ , depending on the unknown parameter  $\gamma$ . The ambiguity is defined as a

<sup>31</sup>Self-insurance refers to a situation where wealth in a specific state (with lower wealth than the certainty equivalent wealth in other states) is increased against a cost incurred in all states.

probability distribution for  $\gamma$  with discrete support  $\{1, \dots, n\}$ . 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 are back to the case described in equation (A1), simply replacing  $r = r(\gamma^*)$ .

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  $\gamma$ .<sup>32</sup> The state-specific expected utilities ( $EU_{r(\gamma)}$ ) are again defined by equation (A1), using  $r = r(\gamma)$ . Thus, the decision maker's expected utility derived from uncertain probabilistic insurance corresponds to:

$$(A2) \quad \Phi^{-1} \left( \mathbb{E}_{\gamma} \Phi(EU_{r(\gamma)}) \right),$$

where  $\mathbb{E}_{\gamma} \Phi(EU_{r(\gamma)}) = \sum_{\gamma=1}^n q(\gamma) \Phi(EU_{r(\gamma)})$ . Using the above formula and plugging in the expected utility definition from equation (A1), we can see that individuals maximize the following expression when deciding about insurance uptake:

$$(A3) \quad \begin{aligned} \mathbb{E}_{\gamma} \Phi(EU_{r(\gamma)}) = & \mathbb{E}_{\gamma} \Phi[(1-p)u(w - I(\varepsilon)) \\ & + p[(1-r(\gamma))u(w - I(\varepsilon) - L + \varepsilon) \\ & + r(\gamma)u(w - I(\varepsilon) - L)]]. \end{aligned}$$

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. As we will show later, this essentially leads 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, lead-

<sup>32</sup>Peter and Ying (2017) suggest that our original results also hold when assuming non-smooth ambiguity preferences such as weighted maxmin expected utility.

ing to an underweighting of contract nonperformance probabilities. An ambiguity-neutral agent uses a linear valuation function. It is easy to show that in this case the resulting objective function  $\mathbb{E}_\gamma EU_{r(\gamma)}$  further simplifies to  $EU_r$  (equation A1), which means that ambiguity-neutral agents behave as if the contract nonperformance probability was known to equal its expected value ( $r(\gamma) = \mathbb{E}_\gamma r(\gamma) = r$ ).

The optimal choice of insurance coverage is the  $\varepsilon$  that maximizes  $\mathbb{E}_\gamma \Phi(EU_{r(\gamma)})$  (or  $EU_r$  in the special case with known contract nonperformance risk, or ambiguity neutrality). Assuming that there is a unique maximum (i.e., concavity of  $\mathbb{E}_\gamma \Phi(EU_{r(\gamma)}) =: V(\varepsilon)$ ), this point is defined by the  $\varepsilon$  satisfying the following first-order condition:

$$(A4) \quad V'(\varepsilon) = \mathbb{E}_\gamma \Phi'(EU_{r(\gamma)}) EU'_{r(\gamma)}(\varepsilon) = 0.$$

Besides the optimal insurance coverage  $\varepsilon$ , we can also derive the marginal willingness to pay for additional coverage from this condition by solving it for the marginal premium increase  $I'(\varepsilon)$  satisfying the equation.<sup>33</sup> We focus our analysis on this object, as we can clearly show how changes in uncertainty and ambiguity aversion are reflected in changes in the marginal willingness to pay, as documented in the following Lemma 1.

**Lemma 1.** 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 compared to when contract nonperformance risk is known.

These effects on willingness to pay also imply corresponding changes in optimal demand (lower marginal willingness to pay implies lower optimal coverage and vice versa).<sup>34</sup> One way to think about this is that the changes in marginal willingness to

<sup>33</sup>Note that the marginal willingness to pay is the marginal premium increase that makes the agent indifferent between purchasing a marginal additional unit of insurance coverage  $\varepsilon$ .

<sup>34</sup>A direct proof for the effect of ambiguity aversion on optimal insurance demand can be obtained by applying the (more general) proof in Alary, Gollier and Treich (2013) to our setup.

pay after introducing uncertainty (as per Lemma 1) imply that the first order condition cannot be fulfilled any more at the initial optimal coverage point  $\varepsilon^*$ . These changes actually lead to  $V'(\varepsilon^*) < 0$  for ambiguity-averse agents after introducing uncertainty, and vice versa for ambiguity-loving agents.<sup>35</sup> Together with concavity of the objective function  $V(\varepsilon)$ , this implies that the the new optimal coverage level  $\tilde{\varepsilon}^*$  is smaller (larger) than  $\varepsilon^*$  for ambiguity-averse (ambiguity-loving) agents.

Having established the relation between changes in marginal willingness to pay and optimal demand in our case, let us now turn back to the dynamics regarding willingness to pay in more detail.

*Proof of Lemma 1:* Taking the derivative of  $EU_{r(\gamma)}$  with respect to  $\varepsilon$  and plugging this into equation (A4) results in the following equation:

$$(A5) \quad \mathbb{E}_\gamma \Phi'(EU_{r(\gamma)}) [(1-p)u'(w-I(\varepsilon))(-I'(\varepsilon)) + p[(1-r(\gamma))u'(w-I(\varepsilon)) - L + \varepsilon)(-I'(\varepsilon) + 1) + r(\gamma)u'(w-I(\varepsilon) - L)(-I'(\varepsilon))] = 0.$$

Solving this for  $I'(\varepsilon)$  defines the marginal willingness to pay for additional coverage:

$$(A6) \quad \frac{pu'(w-I(\varepsilon) - L + \varepsilon)}{(1-p)u'(w-I(\varepsilon))\hat{r} + p[u'(w-I(\varepsilon) - L + \varepsilon) + \bar{r}u'(w-I(\varepsilon) - L)]},$$

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

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. Optimizing equation A1 with respect to  $\varepsilon$  and solving for  $I'(\varepsilon)$

<sup>35</sup>The following holds for ambiguity-averse agents: We know that  $I'(\varepsilon^*) = wtp(\varepsilon^*)$  (the marginal willingness to pay at  $\varepsilon^*$  without uncertainty). Therefore,  $I'(\varepsilon^*) > \tilde{wtp}(\varepsilon^*)$  (marginal willingness to pay with uncertainty) as per Lemma 1. Hence, the first order condition under uncertainty cannot be fulfilled at coverage level  $\varepsilon^*$  (it would only be fulfilled if  $I'(\varepsilon^*)$  was lower, i.e., additional insurance was cheaper). Further, as  $V'(\varepsilon)$  is decreasing in  $I'(\varepsilon)$  (straightforward to show), we know that  $V'(\varepsilon^*) < 0$ . For ambiguity-loving agents, we can proceed analogously to find the reverse.

results in the following simpler equation:

$$(A7) \quad \frac{pu'(w - I(\varepsilon) - L + \varepsilon)}{(1 - p)u'(w - I(\varepsilon)) \cdot \frac{1}{(1-r)} + p[u'(w - I(\varepsilon) - L + \varepsilon) + \frac{r}{(1-r)}u'(w - I(\varepsilon) - L)]}.$$

In order to compare the two equations, it will suffice to compare  $\frac{1}{1-r}$  to  $\hat{r}$  and  $\frac{r}{1-r}$  to  $\bar{r}$ . If  $\hat{r} > \frac{1}{1-r}$  and  $\bar{r} > \frac{r}{1-r}$ , it follows that the marginal willingness to pay decreases, and vice versa. We begin by showing that both conditions are equivalent:

$$(A8) \quad \begin{aligned} & \hat{r} > \frac{1}{1-r} \\ \Leftrightarrow & \frac{\mathbb{E}_\gamma \Phi'(EU_{r(\gamma)})}{\mathbb{E}_\gamma (1 - r(\gamma)) \Phi'(EU_{r(\gamma)})} > \frac{1}{1-r} \\ \Leftrightarrow & \mathbb{E}_\gamma r(\gamma) \Phi'(EU_{r(\gamma)}) > r \cdot \mathbb{E}_\gamma \Phi'(EU_{r(\gamma)}) \\ \Leftrightarrow & \frac{\mathbb{E}_\gamma r(\gamma) \Phi'(EU_{r(\gamma)})}{\mathbb{E}_\gamma (1 - r(\gamma)) \Phi'(EU_{r(\gamma)})} > \frac{r}{1-r} \\ \Leftrightarrow & \bar{r} > \frac{r}{1-r}. \end{aligned}$$

The desired result can now be obtained from equation (A8) 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 (A8) 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 uncertain contract nonperformance risk is lower (higher) than it is in the case where it is known.  $\square$

## A2. Generalizing Lemma 1

Lemma 1 refers to the *introduction* of uncertainty regarding contract nonperformance risk. Other comparative statics such as increasing ambiguity aversion or

increasing the extend of uncertainty are interesting as well. In the following we show that the development of the marginal willingness to pay boils down to one central property:

$$(A9) \quad \frac{\text{cov}(r(\gamma), \Phi'(EU_{r(\gamma)}))}{\mathbb{E}_\gamma \Phi'(EU_{r(\gamma)})}.$$

If this normalized covariance increases, the marginal willingness to pay decreases and vice versa. To see this, consider equation (A6) for two alternative situations with distinct ambiguity in contract nonperformance risk ( $r(\gamma_1)$  versus  $r(\gamma_2)$ ) and distinct ambiguity preferences ( $\Phi_1$  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:

$$(A10) \quad \begin{aligned} & \hat{r}_2 > \hat{r}_1 \\ \Leftrightarrow & \frac{\mathbb{E}_{\gamma_2} \Phi'_2(EU_{r(\gamma_2)})}{\mathbb{E}_{\gamma_2} (1 - r(\gamma_2)) \Phi'_2(EU_{r(\gamma_2)})} > \frac{\mathbb{E}_{\gamma_1} \Phi'_1(EU_{r(\gamma_1)})}{\mathbb{E}_{\gamma_1} (1 - r(\gamma_1)) \Phi'_1(EU_{r(\gamma_1)})} \\ \Leftrightarrow & 1 - \frac{\mathbb{E}_{\gamma_1} r(\gamma_1) \Phi'_1(EU_{r(\gamma_1)})}{\mathbb{E}_{\gamma_1} \Phi'_1(EU_{r(\gamma_1)})} > 1 - \frac{\mathbb{E}_{\gamma_2} r(\gamma_2) \Phi'_2(EU_{r(\gamma_2)})}{\mathbb{E}_{\gamma_2} \Phi'_2(EU_{r(\gamma_2)})} \\ \Leftrightarrow & \frac{\mathbb{E}_{\gamma_2} r(\gamma_2) \Phi'_2(EU_{r(\gamma_2)})}{\mathbb{E}_{\gamma_2} \Phi'_2(EU_{r(\gamma_2)})} > \frac{\mathbb{E}_{\gamma_1} r(\gamma_1) \Phi'_1(EU_{r(\gamma_1)})}{\mathbb{E}_{\gamma_1} \Phi'_1(EU_{r(\gamma_1)})} \\ \Leftrightarrow & \mathbb{E}_{\gamma_2} r(\gamma_2) \Phi'_2(EU_{r(\gamma_2)}) \cdot \mathbb{E}_{\gamma_1} \Phi'_1(EU_{r(\gamma_1)}) > \mathbb{E}_{\gamma_1} r(\gamma_1) \Phi'_1(EU_{r(\gamma_1)}) \cdot \mathbb{E}_{\gamma_2} \Phi'_2(EU_{r(\gamma_2)}) \\ \Leftrightarrow & \frac{\mathbb{E}_{\gamma_2} r(\gamma_2) \Phi'_2(EU_{r(\gamma_2)})}{\mathbb{E}_{\gamma_2} (1 - r(\gamma_2)) \Phi'_2(EU_{r(\gamma_2)})} > \frac{\mathbb{E}_{\gamma_1} r(\gamma_1) \Phi'_1(EU_{r(\gamma_1)})}{\mathbb{E}_{\gamma_1} (1 - r(\gamma_1)) \Phi'_1(EU_{r(\gamma_1)})} \\ \Leftrightarrow & \bar{r}_2 > \bar{r}_1. \end{aligned}$$

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 (A10) by  $r$  ( $= \mathbb{E}_{\gamma_1} r(\gamma_1) = \mathbb{E}_{\gamma_2} r(\gamma_2)$ ), subtracting one, and subsequently multiplying by  $r$

yields the condition:

$$(A11) \quad \frac{\text{cov}(r(\gamma_2), \Phi'_2(EU_{r(\gamma_2)}))}{\mathbb{E}_{\gamma_2} \Phi'_2(EU_{r(\gamma_2)})} > \frac{\text{cov}(r(\gamma_1), \Phi'_1(EU_{r(\gamma_1)}))}{\mathbb{E}_{\gamma_1} \Phi'_1(EU_{r(\gamma_1)})}.$$

The evolution of this normalized covariance 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 1 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 (A11) 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 1.

Beyond the result of Lemma 1, 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 normalized covariance. The above derivation hence delivers a useful criterion which facilitates proving further comparative statics.

### *A3. Relating the Smooth Ambiguity Model to Subjective Expected Utility*

Several concepts can be used to explain reactions to uncertainty in our setup. Those include pessimism and optimism regarding contract nonperformance probabilities in a subjective expected utility model (Savage, 1954), smooth ambiguity aversion (Klibanoff, Marinacci and Mukerji, 2005), and maxmin expected utility (Gilboa and Schmeidler, 1989). In our theory, we only show proofs using smooth ambiguity aversion, but the predictions derived by all those models are nested in the ambiguity model results, as we will show in the following.

In case of maxmin expected utility, this is obvious. Maxmin expected utility simply evaluates options based on the minimum expected utility amongst the set



of expected utilities which are possible under uncertainty. In our case, this would translate to always assuming the highest possible contract nonperformance probability. This is clearly equivalent to setting a pessimistic subjective contract nonperformance probability to this level in a subjective expected utility model.

It is a bit more complex to show that we can represent any level of ambiguity aversion in a smooth ambiguity aversion model by a corresponding subjective contract nonperformance probability (and vice versa), and that this relation is strictly monotone (under CRAA). As a basis for the proof, we can use equation A8, where we showed how marginal willingness to pay for insurance with and without ambiguity relate to each other. Using this equation, we can show under which subjective contract nonperformance probability willingness to pay in a subjective expected utility model equals willingness to pay under smooth ambiguity aversion. Let  $r_{sub}$  denote a pessimistic or optimistic subjective contract nonperformance probability. Then:

$$(A12) \quad r_{sub} = \frac{\mathbb{E}_\gamma[r(\gamma)\Phi'(EU_{r(\gamma)})]}{\mathbb{E}_\gamma[\Phi'(EU_{r(\gamma)})]} = \mathbb{E}_\gamma[r(\gamma)] + \frac{cov[r(\gamma), \Phi'(EU_{r(\gamma)})]}{\mathbb{E}_\gamma[\Phi'(EU_{r(\gamma)})]}.$$

So, a smooth ambiguity averse individual has the identical willingness to pay to a subjective expected utility individual, who adjusts the expected contract nonperformance probability by an optimism/pessimism constant. To see more exactly what happens to  $r_{sub}$  when changing ambiguity aversion, let us write the expected value as a weighted sum of the possible contract nonperformance probabilities  $r(\gamma)$ :

$$(A13) \quad r_{sub} = \frac{\sum_\gamma q(\gamma)r(\gamma)\Phi'(EU_{r(\gamma)})}{\sum_\gamma q(\gamma)\Phi'(EU_{r(\gamma)})} = \sum_\gamma r(\gamma) \frac{w_\gamma}{\sum_\gamma w_\gamma},$$

with  $w_\gamma = q(\gamma)\Phi'(EU_{r(\gamma)})$ . These weights depend on the shape of the smooth ambiguity aversion weighting function. As a result of higher ambiguity aversion, the relative weight for higher contract nonperformance probabilities  $r(\gamma)$  should increase. Let us assume that a higher  $\gamma$  corresponds to a higher contract non-

performance probability and that  $k < l$ . Then the weight of  $r(l)$  relative to  $r(k)$  is:

$$(A14) \quad \frac{\frac{w_l}{\sum_{\gamma} w_{\gamma}}}{\frac{w_k}{\sum_{\gamma} w_{\gamma}}} = \frac{w_l}{w_k} = \frac{q(l)}{q(k)} \frac{\Phi'(EU_{r(l)})}{\Phi'(EU_{r(k)})}.$$

$r(l) > r(k)$  implies that  $EU_{r(l)} < EU_{r(k)}$ . For ambiguity-averse agents (i.e.,  $\Phi'(\cdot) > 0, \Phi''(\cdot) < 0$ ), we know that the relative weight of higher contract nonperformance probabilities must be larger than  $\frac{q(l)}{q(k)}$ . The reverse is true for ambiguity-loving individuals. Intuitively, the relative weight should increase if the weighting function becomes more concave (i.e., higher ambiguity aversion) and vice versa. For a more exact relationship, we specify a CRAA weighting function, such that  $\Phi'(x) = x^{-\zeta}$ . Then the relative weights become:

$$(A15) \quad \frac{q(l)}{q(k)} \left( \frac{EU_{r(l)}}{EU_{r(k)}} \right)^{-\zeta}.$$

Under CRAA, the relative weight of higher contract nonperformance probabilities is hence a strictly increasing function in  $\zeta$ . Also, with  $\zeta \rightarrow \infty$ , these relative weights for higher contract nonperformance probabilities go to infinity (implying that the weighted sum goes to 1), while with  $\zeta \rightarrow -\infty$ , the relative weights go to zero (implying that the weighted sum goes to 0). The simulation presented in Figure A1 shows the relation between  $\zeta$  and  $r_{sub}$  conditional on CRRA parameter  $\rho$  graphically.

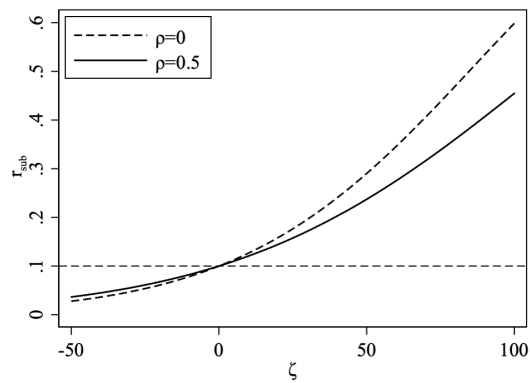


Figure A1: Relationship between Ambiguity Aversion Parameter  $\zeta$  and Subjective Probability  $r_{sub}$

## APPENDIX B: SIMULATIONS

To illustrate the two-way conditionality underlying Hypothesis 4, we show treatment effects of uncertainty for different levels of ambiguity aversion while continuously varying CRRA parameter  $\rho$ . While part (a) of Figure B1 provides a broad indication of the areas in which treatment effects are to be expected based on a deterministic choice model, part (b) shows corresponding results while allowing for stochastic error in choices, where negative (positive) values indicate a higher probability of taking up probabilistic insurance (uncertain probabilistic insurance).

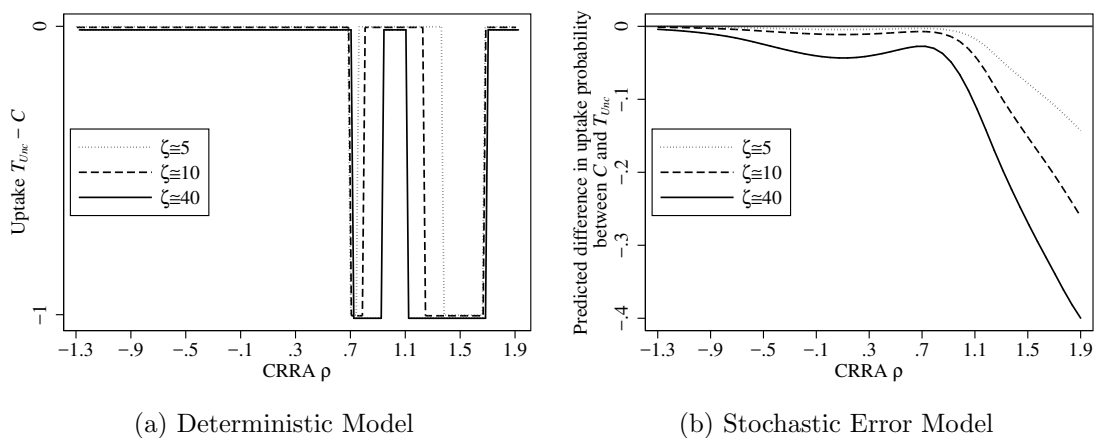


Figure B1: Theoretical Prediction of Uncertainty Treatment Effect by Risk Aversion

*Notes:* This figure shows treatment effects of uncertainty for different CRRA parameters  $\rho$  and conditional on selected values for CRAA parameter  $\zeta$ . (a) Deterministic simulation of uncertainty treatment effect. (b) Difference between the predicted probability of taking up uncertain probabilistic insurance and the predicted probability of taking up probabilistic insurance based on a stochastic error model and noisy estimates of CRRA risk aversion parameter  $\rho$ . The difference is defined as  $F(((EU_r/ EU_0) - 1)/\mu) - F(((EU_{r(\gamma)}/ EU_0) - 1)/\mu)$  if  $\rho \leq 1$  and  $F(((EU_0/ EU_r) - 1)/\mu) - F(((EU_0/ EU_{r(\gamma)}) - 1)/\mu)$  if  $\rho > 1$ , with the cumulative distribution function of the standard normal distribution  $F(\cdot)$  and error sensitivity  $\mu = 0.1$ . To account for noise in our measure of risk aversion, the difference is smoothed using kernel-weighted local polynomial smoothing with a kernel bandwidth of 0.3 (i.e., the average width of the bins in the Holt and Laury (2002) lottery task we apply to elicit risk aversion).

Following the insights of the deterministic simulation in Figure B1 (a), we would expect two areas in which the effects of uncertainty should materialize. Accounting for stochastic errors in decisions as well as noisy estimates of the CRRA parameter  $\rho$ , however, Figure B1 (b) suggests that we should expect the strongest uncertainty treatment effects among the risk-averse. With even greater risk aversion ( $\rho > 1.9$ ),

the differences between probabilistic and uncertain probabilistic insurance should start to decrease again, but this is outside of the parameter space we observe with our experimental measures of risk aversion.

APPENDIX C: LINEAR PROBABILITY AND PROBIT MODELS FOR AVERAGE  
TREATMENT EFFECTS

Table C1: Average Treatment Effects

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

*Notes:* Linear probability models are used, with the dependent variable set to 1 if the subject takes up insurance. For the treatment variables, the control treatment  $C$  serves as the reference category. Standard errors (reported in parentheses) are corrected for clustering at the session level. Covariates are age, gender, financial responsibility, marital status, education, employment, dwelling ownership, land ownership, reduced meals within the last month, score on mathematical and numerical capabilities, insurance ownership, health or accident shocks, and weather or livestock shocks. <sup>a</sup> 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.

Table C2: Average Treatment Effects by Ambiguity Aversion

	Ambiguity-averse		Non-ambiguity-averse	
	(1)	(2)	(3)	(4)
$T_{NoDef}$	0.166** (0.0677)	0.135* (0.0694)	0.194** (0.0803)	0.208** (0.0821)
$T_{Unc}$	-0.182** (0.0909)	-0.184** (0.0872)	-0.117 (0.0927)	-0.114 (0.0919)
$T_{Fr}$	-0.192** (0.0897)	-0.191** (0.0851)	-0.0676 (0.0974)	-0.061 (0.095)
$T_{Unc-Fr}$	-0.220** (0.0934)	-0.229** (0.0891)	-0.0368 (0.0974)	-0.0424 (0.096)
Typhoon		0.04 (0.0507)		0.015 (0.051)
Round		0.00941 (0.00491)		-0.00183 (0.00523)
Constant	0.747*** (0.0638)	0.822*** (0.233)	0.68*** (0.0735)	0.673*** (0.209)
Observations	2,004	1,986	2,532	2,526
R-squared	0.101	0.158	0.0518	0.079
F test	17.48	8.812	8.50	2.50
Covariates	No	Yes	No	Yes

*Notes:* Linear probability models are used with the dependent variable set to 1 if the subject takes up insurance. For the treatment variables, the control treatment  $C$  serves as the reference category. Standard errors (reported in parentheses) are corrected for clustering at the session level. Covariates are age, gender, financial responsibility, marital status, education, employment, dwelling ownership, land ownership, reduced meals within the last month, score on 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.

## 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 uncertainty 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  $\gamma = h \in [0, \dots, 10]$ , given the observation of  $K$  orange balls out of  $N$  draws, as:

$$(D1) \quad P(\gamma = h | K \text{ of } N) = \frac{P(K \text{ of } N | \gamma = h) \cdot P(\gamma = h)}{\underbrace{\sum_i (P(K \text{ of } N | \gamma = i) \cdot P(\gamma = i))}_{P(K \text{ of } N)}}$$

where  $P(\gamma = i)$  is the initial prior for the probability of the respective mix in the uncertain bag. The uncertain 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  $K$  contract nonperformance outcomes out of  $N$  draws ( $P(K \text{ of } N | \gamma = i)$ ) is easy to compute for each of the different possible numbers of orange balls  $\#_i$  in the uncertain 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. Note that, given observed beliefs, we assume individuals to start with *pessimistic priors*. In particular, we assume them to use hypergeometric dis-



tribution for probabilities that averages to 2.5 orange balls out of 10 balls in the uncertain bag, which is close to the observed empirical beliefs. Technically, this is achieved by assuming the big bag to hold 25 orange balls out of 100 balls.

Figure D1 shows two main statistics. The first line shows how average beliefs about the number of orange balls should develop, given the experiment history, Bayesian updating, and pessimistic initial priors ( $E[\#_{\gamma}|K \text{ of } N]$ ). This simulation of the “best guess” clearly decreases over rounds. The second statistic describes the remaining “subjective uncertainty” individuals face. This is calculated as the standard deviation of the possible contract nonperformance probabilities ( $SD[\#|K \text{ of } N]$ ); 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, both some bias and some uncertainty remain until the end of the experiment in our simulation. 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. This picture is qualitatively very similar if we start out with *heterogeneous* individual priors based on initial best guesses.

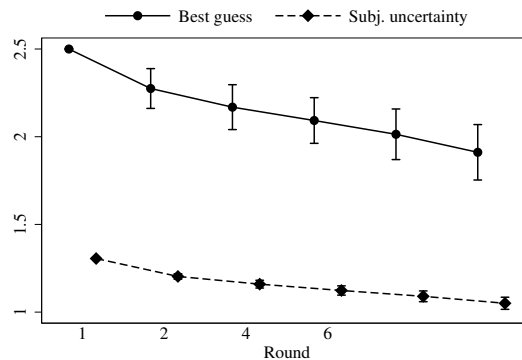


Figure D1: Bayesian Updating Simulation for  $T_{Unc}$  and  $T_{Unc-Fr}$

*Notes:* “Best guess” measures the expected number of orange balls, given the experiment history and pessimistic initial priors for the Bayesian updaters. “Subjective Uncertainty” is the standard deviation of orange balls, given the updated probability distribution for the number of orange balls.

## APPENDIX E: SUPPLEMENTARY EXPERIMENTAL MATERIALS

*E1. Insurance Experimental Protocol***General Information**

§1. Thank you all for coming today. My name is [Name RA] and this is [Researcher]. [Researcher] is a researcher at the University of Mannheim, in Germany. In this experiment today, you can earn a considerable amount of money that you are permitted to keep and take home. In the experiment you will have to make decisions that will influence your personal outcome, but each of you will be given a show-up fee of 100 Pesos at the end for sure. [Show a 100 Peso bill.] The whole procedure will last around 3 hours. Thank you in advance for your effort and time. You should understand that the money you can earn in this experiment is not [Researcher]'s own money. It is money given by the Swiss Government to do a research study. [Researcher] is working together with other researchers who are carrying out similar experiments all around the world.

§2. If at any time you find that this is something that you do not wish to participate in for any reason, you are of course free to leave whether we have started the experiment or not. **But if you feel uncomfortable already now, or you already know that you will not be able to stay for the three to four hours, then you should tell us now.**

§3. It is important that you understand the experiment. Therefore we will check your understanding by asking each of you test questions about the rules. If you do not understand the rules you may always ask the assistants to explain them. **But if you cannot answer the test questions after explaining them again, we will have to exclude you from the experiment and you receive only the show-up fee of 100 Pesos.** But don't worry; we will do our best to help you understand.

§4. Before the experiment you have answered a first set of questions. Before you get handed out your money at the end of the workshop, you are asked to answer the second part of the questionnaire. It is very important for our research, that you answer **all questions seriously**. You will receive your payment only after completing the questionnaire. After knowing these rules, is there anybody who does not like to participate anymore? [Wait some moments.]

§5. You will be paid 100 Pesos for coming to the workshop plus the additional earnings that you have kept throughout the experiment. During the first part of the workshop we will conduct the Lottery Experiment. Here you will have the chance to win some money, but also to lose some money. During the second part of the workshop we will conduct the Insurance Experiment. Here you will have the

possibility to keep some money from an initial endowment of 210 Pesos. At the end, we will sum your earnings from the Lottery Experiment and from the Insurance Experiment, and this amount will be paid out to you. In the case that your total balance from the experiments is negative, we will set your balance for the experiments to zero. **Your private money is always untouched**, so you can only lose money that you received from us for the experiment. **You will for sure receive the show up fee of 100 Pesos. The minimum you receive will be 100 Pesos, and the maximum will be 310 or even more.**

§6. After you went through the experiment and answered your questionnaire at the end, one by one will come to [Researcher], who will hand out your earnings and you sign the receipt. You all received a name tag with player number and group number already. The player number is your personal number and the group number is the same for all of you. Please keep these numbers throughout the experiment; you will have to show them at the end in order to get paid. **So always remember to keep your name tag with you.** If you have questions, please always raise your hand and wait until one of the assistants comes to you. Then you can ask your question and the assistant will answer it.

**Lottery Experiment** [Instructions in next appendix section]

### **Introduction to Insurance Experiment**

§7. This experiment consists of an insurance experiment. In this experiment, you will receive an initial amount of 210 Pesos. We conduct the experiment with play money. That means the bills look similar to real bills and have the same value. At the end of the workshop you get your earnings for this experiment as real Peso money. Here you can see some of the play money. [Show play money]. The insurance experiment consists of 6 rounds. At the end of the session, each participant will receive the payment of **only one of the rounds**, and this round will be chosen randomly.

§8. During each round, you have the risk of losing 150 Pesos from a new initial endowment. Think of an unexpected event that might happen, such as getting sick and not being able to work, or having an accident with the motorcycle and having hospital costs. You will have the chance to buy insurance against this loss for the cost of **50 Pesos** [60 Pesos if  $T_{NoDef}$ ].

§9 [ $C T_{Amb}$ ]. However, there is a chance that the specific type of cost is not covered by the insurance. Then the insurance does not pay out your claim.

§9 [ $T_{Fr} T_{Amb-Fr}$ ]. However, there is a chance that the insurer does not pay your valid claim. For example because a **fraud or scam by the insurance agent, or because the insurer does not want to pay your claim**. Then the insurance does not pay out your claim.

§10. It is important that you understand that there is no correct decision whether to buy insurance or not. It might be good for you, for example, if you have a shock, and the insurance pays out. Or it might be bad for you, for example, if you paid for it and you have no shock [if  $T_{NoDef}$ : or if you have a shock and it does not pay out]. You are free in your personal decision.

§11. How will the experiment work exactly? First, each participant chooses whether to take up insurance or not, before the loss is determined. To determine whether you lose 150 Pesos or not, you will draw a ball from bag 1 [show bag 1] that has 10 balls. Of the 10 balls, 3 are orange and 7 are white. If you draw an orange ball, then that means that you lose 150 Pesos. If you draw a white ball, then that means that you do not lose any money and this round is completed for you. For this round you will have ended up with 210 Pesos if you did not buy insurance and with 160 Pesos [150 Pesos if  $T_{NoDef}$ ] if you bought insurance.

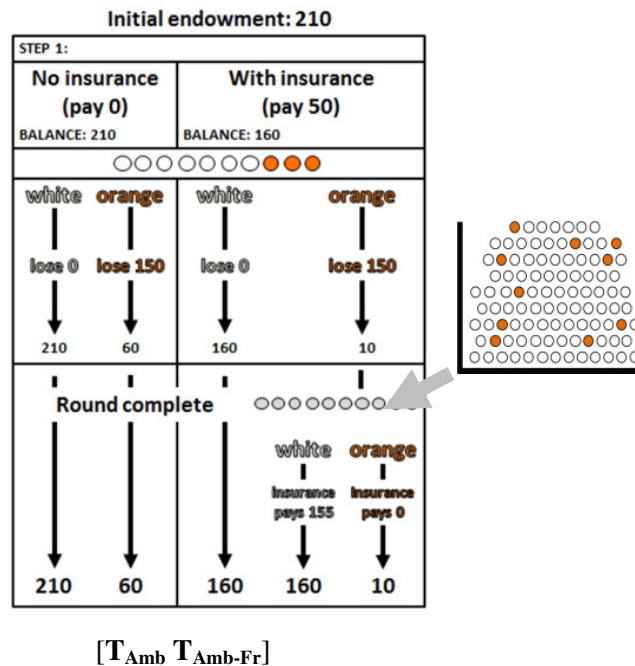
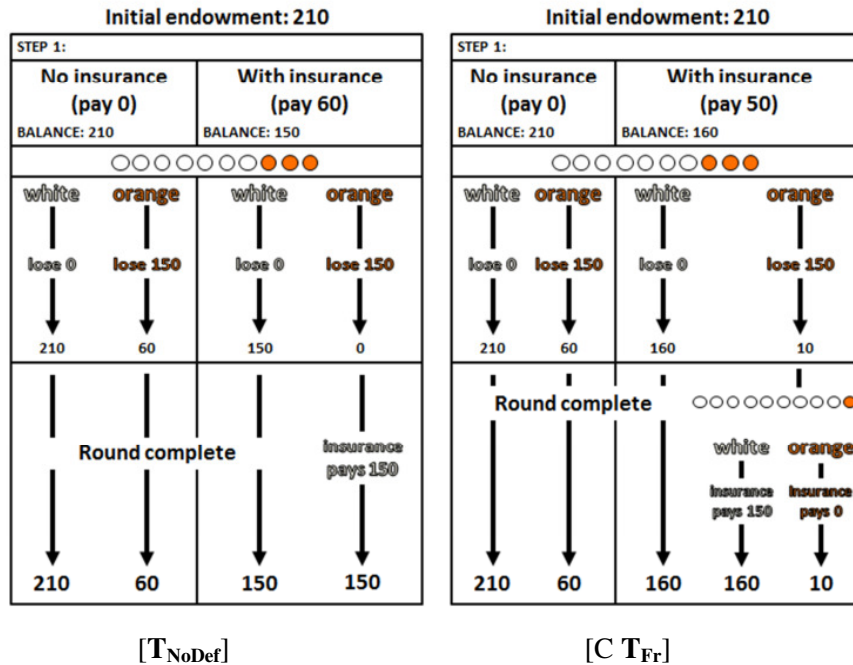
§12 [ $T_{NoDef}$ ]. If you have drawn an orange ball, you lose your 150 Pesos. In this case, if you did not buy insurance before, then you end up with 60 Pesos and this round is complete for you. If you bought insurance before, then you end up with 150 Pesos and this round is complete for you.

§12 [ $C T_{Fr}$ ]. If you have drawn an orange ball, you lose your 150 Pesos. In this case, if you did not buy insurance before, then you end up with 60 Pesos and this round is complete for you. If you bought insurance before, you can claim a payment from the insurer. Once you claim your payment, you have to see whether the insurance pays your claim or not. How is this determined? You will then draw a ball from bag 2 [show bag 2] with 10 balls. If you draw an orange ball from bag 2, then the insurer does not pay your claim and this round is over for you. You will then end up with 10 Pesos in this round. If you draw a white ball, then the insurer pays your claim of 150 Pesos and this money is again yours. Then the round ends for you and you end up with 160 Pesos for this round.

§12 [ $T_{Amb} T_{Amb-Fr}$ ]. If you have drawn an orange ball, you lose your 150 Pesos. In this case, if you did not buy insurance before, then you end up with 60 Pesos and this round is complete for you. If you bought insurance before, you can claim a payment from the insurer. Once you claim your payment, you have to see whether the insurance pays your claim or not. How is this determined? You will then draw a ball from bag 2 [show bag 2] with 10 balls. How many orange balls and how many white balls are in bag 2? We do not know. Why? The balls in bag 2 come from a big black bag with 100 balls. From the 100 balls 10 balls are orange, and 90 balls are white. We will then take 10 balls from the 100 balls, and place them inside bag 2. The number of orange balls in bag 2 will be important for you, because if you draw an orange ball from bag 2, then the insurer does not pay your claim and this round is over for you. You will then end up with 10 Pesos in this round. If you draw a white ball, then the insurer pays your claim of 150 Pesos and this money is again yours. Then the round ends for you and you end up with 160 Pesos for this round.

Let us do some examples [use Poster 1 to illustrate]:

**Poster 1: Illustration of Insurance Experiment**



§13. These rounds will be played 6 times. We will record the amount of money you had for each round and at the end we will pay out one of these 6 rounds. **Only one of the rounds of the experiment is**

**finally paid out.** The round to be paid will be chosen randomly by drawing numbered balls from bag 3 [show bag 3].

§14. So, how many rounds will be played? [Wait for answer]. And how many rounds will be paid out? [Wait for answer]. Once the round to be paid is chosen, we will then proceed to the last part of the questionnaires and then the payments. Are there any questions? [Wait some moments and answer questions]. If there are no further questions, we will now proceed with the test questions. [Administer test questionnaire to confirm understanding]

## Insurance Experiment

§15. We will now start the experiment. The research assistants (RAs) will now provide you with the initial endowment of 210 Pesos in play money; immediately afterwards they will call you by your player number and ask you for your decisions. We ask you to please remain silent for the first round of the experiment. From the second round onwards you are free to talk with the other participants. Are there any questions?

[Wait some moments and answer questions.]

[Assisting RAs (not Instructor) hand out play money to all participants.]

[RA visibly introduces 3 orange balls and 7 white balls in bag 1.]

[if  $C_{T_{Fr}}$ : RA visibly introduces 1 orange balls and 9 white balls in bag 2.]

[if  $T_{Amb} T_{Amb-Fr}$ : RA introduces 10 orange balls and 90 white balls in a big black bag. Afterwards, the RA blindly selects 10 balls from the big black back and introduces it in bag 2. One of the participants checks that bag 2 has 10 balls.]

[RAs start calling the participants by player number in sequential order and ask insurance take-up decision (see Box 1) until all 6 participants are done.]

### Box 1: Initial Take-up of Insurance

§16. Player [insert player number], please follow me. Would you like to take up insurance against the chance of losing 150 Pesos of your initial endowment at the cost of 50 Pesos [60 Pesos if  $T_{NoDef}$ ]? [Mark yes or no in the tablet] Many thanks [insert player name], your available amount is now [160 if bought insurance [150 Pesos if  $T_{NoDef}$ ], 210 if did not buy insurance]. Please take your seat again.

[RAs start calling the participants by player number, in sequential order to draw balls (see Box 2) until all participants are done]

### Box 2: Draw Balls

§16. Player [insert player number], please follow me. I will now ask you to please take a ball from bag 1. If you get an orange ball that means that you lose 150 Pesos of your available amount of [160 Pesos if Insured [150 Pesos if **T<sub>NoDef</sub>**] / 210 if not insured], if you get a white ball that means that you do not lose 150 Pesos of the available amount. [RA presents bag 1 to participant and allows him to blindly take a ball]

[if WHITE BALL and UNINSURED]

§17. Many thanks [insert player name], you drew a white ball and you did not buy insurance. That means you lose 0 of your available amount of 210 Pesos. You end up with 210 Pesos. This round is now complete for you. I have registered what you have earned and I will now take back the play money. Once we are done with all other participants we will start the next round. Please take your seat again.

[if WHITE BALL and INSURED]

§17. Many thanks [insert player name], you drew a white ball and you bought insurance. That means you lose 0 of your available amount of 160 Pesos [60 Pesos if **T<sub>NoDef</sub>**]. You end up with 160 Pesos [150 Pesos if **T<sub>NoDef</sub>**]. This round is now complete for you. I have registered what you have earned and I will now take back the play money. Once we are done with all other participants we will start the next round. Please take your seat again.

[if ORANGE BALL and UNINSURED]

§17. Many thanks [insert player name], you drew an orange ball and you did not buy insurance. That means you lose 150 of your available amount of 210 Pesos. You end up with 60 Pesos. This round is now complete for you. I have registered what you have earned and I will now take back the play money. Once we are done with all other participants we will start the next round. Please take your seat again.

[if ORANGE BALL and INSURED]

§17. Many thanks [insert player name], you drew an orange ball and you bought insurance. That means you lose 150 of your available amount of 160 Pesos [150 Pesos if **T<sub>NoDef</sub>**].

§18 [**T<sub>NoDef</sub>**]. You claim the insurance and the insurance reimburses you 150 Pesos. You end up with 150 Pesos. This round is now complete for you. I have registered what you have earned. Once we are done with all other participants we will start the next round. Please take your seat again.

§18 [**All but T<sub>NoDef</sub>**]. You end up with 10 Pesos. You now can claim an insurance payout. Please draw a ball from bag 2. If you get an orange ball that means that the insurer does not pay out your claim, if you get a white ball that means that the insurance reimburses your loss of 150 Pesos [RA presents bag 2 to participant and allows him to blindly take a ball].

**Box 2: Draw Balls (cont.)**

[if WHITE BALL] Many thanks [insert player name], you drew a white ball. That means the insurance reimburses your loss of 150 Pesos. You end up with 160 Pesos. This round is now complete for you. I have registered what you have earned and I will now take back the play money. Once we are done with all other participants we will start the next round. Please take your seat again.

[if ORANGE BALL] Many thanks [insert player name], you drew an orange ball. That means the insurance does not reimburse your loss of 150 Pesos. You end up with 10 Pesos. This round is now complete for you. I have registered what you have earned and I will now take back the play money. Once we are done with all other participants we will start the next round. Please take your seat again.

[After all participants are done with round 1, specify that now they are free to talk]

[DO 6 ROUNDS]

[Start next round of the experiment and distribute once more the initial endowment of 210 Pesos]

§19. Now the six rounds are done and the experiment is over. We will now randomly choose the round that will be paid out to you. [Each subject draws one of six balls from a bag, and the number that comes out will be the round paid out. Please register the number drawn by your participant in the tablets]

[ADMINISTER POST QUESTIONNAIRE]

[Participants get their money and sign their receipt]



*E2. Lottery Choice Task Protocol*

§1. For the following game, you will need to work with tablets. You can work with the tablets simply by pressing the buttons on the screen. If you have any questions, you can always raise your hand and a research assistant will come and help you. If you have problems with reading information on the tablets, please raise your hand and we will assist you [if someone raises his/her hand, RA comes and talks to the person. If problems are too serious, the person has to skip the lottery game + waits outside]. Please switch off your mobile phone before the game starts. Before we start, we would again ask you to confirm that you agree with the rules we just explained to you. If you agree please press “I agree” on the tablet.

§2. The current game deals with decisions between lotteries. I will explain what these lotteries are and how they work next. After this you will receive some information about your task. Then you will work on the task. Everything together will take around 45 minutes. Please all press the “Start” button now [wait for everyone to press the Start button].

§3. Example urn. On your tablet, you see a box [RA prepares the bag with the balls]. This box is a lottery. It contains 10 balls with different values. This is the box on your tablet [show bag]. As you can see, this box contains 6 balls with a value of 70 [show balls]. And it contains 3 balls with a value of 230 [show balls]. It contains 1 ball with a value of -120 [show ball]. To determine the payout of the lottery in the following game, we randomly draw one ball from this box. This means that we stir the balls in the box and draw one ball without looking. You gain or lose the amount of money that is shown on the ball. Values greater than 0 mean that you win this amount of money. Values smaller than 0 mean that you lose this amount of money.

§4. In our example, this means, you could win 70 pesos, if you draw a ball with the value 70. You could win 230 pesos, if you draw a ball with the value 230. And you could lose 120 pesos, if you draw a ball with the value -120 [show corresponding balls during explanation]. Remember that in the game we only draw 1 ball from the box. In the game, you will also see a description of the lotteries. Please press the “Next” button to see what this description looks like [wait for everyone to press the “Next” button].

§5. As you can see, the description of the lottery has the same information as the box [RA puts poster 1 on the wall for the length of explanation]. In this illustration, you can see the values and the probabilities of the lottery. As you can see, in the “value” column there are the different values that you can win or lose in this lottery [point to values]. And in the “probability” column you can see the chances that you get each of the values when we randomly draw one ball from the box without looking.

### Which Lottery would you prefer?

Lottery A			Lottery B		
	Value	Probability		Value	Probability
Win	70	6 out of 10	Lose	130	4 out of 10
Win	230	3 out of 10	Lose	60	6 out of 10
Win	120	1 out of 10			



**Poster 1: Illustration of Lotteries**

§6. As you can see, 6 out of 10 balls have a value 70, but only 3 out of 10 balls have a value of 230 [point to the value that corresponds to that chance]. This means that it is more likely to draw a ball with 70 than a ball with 230. Finally, only 1 out of 10 balls has a value of -120. This means that there is a less chance that you will draw -120 than drawing 230 and much lesser chance compared to 70. Do you have any question what the lottery means so far? [wait for questions]. Please press the “Next” button.

§7. In the current game, you will always be presented with two lotteries. Your task is to decide which of these two lotteries you would prefer to play. Note that there is no right or wrong answer. We are simply interested in your personal preference. Please take a look at the following two lotteries called “Lottery A” and “Lottery B”. You can indicate which lottery you prefer to play by pressing the corresponding button. For Example, if you choose “Lottery A”, it is like drawing a ball from the box shown here [point at “Lottery A” box]. And if you choose “Lottery B”, it is like drawing a ball from the box shown here [point at “Lottery B” box]. Please pick one of the lotteries – this choice is just an example which has no consequence for your earnings [wait for everyone to pick a lottery] [RAs come to participants and ask them if they understand what the instructing RA explained to them]. Do you have any questions regarding your task? [wait for questions]. Please press the “Next” button so I can give you some additional details.

§8. The current game has 5 blocks – 1 practice block and 4 real blocks. In each block you decide between several lottery pairs. Please have a look at the lotteries first before you press a button. In some blocks you can win money, in some blocks you can lose money. At the end of the game, we will randomly select 4 lotteries that you have chosen – one from each real block. We will randomly draw a ball from each of these lotteries. The value on the ball shows how much money you gain or lose. We will add up the gains, subtract the losses, and divide them by 4. This will be your final earnings for the game. You will now start with your task. Please

work alone and do not talk to each other so you don't disturb the other participants. Please take the task seriously. This is very important for our study. Please remember that your final payout depends on your choices. Please press the "Next" button.

§9. First lottery block (practice block). In the following, you will work on the practice block to help you understand more of the task. The choices you make in this block will not affect your final earnings. You will be presented with 10 lottery pairs. After your choice, we will randomly draw one ball for each lottery in the pair. We will show these balls to you. This way, you can see what the result is for your lottery and for the lottery that you did not choose. This means you can compare the pesos you win or lose in each lottery. We only show you the results in this practice block. Please raise your hand after you have finished the block or if you have questions. Please start the game by pressing the "Start game" button.

[RAs stay with the participants to answer questions – in case participants have a question about their task, please use the following explanation:] [your task is to decide which of 2 lotteries you prefer to play. A lottery means that we randomly draw 1 ball from a box. You gain or lose the amount of money that is shown on the ball. In the "value" column you see the different values that are possible in the lottery. These are the different amounts of money you can win or lose. In the "probability" column, you find the probability of each value. For example: \_\_\_ of the 10 balls in the box have the value \_\_. \_\_\_ of the 10 balls in the box have the value \_\_. This means that it is more likely to get a value of \_\_\_ than a value of \_\_.]

[if participants only press one button all the time in the first block, the following message appears on the tablet: Please raise your hand to contact the research assistant. You have pressed the same button many times. Because of this, we just wanted to remind you of your task: Your task is to decide which of 2 lotteries you would prefer to play. Please take the task seriously. This is very important for our study. A lottery means that we randomly draw 1 ball from a box. This means that we stir the balls in the box and draw one ball without looking. You gain or lose the amount of money that is shown on the ball. In the "value" column there are the different values that you can win or lose in the lottery. And in the "probability" column you can see the chances that you get each of the values when we draw one ball from the box without looking] [RA presses Next to go to next slide]

§10. [RAs read out text on tablet, it mentions gains/losses for different participants]. You have finished the first block of the game. All previous decisions were practice decisions that did not affect your earnings. Now you will start with the real decisions. This means that from now on you will no longer see the result of the lotteries after your choice. It also means that you from now on you can win or lose actual money on the following rounds.

[IN THIS STUDY, WE ONLY MAKE USE OF A SUBSET OF LOTTERY CHOICES. FOR SIMPLICITY OF PRESENTATION WE RESTRICT THE PRESENTATION HERE TO THOSE LOTTERIES USED TO ELICIT RISK AND AMBIGUITY PREFERENCES]

§11. Second lottery block. In the next block, you will be presented with \_\_\_ lottery pairs. Each lottery can have values between 0 pesos and 250 pesos. This means that in the following

part you can only win different amounts of money. Higher values mean that you win more money. Smaller values mean that you win less money. Please press “Start block” to start the next block [wait for participants to finish the second block and raise their hand] [RAs stay with the participants for the first item (filler item) to answer questions and then go to the back] [only come to participants in case they have a questions/raise their hand]. You have finished the second block of the game.

[IN THIS STUDY, THE LOTTERY PAIRS PRESENTED IN TABLE 1 WERE USED]

Table 1: Risk Lottery Pairs

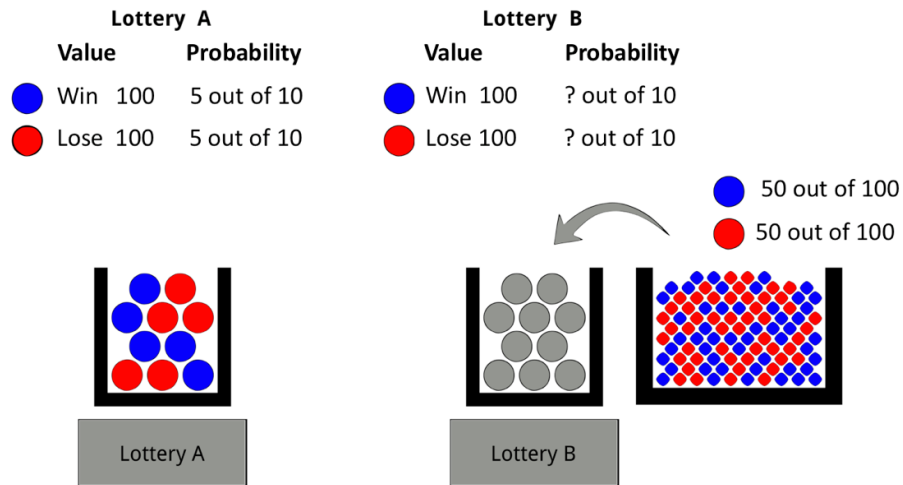
Lottery A (“safe”)	Lottery B (“risky”)	Expected payoff difference
9/10 of 110, 1/10 of 130	9/10 of 10, 1/10 of 250	78
8/10 of 110, 2/10 of 130	8/10 of 10, 2/10 of 250	56
7/10 of 110, 3/10 of 130	7/10 of 10, 3/10 of 250	34
6/10 of 110, 4/10 of 130	6/10 of 10, 4/10 of 250	12
5/10 of 110, 5/10 of 130	5/10 of 10, 5/10 of 250	-10
4/10 of 110, 6/10 of 130	4/10 of 10, 6/10 of 250	-32
3/10 of 110, 7/10 of 130	3/10 of 10, 7/10 of 250	-54
2/10 of 110, 8/10 of 130	2/10 of 10, 8/10 of 250	-76
1/10 of 110, 9/10 of 130	1/10 of 10, 9/10 of 250	-98

§12. Third lottery block. [NOT USED IN THIS STUDY]

§13. Risk urn. [after everyone is done with first 3 blocks] For the last blocks of the game, we will change the lotteries a bit. Please press “Next” to see the first example [RA shows poster 2]. As in the previous blocks, each lottery has 10 balls. However, in the following blocks the balls have colors on it – either blue or red. In Lottery A, there are 5 blue balls and 5 red balls. Again, we randomly draw one ball from the box to determine your payoff. Depending on the color, you gain or lose a specific amount of money. In this lottery, you would gain 100 pesos if you draw a red ball. And you would lose 100 pesos, if you draw a blue ball.

§14. Ambiguity urn. Lottery B is different. Please press “Next” to see what it looks like. Lottery B is constructed in a different way. For this lottery, you also have 10 balls in the box, but you don’t know the color of each ball. Therefore, the balls are shown in grey. However, you do know that the 10 balls have been randomly drawn from a larger box with 100 balls [show large box]. Randomly means that we stir the balls in the large box, draw 10 balls without looking and put them in the small box [show this process on poster 2]. As you can see, you know how many balls of each color are in this large box. There are 50 blue balls and 50 red balls in the large box. To determine your payoff for lottery B, we randomly draw a ball from the small box. Depending on the color, you gain or lose a specific amount of money. In this lottery, you would gain 100 pesos if you draw a red ball. And you would lose 100 pesos, if you draw a blue ball. Please press “Next” and I will tell you about your task.

### Which Lottery would you prefer?



### Poster 2: Illustration of Ambiguity Task

§15. Ambiguity task. Your task is again to decide which of the two lotteries you would prefer to play. As I explained to you, you have one lottery where the colors of the balls in the urn are known and one lottery where you don't know the colors of the balls. However, for this lottery you know the colors of the balls in the large box from which the balls came from. You will now start with the last 2 blocks. Please press the "Next" button.

§16. Fourth lottery block. In the following, you will work on the fourth block of the game. Please press "Start block" to start the next block [take down poster 2 + wait for participants to finish the fourth block and raise their hand] [RAs stay with the participants for the first item to answer questions and then go to the back] [only come to participants in case they have a questions/raise their hand] You have finished the fourth block of the game.

[IN THIS STUDY, THE LOTTERY PAIRS PRESENTED IN TABLE 2 WERE USED]

Table 2: Ambiguity Lottery Pairs

Lottery A ("risky")	Lottery B ("ambiguous")
5/10 of 100, 5/10 of 0	?/10 of 100, ?/10 of 0
5/10 of -100, 5/10 of 0	?/10 of -100, ?/10 of 0

§17. Fifth Lottery block. [NOT USED IN THIS STUDY]

You have finished all blocks. Please raise your hand to contact the research assistant. Thank you for your work. You will learn about your payout after all games are finished.

*E3. Sample Test Questionnaire for  $T_{Unc}$  and  $T_{Unc-Fr}$*

[Participation was conditional on answering test questions correctly]  
 [One re-explanation allowed, but large majority passed in first attempt]

Q1. How many balls in bag 1 are orange? \_\_\_\_\_  
 CORRECT? YES  NO

Q2. How many balls in bag 2 are white? \_\_\_\_\_  
 unknown  
 CORRECT? YES  NO

Q3. How is the number of orange and white balls in bag 2 determined?  
 10 balls are drawn from a big black bag  
 By myself  
 I cannot know  
 CORRECT? YES  NO

Q4. How many balls in bag the big black bag are orange? \_\_\_\_\_  
 CORRECT? YES  NO

Q5. What does it mean if you draw a white ball from bag 1?  
 You can claim insurance  
 You lose 150 Pesos  
 You lose 0 Pesos  
 CORRECT? YES  NO

Q6. What does it mean if you draw an orange ball from bag 1?  
 You lose 250 Pesos  
 You lose 150 Pesos  
 You lose 0 Pesos  
 CORRECT? YES  NO

Q7. Which conditions have to be fulfilled for you to receive an insurance payout?  
 (May chose more than one)  
 You pay 30 Pesos  
 You had a loss of 150 Pesos by drawing an orange ball from bag 1  
 You drew a white ball from bag 1  
 You paid 50 Pesos to be insured  
 You drew an orange ball from bag 2  
 You drew a white ball from bag 2  
 CORRECT? YES  NO

Q8. With how much do you end up with...  
 ...when you have insurance and have no loss (white)? \_\_\_\_\_  
 ...when you have insurance and have a loss (orange) and the claim is paid (white)? \_\_\_\_\_  
 ...when you have insurance and have a loss (orange) and the claim is not paid (orange)? \_\_\_\_\_  
 ...when you have no insurance and have no loss (white)? \_\_\_\_\_  
 ...when you have no insurance and have a loss (orange)? \_\_\_\_\_  
 CORRECT? YES  NO