On Information and the Demand for Insurance

Amit Gandhi
University of Pennsylvania

Anya Samek
University of Southern California

Ricardo Serrano-Padial*
Drexel University

December 20, 2019

Abstract

New computing tools and big data are transforming the insurance industry. Insurers may now have more information about underlying risks than consumers do. We evaluate the individual and market equilibrium effects of this rising information asymmetry using an incentivized survey. We find that consumers are willing to pay higher premiums for insurance when there is uncertainty about underlying risks, which leads to a right-ward shift in demand for insurance. Importantly, we find that the information premium is negatively correlated with risk aversion, which leads to a selection effect. Individuals who are willing to pay more for insurance when underlying risk information is uncertain are not necessarily those who are most risk averse. We show that these effects can lead to substantial reductions in consumer welfare and induce insurers to selectively disclose information to consumers depending on their risk profile.

JEL classification: D12, D14, D81, G22, J33

Keywords: risk, uncertainty, ambiguity, insurance, compund lottery, field experiment, demand analysis

*Corresponding Author: Ricardo Serrano-Padial, email: rspadial@gmail.com. This paper was funded as a pilot project as part of a Roybal grant awarded to the University of Southern California, entitled "Roybal Center for Health Decision Making and Financial Independence in Old Age" (5P30AG024962-12). The project described in this paper relies on data from surveys administered by the Understanding America Study (UAS) which is maintained by the Center for Economic and Social Research (CESR) at the University of Southern California. The opinions and conclusions expressed herein are solely those of the authors and do not represent the opinions or policy of any institution with which the authors are affiliated nor of USC, CESR or the UAS.

1 Introduction

The insurance industry plays a central role in the economy. In the United States, insurance premiums amount to $1.2 trillion each year, or about 7% of gross domestic product.[1] The industry is experiencing a technological transformation with the emergence of InsurTech companies using big data, artificial intelligence and machine learning to assess consumer risk.[2] The increasing availability of personal-level data and computing tools to insurers means that they may be able to obtain more precise estimates of underlying risks than those available to consumers, who have difficulty estimating their own risks (Handel and Kolstad, 2015).

The impact of the change in information asymmetry between insurers and consumers is not well understood. Understanding the nature of these effects requires data on two key factors that are typically unobserved in insurance claim data. The first factor is consumers' attitudes toward complex information and their ability to process risk-related information, which affects the extent of information frictions. Related work has documented that individuals are ambiguity and complexity averse. This suggests that willingness-to-pay (WTP) for insurance should be higher when risk-related information is complex (i.e., a level effect).

The second factor is the relationship between risk preferences and attitudes toward complex information. This factor is critical since it determines the allocative effect of information frictions (i.e., a selection effect). A positive correlation implies that as risk-related information becomes more complex, more risk averse agents are more likely to buy insurance, whereas a negative correlation implies that more risk averse agents are *less* likely to buy insurance. The latter possibility suggests negative welfare consequences for consumers, since those who need insurance most based on their risk preferences will be less likely to purchase it when information about underlying risks is complex. Since both risk aversion and the attitudes toward information about risk may drive WTP for insurance, estimating both preference parameters from existing administrative data on insurance take-up is not tractable.

In this paper, we collect evidence on these two factors by using an incentivized survey. In our survey, over 4,000 Americans representative of the U.S. population are asked their willingness to pay to fully insure a hypothetical product that has a known value. We experimentally vary underlying risks and the risk-related information

[1] https://www.iii.org/fact-statistic/facts-statistics-industry-overview

[2] For an overview of recent technological trends, see the 2019 report on "Insurance and Big Data" (https://www.genevaassociation.org/big-data-and-insurance. Companies like Google and Amazon invested in InsurTech companies in 2018 and are considering entering insurance markets. See https://www.insurancejournal.com/news/national/2019/01/02/513324.htm.

structure, including certain risks, a range of risks, and compound risks. Our survey has several attractive features. First, the experimental variation in underlying risk and risk-related information allows us to jointly estimate the distribution of risk, risk aversion and attitudes toward complex information. Second, we assign each respondent to experience a string of scenarios with varying risks, which allows us to explore the inter-personal ranking of insurance take-up. Finally, we take advantage of a rich set of background data on survey respondents, including demographic background, socio-economic status, cognitive ability and financial literacy, which allows us to explore the sources of information frictions.

We find that willingness to pay for insurance is significantly higher in settings with more complex or ambiguous information. The average 'information premium,' defined as the difference in WTP under compound/complex risks and under simple risks, is as high as 100% of the expected loss. Crucially, we find a negative correlation of about -0.3 between risk aversion and aversion to complex or ambiguous information across individuals. This negative correlation is remarkably robust to variation in underlying risk probability or to the sources of informational effects and holds up to measurement error correction. In addition, we find that the information premium goes down as losses become more likely, even becoming negative. We replicate the pattern of results in a laboratory experiment that we also conduct and in data that we obtained from three laboratory experiments in the literature.[3]

We next conduct a demand analysis by combining data from our survey with existing estimates of the distribution of risks in actual insurance markets. Specifically, we sample the WTP data from our survey using the empirical distribution of insurance claims in existing markets and construct a synthetic demand curve. We consider different supply-side scenarios that vary in terms of degree of market competition (from perfect competition to monopoly) and ability of insurers to price discriminate on the basis of risk (uniform pricing versus risk-based pricing). Motivated by the advent of InsurTech, We also analyze the strategic choice of information disclosure by a monopolist with precise estimates of the risks faced by consumers.

The results of this analysis point to a significant misallocation of insurance associated with information frictions, which is largely driven by the negative correlation between risk aversion and the information premium, and to selective disclosure policies that discriminate against low risk consumers. First, the presence of complex or

[3] We evaluate the data from Halevy (2007), Abdellaoui et al. (2015) and Chew et al. (2017). In our own data and in the one related study that allows it (Abdellaoui et al., 2015), we also apply the *obviously related instrumental variables* (ORIV) approach (Gillen et al., 2017) to correct for potential measurement error and obtain unbiased estimates that are in line with the raw estimates.

ambiguous risk information drives up the average WTP at low and moderate risk probabilities, which implies that aggregate demand is higher relative to a world with simple and non-ambiguous information. Second, since risk aversion and the information premium are negatively correlated, the average risk premium will be lower in a market where agents are exposed to complex information than in a market where agents face equivalent risks but are fully informed about these risks. We estimate the welfare loss associated with complex information to range between 7% under perfect competition to 40% under monopoly. The results are quantitatively similar whether or not insurers are allowed to price discriminate. Third, due to the negative relationship between information premium and underlying risk, a monopolist would strategically withhold information about risks from low risk consumers and disclose risk information to high risk consumers. These results suggest that a policy of mandatory disclosure of risk estimates by insurers can improve welfare.

Finally, we consider the drivers of the heterogeneity in the information premium. We find that the features of information risks - e.g., the size of the range of probabilities - have a significant impact on information premia. Moreover, while individual characteristics - sociodemographic characteristics, financial literacy and the ability to reduce compound lotteries - account for about 20% of the variation in risk premia, they only account for about 1% of the variation in information premia. The main covariate of information attitudes are risk attitudes themselves, which alone account for 10% of the variation in information premium.

Our first contribution is to the empirical literature that uses naturally occurring data on insurance take-up and claims to study the demand for insurance (Einav et al., 2010; Jaspersen, 2016). Much of the related literature has made the assumption that consumers are perfectly able to estimate their underlying risks (Barseghyan et al., 2011; Einav et al., 2012; Sydnor, 2010). However, recent work has noted that welfare analysis and the effect on market competition is sensitive to information frictions (Handel and Kolstad, 2015) and to the specification of risk preferences (Einav et al., 2010). We propose that in addition, the joint distribution of risk, risk preferences and attitudes toward information need to be considered. Specifically, our results reject the assumption in Handel and Kolstad (2015) that informational frictions and risk preferences are orthogonal. In addition, we propose that ignoring the information premium in related work can lead to biased estimation of risk preferences. Our analysis is also related to measuring asymmetric information in insurance markets (Chiappori and Salanié, 2013). Specifically, our estimates of the relationship between risk, risk preferences and information attitudes cast doubt into using the correlation between risk and insurance coverage as a gauge of the degree of adverse selection in the market.

Our second contribution is to the experimental literature on risk preferences, which has a long tradition in economics (Harrison and Rutström, 2008). For example, this literature evaluates the invariance of risk preferences to the choice domain (Dawling et al., 2011; Harrison, 2011; Vieider et al., 2015) and to violations of the reduction principle - i.e., the inability of individuals to reduce compound lotteries (Starmer, 2000). The literature also documents aversion to compound lotteries and aversion to ambiguity (Halevy, 2007; Abdellaoui et al., 2015; Chew et al., 2017). Some of our results - for example that risk aversion decreases with the underlying risks - are in line with related work (Abdellaoui et al., 2015). However, our paper is entirely new in estimating the correlation between risk preferences and attitudes toward information.

Our findings also have policy relevance. Specifically, they yield a policy recommendation regarding information disclosure in insurance markets that is timely to the existing technological transformation of insurance with the advent of InsurTech. Policies aimed at simplifying the information conveyed to potential insurance buyers, such as risk assessments associated with individual socio-demographic profiles and behavior data, may lead to significant welfare gains by mitigating the selection effect that we observe.

In what follows, Section 2 lays out the theoretical framework, Section 3 provides an overview of the survey design, Section 4 describes our results, Section 5 presents our demand simulation results, Section 6 investigates the sources behind information attitudes and Section 8 concludes.

2 Framework

We are interested in environments in which an agent's demand for insurance might vary with the information about the underlying (objective) risks. To motivate our analysis, consider the following thought experiment. Imagine an urn containing red and blue balls. If a red ball is drawn from the urn, the agent suffers a \$100 loss. No loss occurs if a blue ball is drawn from the urn. The agent does not know the precise proportion of red and blue balls in the urn and instead observes a sample of draws from the run. Figure 1 illustrates two possible scenarios. In the first scenario, the agent receives a sample of two balls – one red and one blue. In the second scenario, the agent receives a sample of ten balls – five red and five blue. The question is whether we should expect the willingness to pay for insurance against the loss to be the same across the two

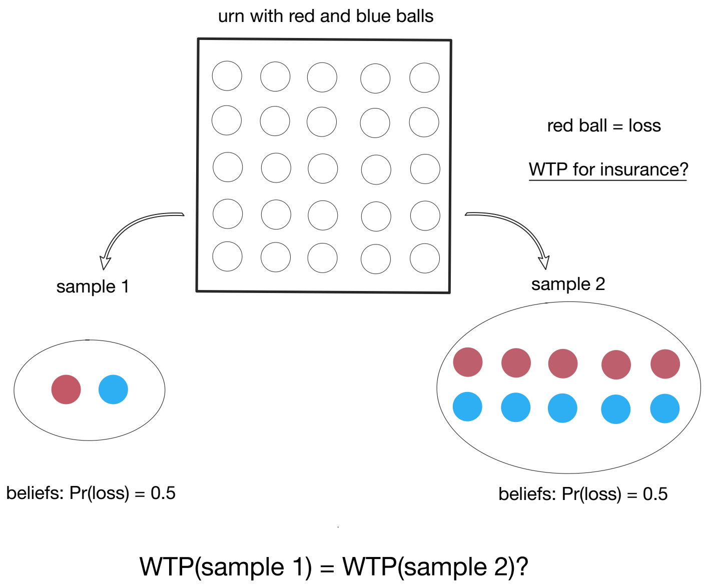

Figure 1: Urn Thought Experiment

scenarios.

In principle, it is reasonable to assume that the agent's expected probability of suffering a loss is the same across the two scenarios. However, we argue that it is also reasonable to expect that the agent's demand for insurance will differ across scenarios given that the first sample is less informative than the second. This situation finds its parallel in actual insurance markets. For instance, an experienced driver is typically better informed about the risks of driving than a novice driver (all else equal), while a person living in her home for a while has a better grasp of the various perils that can affect the house (flood, fire, etc.) than a new homeowner.

We formalize our ideas by focusing on the following insurance framework. An agent is exposed to an objective binary risk, defined as the probability $p \in [0,1]$ that he suffers a loss. That is, the set of outcomes is $X = \{0,1\}$, where $x = 0$ refers to experiencing a loss and $x = 1$ refers to the absence of it, with $p := Pr(x = 0)$.

The agent has access to information $I \in \mathcal{I}$ about risk p. We define an information environment $\mathcal{I}(p) \subset \mathcal{I}$ as a subset of possible I when the risk is p.[4] Information I can represent different things. For instance, I can represent a sample of realizations of x as in the urn example described previously. I can also represent information about the possible values or the distribution of risk p. Different I will typically lead to different beliefs about p, even if these beliefs *reduce* to p, i.e., lead to the same expected

[4]We implicitly assume the existence of a data generating process that maps p to a set of possible I the agent may receive.

probability of a loss. For instance, if the agent's beliefs are represented by a probability distribution over possible values of p as in the urn example, an increase in the sample size would lead to a less dispersed distribution.

We consider the agent's demand for insurance, expressed as the willingness to pay (WTP) for full insurance, i.e., for a policy that ensures an outcome $x = 1$ after risks are realized. Specifically, demand is given by a mapping $W : \mathcal{I}(p) \to \mathbb{R}$, where $W(I)$ denotes the WTP for insurance under information $I \in \mathcal{I}(p)$.[5] Note that if the agent's preferences are represented by an utility function $V : \mathcal{I}(p) \to \mathbb{R}$, then $1 - W(I)$ represents the certainty equivalent of I. Risk aversion is associated with a WTP higher than the actuarially fair price of insurance when $I = p$, i.e., when the agent knows p.

Definition 1. The agent is risk averse (loving) at $p \in (0, 1)$ if $W(p) > (<)\ p$. The agent is risk neutral if $W(p) = p$.

If the specific attributes of I do not affect the agent's demand for insurance we say that the agent satisfies the *reduction principle*, i.s., her WTP only depends on p. That is, she acts as if she reduces any information $I \in \mathcal{I}(p)$ into risk probability p.

Assumption 1 (Reduction Principle)**.** *$W(I) = W(p)$ for all $I \in \mathcal{I}(p)$ and all $p \in [0, 1]$.*

The reduction principle underlies most of the empirical analysis of insurance and it implies that, fixing the distribution of underlying risks in the population and insurance prices, both the aggregate demand for insurance and the risk profile of those who acquire insurance in the market is invariant to the information structure.[6] That is, demand analysis assuming the reduction principle abstracts from the information environment faced by the agent and from any potential heterogeneity in both information and information attitudes in the population. An implication under Assumption 1 is that the agent's risk preferences can be estimated from a sample of observations $(W(p), p)$.[7]

---

[5] Since the agent observes I and not necessarily p, we consider information as the primitive over which preferences are defined, in a similar spirit as in Blackwell (1951). One possibility is that the agent has intrinsic preferences for information, as defined by Grant et al. (1998). That is, the agent may experience different utility depending on which I he has, even if she cannot act upon I to affect her risks. Nonetheless, the above definitions imply that W also reflects the instrumental value of I in environments where actions contingent on I that affect p are unobserved by the econometrician.

[6] We refer the reader to Barseghyan et al. (2016) for a review of existing approaches to estimate risk preferences using field data and of potential identification issues. A notable exception is Handel and Kolstad (2015) who find significant biases in consumers' perception of risks and health insurance use.

[7] For instance, if we assume that the agent has EU preferences with constant absolute risk aversion (CARA) utility, given by $u(x) = -\frac{e^{-\theta x}}{\theta}$, then a single observation $(W(p), p)$ is enough to identify the CARA coefficient θ. Since WTP satisfies $u(1 - WTP) = pu(0) + (1 - p)u(1)$, θ satisfies $e^{-\theta(1-WTP)} = p + (1 - p)e^{-\theta}$.

The central tenet of our analysis is that violations of Assumption 1 are pervasive, implying that market demand and insurer decisions about prices and information will be shaped by both risk preferences and attitudes towards information *and* their relationship to underlying risks. Specifically, as suggested by the urn example and by the experimental evidence, individuals are typically more risk averse in environments where underlying risks are uncertain.[8] These attitudes are associated with a lower WTP under simple information in our framework, where simple information is defined as having perfect information about underlying risk p.

Definition 2. The agent prefers simple information (SI) at p if $W(I) > W(p)$, for all $I \in \mathcal{I}(p) \setminus \{p\}$.

Aversion to SI and SI-neutrality are defined in a similar fashion. To provide a measure of the impact of information and how it relates to risk preferences we decompose the WTP for insurance into a risk premium and an (simple) information premium.

Definition 3. The *information premium* of $I \in \mathcal{I}(p)$ is given by $\mu(I) := W(I) - W(p)$. The *risk premium* is $\mu(p) := W(p) - p$.

A positive $\mu(I)$ and a positive $\mu(p)$ are respectively associated with a preference for SI and to risk aversion.

2.1 Informational effects on the demand for insurance

We decompose the impact of the information structure on aggregate demand into a level effect and a composition or selection effect. The former measures how information changes the *level* of aggregate demand at any given price. The latter looks at how information changes the *composition* of demand in terms of both preferences for information and risk profiles of those acquiring insurance, keeping the level of aggregate demand fixed.

Let the population be given by a set of agents T,[9] with each agent $t \in T$ being represented by the tuple (W_t, p_t, I_t), where W_t is the agent's WTP function, p_t is her underlying risk, and $I_t \in \mathcal{I}(p_t)$ is the information she possesses about risk p_t. Aggregate demand is given by the set of agents in T with WTP W_t above the price for insurance $\rho(p_t)$, which is allowed to vary with underlying risk. That is, we assume that insurers could potentially price discriminate based on underlying risk. This possibility captures

[8]Most of the evidence pertains to compound and ambiguous risks and framing effects, although there is also evidence of sensitivity to the complexity of information (Moffatt et al., 2015).

[9]T can represent a finite set of agents $T = \{1, \cdot, N\}$ or a large market with a continuum of agents $T = [0, 1]$.

the recent technological advances in risk assessment experienced by the insurance industry. Accordingly, given a price function $\rho(\cdot)$ aggregate demand is pinned down by the joint distribution of (W_t, p_t, I_t). Abusing notation, let $\mathcal{I} = \{I_t \in \mathcal{I}(p_t), t \in T\}$ denote the information held by agents in market T. Also, let $F_{\mathcal{I}}$ denote the cdf of $W_t(I_t)$ under information structure $\mathcal{I}$. Aggregate demand at risk p and price schedule ρ is then given by $1 - F_{\mathcal{I}}(\rho(p)|p_t = p)$.

The next result (trivially) provides the necessary and sufficient condition under which demand is lower under simple information. Let the information structure in which all agents receive simple information be denoted by $\mathcal{P} = \{I_t = p_t, t \in T\}$.

Remark 1 (Level Effect)**.** *Aggregate demand is lower under simple information $\mathcal{P}$ than under $\mathcal{I}$ for any price schedule ρ if and only if $F_{\mathcal{I}}(\cdot|p_t = p)$ first order stochastically dominates $F_{\mathcal{P}}(\cdot|p_t = p)$ for all p.*

A sufficient condition for Remark 1 is that agents have a preference for simple information.

Remark 2. *If all agents have a preference for simple information, then aggregate demand is lower under $\mathcal{P}$ than under $\mathcal{I}$ for any price schedule ρ.*

Beyond acting as a demand shifter, information can also affect the composition of demand, i.e., the preference and risk profiles of those acquiring insurance. The composition depends on the relationship between $W_t(I_t)$ and $W_t(p_t)$ and p_t. For instance, if $W_t(I_t)$ and $W_t(p_t)$ are not aligned for some fixed p_t, i.e., if the interpersonal ranking of $W_t(I_t)$ does not coincide with the ranking of individuals according to their risk aversion $W_t(p_t)$) then those acquiring insurance under information structure $\mathcal{I}$ may exhibit a different degree of risk aversion than those buying insurance under $\mathcal{P}$. The following simple example illustrates this composition effect.

Example 1. *There are three agents, $T = \{1, 2, 3\}$, facing the same probability $p_t = p = 10\%$ of losing \$100. Their WTP when $I_t = p$ are $W_1(p) = 9$, $W_2(p) = 8$ and $W_3(p) = 7$. The price for insurance is \$10. Consider the following two scenarios:*

1. *Aligned preferences: $\mu_1(I_1) = 4$, $\mu_2(I_2) = 2$ and $\mu_3(I_3) = 0$.*
2. *Negative Correlation: $\mu_1(I_1) = 0$, $\mu_2(I_2) = 2$ and $\mu_3(I_3) = 4$.*

In this example, no agent would buy insurance under simple information. In the 'aligned preferences' scenario, agents 1 and 2 buy insurance at the market price, since $W_t(I_t) = W_t(p) + \mu_t(I_t) \geq 10$ for $t = 1, 2$. In the 'negative correlation' scenario, agents

2 and 3 buy insurance. Hence, the *level effect* involves raising demand from 0 to 2 agents. However, in the aligned preferences scenario it is the two most risk averse agents who buy insurance, while in the negative correlation scenario the two least risk averse agents end up acquiring insurance. Hence, while aggregate demand is the same across the two scenarios, the composition or *selection effect* implies an average WTP for simple risks of 8.5 when preferences are aligned, and only 7.5 when preferences are negatively correlated.

The next result formally establishes that the misalignment of preferences across information structures reduces the average degree of risk aversion among insured agents, keeping the aggregate level of demand fixed. To do so we introduce the following partial order over WTP rankings that captures the degree of preference alignment across information structures.

Definition 4. Risk and information preferences are misaligned if there exist a set of agents $T' \subseteq T$ such that for all $t \in T'$ there exist a subset $\tau(t) \subset T$ such that $W_t(p_t) > W_{t'}(p_{t'})$ and $W_t(I_t) < W_{t'}(I_{t'})$ for all $t' \in \tau(t)$.

In the context of a large market with a continuum of agents, a sufficient condition for preference misalignment is that the risk and information premia are negatively correlated.

Remark 3. *If there is a continuum of agents $T = [0, 1]$ and F has full support then a sufficient condition for preferences to be misaligned is $corr(\mu(p), \mu(I)) < 0$.*

Fixing the level of aggregate demand, preference misalignment is associated with a reduction in the average degree of risk aversion of the pool of insured agents. For any fixed aggregate demand level D, which represents the number (or measure) of agents acquiring insurance, let T_D be the set of size $|T_D| = D$ of agents with the highest WTP.

Remark 4 (Selection Effect)**.** *The average risk premium of agents in T_D is (weakly) lower under $\mathcal{I}$ than under $\mathcal{P}$ at any given demand level D and strictly so for some $D < |T|$ if and only if preferences are misaligned.*

The level effect can lead to over-provision of insurance. In addition, the selection effect can have a large impact on welfare in insurance markets due to a substantial reallocation of insurance towards less risk averse individuals, even if the underlying risk profile of the pool of insured agents does not change substantially across information structures.

These effects also impact the estimation of risk preferences using data from insurance buyers. Specifically, the level effect will introduce a positive bias in risk aversion estimates while the selection effect will lead to selection bias.

2.2 Implications for information disclosure

The presence of informational effects impacts insurers' incentives to disclose information to potential buyers. To illustrate the case, consider a monopolist with access to sophisticated risk assessment tools. Specifically, assume that the monopolist observes p_t or is able to accurately estimate it. In addition to choosing the price schedule $\rho(p)$, the monopolist can decide whether to disclose p_t to the agent.[10] To maximize profits the monopolist will disclose information or not depending on whether aggregate demand conditional on risk goes up or not, i.e., on whether the level effect is negative or positive, respectively.

Remark 5 (Information Disclosure). *Disclosure of simple information to agents with $p_t = p$ is optimal for a monopolist at all price schedules if and only if $F_{\mathcal{I}}(\cdot|p_t = p)$ first order stochastically dominates $F_{\mathcal{P}}(\cdot|p_t = p)$.*

3 Data and Survey Design

Our primary empirical evidence comes from an incentivized survey that we conducted with a representative sample of the U.S. population who are part of the Understanding America Study (UAS) at the University of Southern California. The UAS is an internet panel with a representative sample of U.S. households. Over four thousand respondents participated in the survey.[11] A key benefit of conducting research on the UAS is that the sample includes adults ages 18+ from many different backgrounds and educational levels. Another advantage is that we have interesting information on this sample regarding their real-world insurance decisions. Appendix A provides the summary statistics of the respondents.

In the survey, we asked each participant to make a series of 10 decisions in private. Each participant was the owner of a machine, which was described to have some probability p of being damaged and some probability of remaining undamaged. Undamaged machines paid out \$10 to the subject at the end of the survey, while damaged machines paid out nothing. The probability of damage, including information available about said probability, was varied in each decision. Specifically, we considered the following information environments:

[10] Similar arguments apply to the case in which the monopolist has more accurate information about risk than the agent and can choose the degree of complexity of the information conveyed to the agent, i.e., can decide whether to obfuscate or simplify information.

[11] All 5,674 UAS panel members were recruited to complete the survey online, and 4,534 respondents accessed and completed the survey. 62 respondents started but did not complete the survey and are excluded from our analysis.

Table 1: Summary of Decisions Presented to Respondents

Group	Decision # (within block)	(1) Probability of Loss (%)	(2) Range Probability (%)
1	1	5	3-7
	2	10	1-19
	3	20	13-27
	4	50	46-54
	5	80	68-72
2	1	5	1-9
	2	10	3-17
	3	20	18-22
	4	40	28-52
	5	70	61-79
3	1	2	1-3
	2	10	6-14
	3	20	8-32
	4	40	38-42
	5	90	83-97
4	1	2	0-4
	2	10	8-12
	3	20	16-24
	4	30	21-39
	5	60	48-72

Notes: Respondents were assigned to one of four groups, and were presented both the probabilities described in (1) and (2) in the order displayed here. Half of respondents were told that each probability in the range is equally likely, while half were not given information about the probability distribution within a range.

(i) *Simple risk*: I represents the underlying risk probability, i.e., $\mathcal{I}^S(p) = \{I = p\}$.

(ii) *Compound risk*: I represents the uniform distribution on a range of probabilities centered around p, i.e., $\mathcal{I}^{CR}(p) = \{I = U[p-\varepsilon, p+\varepsilon], \varepsilon \in (0, \min\{p, 1-p\}]\}$

(iii) *Ambiguous risk*: I is given by a range of possible risk probabilities centered around p, i.e., $\mathcal{I}^{AR}(p) = \{I = [p-\varepsilon, p+\varepsilon], \varepsilon \in (0, \min\{p, 1-p\}].\}$

We elicited the maximum willingness to pay for full insurance using the Becker-DeGroot-Marschak mechanism (Becker et al., 1964),[12] where the actual price of insurance was drawn at random by the computer from a uniform distribution on (0,100). Appendix D contains the survey instructions. Since we did not have enough time in the session to ask questions about all probabilities that we wanted to include, we divided participants into four groups, as described in Table 1. All participants received a block

[12]This is a common mechanism in similar experiments, for instance see Halevy (2007).

of decisions with 5 risk probabilities under simple risk, and a block of decisions with 5 range probabilities under either compound or ambiguous risks. The order of blocks was randomized, but the order of probabilities within each block was kept constant and was ordered from smallest to largest. In addition, half of the participants received a range noting that 'all numbers within this range are equally likely' while the other half did not receive this information (ambiguous risk). Hence, the former group received a compound risk, while the latter group received an ambiguous risk.

After the main survey, participants were asked a question eliciting their ability to solve compound lotteries, and received \$1 for a correct answer. Earnings were in virtual dollars, which were translated to US dollars at the rate of 20 virtual dollars = \$1. Participation in all parts of the survey required approximately 15 minutes, and participants earned \$10 for survey completion, in addition to \$8.6 on average on the insurance experiment.[13]

We also conducted a companion laboratory experiment with approximately 100 university students, which included a similar set of decision questions. The advantages of the laboratory experiment are that it was conducted in person with a relatively higher-educated population so we can assure that subjects understand the instructions. The laboratory session was also longer and involved a greater number of decisions, which allows us to obtain more precise estimates. Our results are qualitatively similar between the incentivized survey as the laboratory experiment. The fact that we obtain similar results despite different survey wording and different respondent populations is reassuring since it speaks to the reproducibility of our results. We describe the experiment design and results of the laboratory experiment in Section 7 when we discuss the robustness of our results.

4 Empirical Analysis

This section presents the main empirical patterns regarding risk attitudes and preferences for simple information while Section 6 shows their relationship to sociodemographic variables. First, we illustrate the magnitude of risk and information premia and how they change with the underlying risk probability. Next, we explore the relationship between risk attitudes and preferences for simple information by focusing on the correlation structure, controlling for underlying risk probabilities. In what follows, to facilitate comparisons, we report underlying risk probabilities, WTP, as well

[13] It is common in the UAS to combine multiple studies in one survey session. As such, prior to completing the experiment, participants also received a series of un-incentivized questions designed to evaluate understanding of annuity products for another project (Brown et al., 2017).

as risk and information premia in percentages (e.g., $\mu(p=10)=15$ means that the risk premium for full insurance against a 0.1-likely loss is 0.15).

4.1 Risk Attitudes and Preferences for Simple Information

Figure 2 displays the risk preferences of respondents when the probability of failure is known (i.e., simple risk). The risk preferences are measured by the average risk premium ($\mu(p)=W-p$) at each possible p. The 0 line represents risk neutrality. A clear pattern emerges from the figure: average risk aversion decreases as losses become more likely, suggesting that agents transition from exhibiting significant risk aversion at small probabilities to becoming risk lovers at very high p. Table 7 in Appendix B reports the estimates and their statistical significance. In addition, we find risk premium to be widely heterogeneous: the standard deviation ranges from 25% to 30%.

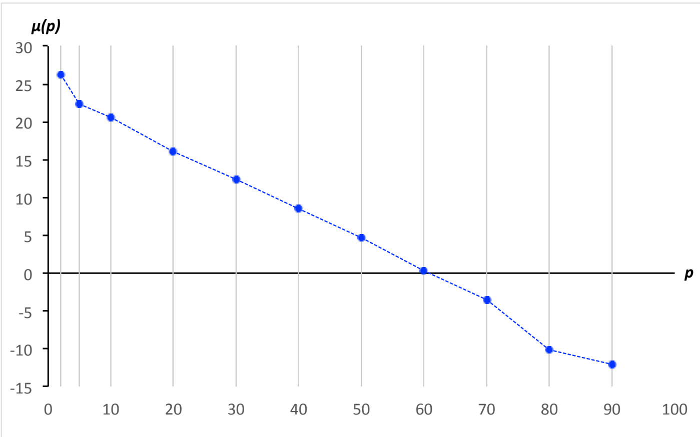

Figure 2: Average Risk Premium at Different Probabilities.

Turning to informational effects, Figure 3 presents the average information premium ($\mu(I)=W(I)-W(p)$) at each possible p. Each data point shows the range size associated with it. Since our design includes two range sizes for most of the probabilities, the graph displays two lines, respectively associated with small and big ranges.[14]

On average, agents exhibit significantly large information premia at $p<50\%$ when range sizes are big, leading to an increase in WTP as high as 100% of the expected loss. Smaller range sizes still elicit a strong response for $p<50\%$.[15] Information premia decrease with the underlying risk probability, which is consistent with Abdellaoui et al.

[14] Table 7 in AppendixB shows the average information premium at each p by group.

[15] The companion laboratory experiment results in similar information patterns as the survey, but the information premia for the small range are only substantial for the 5% and 10% loss probabilities.

(2015), who find that aversion to compound and ambiguous lotteries increases with the probability of winning the lottery. However, as we show in Section 6 and in Appendix B, the presence of large information premia does not seem to be driven by ambiguity or by the inability to reduce compound lotteries. Information premia are somewhat less heterogeneous than risk premia, and have a standard deviation between 14% and 20%.

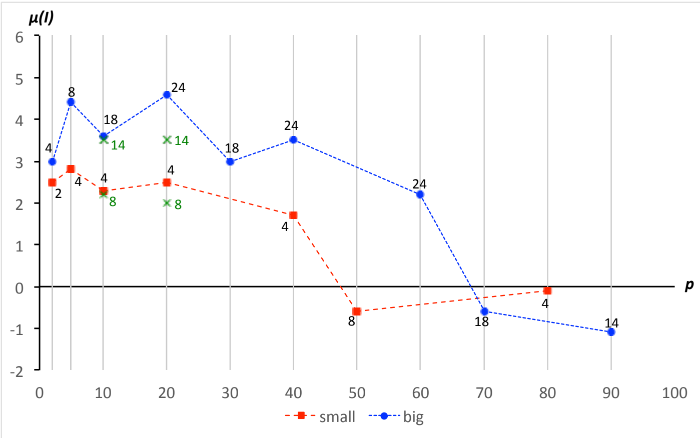

Figure 3: Information Premium at Different Probabilities (point labels represent range size).

While we included a large range of possible p in our survey, for practical purposes the smaller p are most interesting since the typical probability of a loss against which people insure are lower than 50%. The fact that we observe large imformation premia at these small probabilities suggests that the information structure in insurance markets can have a large influence in the demand for insurance. Specifically, markets with complex or ambiguous information environments would exhibit greater demand for insurance due to strong level effects.

4.1.1 Relationship Between Risk Aversion and the Information Premium.

A pattern that emerges in our analysis of risk and information attitudes is that both risk aversion and preferences for simple information are prevalent at low risk probabilities. We next look at the correlation between the insurance premium and the information premium, normalized by range size. We do so for each underlying probability point separately to control for the negative relationship between underlying risk p and both $\mu(p)$ and $\mu(I)$.

Figure 4 plots the correlation coefficients, showing that risk and information premia are negatively correlated at all risk probabilities. Furthermore, the correlation coefficient is remarkably invariant to underlying risk regardless of whether we control for individual characteristics (partial correlation) or not (total correlation): it consistently lies between -0.24 and -0.35, even after controlling for cognitive ability, financial literacy and demographic background.[16] As we show in Section 7, the negative correlation is robust to measurement error and replicated in the companion laboratory experiment we conducted and in data from existing experimental studies.

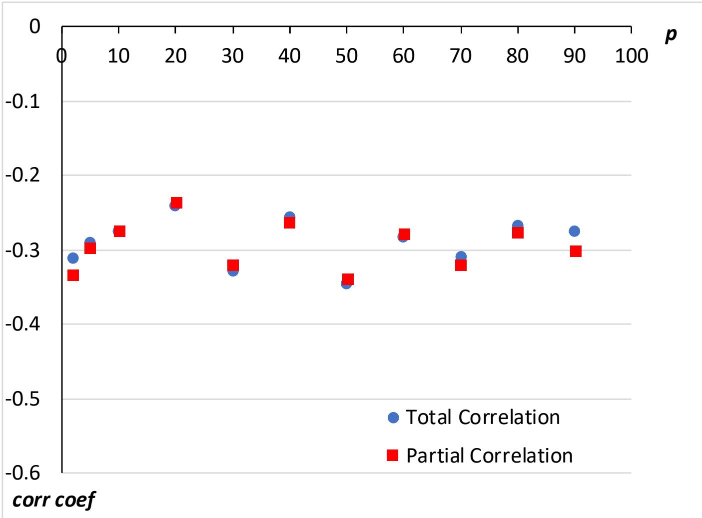

Figure 4: Correlation Coefficients between Risk Premium and Information Premium.

The fact that risk averse agents tend to exhibit a lower preference for simple information has several implications. First, it can lead to substantial selection effects in insurance markets, since those who buy insurance may not necessarily exhibit higher risk aversion than those who do not buy. That is, the ranking of individuals according to their WTP may not be invariant to the information structure. As we show in Appendix C.3, the correlation of WTP rankings is high, consistent with the findings of Einav et al. (2012), but it goes down with range size. Second, empirical estimates of risk preferences that do not control for information will tend to underestimate the degree of risk aversion of those who are more risk averse and overestimate the degree of risk aversion of those that are less risk averse. We provide a quantitative exploration of these issues in the next section.

[16] Table 4 in Section 7 reports the (total) correlation coefficients in columns two and four and shows that they are highly significant. The partial correlation coefficients are virtually identical to the total correlation estimates and are therefore omitted.

5 Demand Analysis

Our findings show that information about underlying risks has a significant impact on agents' demand for insurance. Hence, as described in Section 2, the lack of simple information can have two different effects on aggregate demand: a *level* effect and a *selection* or composition effect. First, information premium drives up average WTP at low and moderate risk probabilities, which essentially represent the relevant range of risks in most insurance markets. The level effect thus implies that aggregate demand will be higher in a market without simple information ($I \neq p$) than in a market where all agents receive simple information ($I = p$). Second, since information and risk premia are negatively correlated, those who buy insurance may have high information premia and may not necessarily be the most risk averse.

To illustrate the extent of these effects, we use our data to simulate the demand for full insurance against binary risks. To do, so we construct a demand curve for insurance by applying our sample of (W_t, p_t, I_t) data to the empirical distribution of risk probabilities in existing insurance markets. Specifically, we use the claim rates for auto-collision insurance estimated by Barseghyan et al. (2011) to generate a distribution of risk probabilities. We then discretize this distribution using as a support the eleven risk probabilities (from 0.02 to 0.90) covered by our survey. Finally, we calculate aggregate demand for insurance, given by the share of agents with WTP above the price, by weighting each observation according to how likely its associated risk probability is given the estimated discrete distribution of risk probabilities.

Equipped with this demand curve, we consider two scenarios. In the first scenario, insurers charge a single price for full insurance and do not price insurance contingent on the underlying risk (*uniform pricing*). This might be due to regulation banning risk-based pricing (e.g., the ACA bill in the US does not permit risk based pricing for health insurance) or because insurers do not observe underlying risk probabilities, and thus are exposed to adverse selection. In the second scenario, we allow insurers to charge prices contingent on the underlying risk (*risk-based pricing*). In each scenario, we look at the market allocation for prices that range from perfect competition to monopoly. By covering the whole range of profitable prices we do not need to impose further assumptions on the structure of competition among insurers.

In each scenario we then compare outcomes under two information environments, namely, simple risk and compound or ambiguous risk. We pool together the compound and ambiguous risk samples since ambiguous and compound ranges elicit similar effects in our data. In addition, we also consider the case in which information is endogenously determined by a monopolist who decides whether to selectively disclose simple information to agents as a function of their risk.

Constructing the demand for insurance We assume that the need of agent i to fill an insurance claim follows a Poisson process with arrival rate λ_i. Given this, agent i's probability of suffering a loss, i.e., of filing at least one claim, is given by $p_i = 1 - e^{-\lambda_i}$. To construct the distribution of p_i, we assume that λ_i follows a gamma distribution with mean $\bar{\lambda} = 0.116$ and standard deviation 0.272, which correspond to the (annualized) mean and standard deviation of claim rates in auto-collision insurance estimated by Barseghyan et al. (2011).[17]

Accordingly, the cdf of risk probabilities is given by $H(p) = G(-\log(1-p); 0.182, 0.638)$, where $G(\cdot; \alpha, \beta)$ is the cdf of a gamma distribution with shape parameter α and scale parameter β. Next, we discretize this distribution to generate a cdf $\hat{H}$ whose support points coincide with the eleven different risk probabilities covered in our survey data.[18] Finally, we use this distribution to weigh each observation (W_t, p_t, I_t) under simple risk and range risk in our survey data by how likely p is according to $\hat{H}$.[19]

Focusing first on the uniform pricing scenario, to determine the market allocation for insurance, we consider the set of prices, up to the monopoly price, that yield non-negative profits to insurers taking into account the presence of adverse selection. Let ρ denote the price for insurance and $s(\rho) = 1 - \hat{F}(\rho)$ the fraction of agents in the population with $W_t(I_t) > \rho$, i.e., the share of agents who buy insurance when the price is ρ. Profits are given by

$$\pi(\rho) = (\rho - E(p|W_t(I_t) \geq \rho))s(\rho).$$

Figure 5 (left panel) depicts the demand for insurance ($s(\rho)$) and the range of possible prices for simple and range risks. It turns out that in both cases the set of prices associated with non-negative profits is the interval $[13, 50]$, where $\rho = 13$ is the price under perfect competition and $\rho = 50$ is the monopoly price. The level effect on aggregate demand is substantial: for $\rho \in [13, 50]$, the absence of simple information

[17] Barseghyan et al. (2011) estimate that the average *semiannual* claim rate in auto collision insurance is 0.058 with a standard deviation of 0.136.

[18] We use the following discretization: $\hat{H}(0.02) = H(0.025)$; $\hat{H}(0.05) = H(0.075) - H(0.025)$; $\hat{H}(0.1) = H(0.15) - H(0.075)$; $\hat{H}(0.1n) = H(0.1n + 0.05) - H(0.1n - 0.05)$ for $n = 2, 3, \cdots, 8$; and $\hat{H}(0.9) = 1 - H(0.85)$. The mean under $\hat{H}$ is higher than under H (0.096 versus 0.070) since the latter places substantial probability mass below $p = 0.02$.

[19] Our approach implies that observations with the same p but different range size are equally probable. Results do not qualitatively change if we focus on a subsample in which each p is assigned to a unique range size.

leads to a $10-14\%$ higher demand.

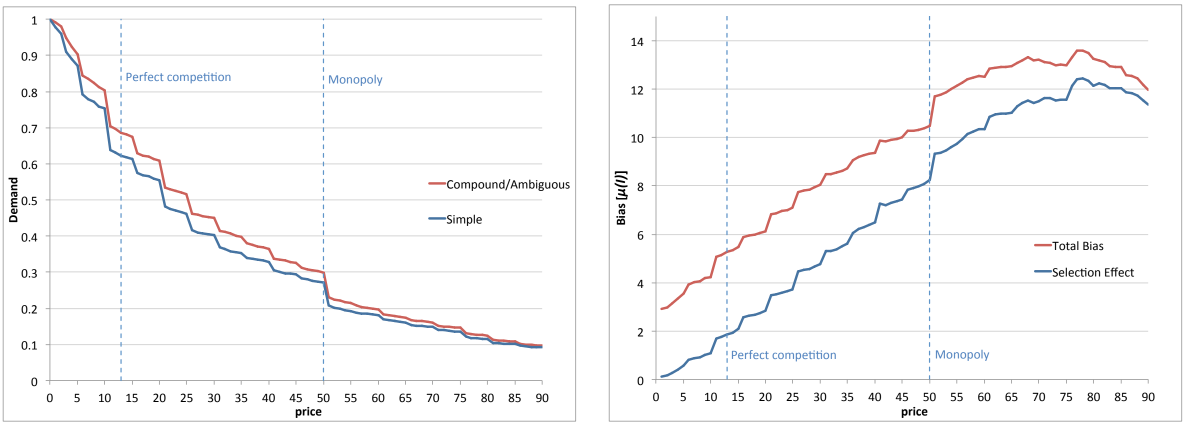

Figure 5: Demand for Insurance (left) and Bias in Risk Premium Estimates (right).

The higher demand is driven by the higher WTP of agents with positive information premia, some of which become insurance buyers in the absence of simple information. In addition, there are important differences across markets in the population of agents who buy insurance.

Table 2 provides a comparative of the main features, such as average risk premia and risk probabilities, of the simple risk and compound/ambiguous risk markets for the case of perfect competition ($\rho = 13$) and monopoly ($\rho = 50$). In both markets, the presence of adverse selection implies that the risk probability of the pool of insured agents is between 25-33% higher than in the population when the market is competitive (under monopoly risk probabilities are more than 50% higher).

More importantly, the average risk premium is lower under compound risk than under simple risk, while the information premium of the insured population is at least twice as large under compound risk than in the whole population. These differences are due to both the level effect associated with higher demand, and to the selection effect induced by the negative correlation between risk and information premia.

The presence of information premia means that if we were to use data on (W_t, p_t) from the pool of insured agents to estimate risk attitudes, our estimates would be biased. The left panel of Figure Figure 5 and Table 2 show the size of the bias, given by the average information premium, i.e., the average difference between WTP and risk premium. On average, risk premium estimates are 18-22% higher than the actual level of risk premium in the pool of insured agents. To quantify the relative contribution of the selection effect to the overall bias we proceed as follows. First, we keep aggregate demand constant under compound risk but reallocate insurance to those with the highest risk premium. Second, we compute the selection effect as the change in the average risk premium in the pool of insured agents caused by the reallocation. Figure 5 shows that the selection effect increases with the price of insurance, accounting for 35% of the bias under perfect competition and 79% of the bias under monopoly.

Regarding the efficiency of the allocation of insurance, the absence of simple information can lead to large welfare losses. To assess these losses, we measure the welfare from being insured as the difference between the WTP for insurance under simple information ($\mu(p) + p$) and the price (ρ) for those who buy insurance. That is, we do not include the information premium since the underlying risks covered by the policy are not altered by the information provided to agents. Nonetheless, it can be shown that this welfare measure would differ from one that takes into account preferences for information only on the welfare of the pool of agents that remain uninsured in either scenario. According to our measure, the average welfare in the market is given by

$$E\left((\mu(p) + p - \rho)1_{\{W(I)>\rho\}}\right),$$

where $1_{\{.\}}$ is the indicator function. The bottom panel in Table 2 shows the welfare estimates. The lack of simple information leads to welfare losses ranging from 7% to about 40%, depending on how competitive the market is. They are primarily driven by the selection effect, with roughly 90% of overall welfare losses caused by the negative correlation between risk and information premia.

The magnitude of the welfare losses suggests that regulation aimed at providing simple information about underlying risks in insurance markets would be beneficial, regardless of other aspects of the market such as the degree of competition among insurers.

Finally, the negative relationship of both risk and information premia with underlying risk depicted in Figures 2 and 3 has important implications for measuring the extent of asymmetric information in insurance markets. Existing research emphasizes the positive correlation between risk (p) and coverage ($W(I) \geq \rho$) as evidence of asymmetric information (Chiappori and Salanié, 2013). However, when risk premium is negatively correlated with risk this correlation will be lower than under independence of risk premium and underlying risk (the correlation between the insurance premium $W(I) - p$ and risk probability p is roughly -0.4 in our data). To show these potential differences, we compute a conterfactual correlation between risk and coverage under independence by randomly drawing p and $W(I) - p$ from their marginal distribution in each market to construct synthetic individual WTP for insurance.

Table 2: Demand for Insurance - Aggregate Outcomes

		Uniform Price				*Risk-based Pricing*			
	Overall	Perfect Competition		Monopoly		Perfect Competition		Monopoly	
	Population	Simple	Compound	Simple	Compound	Simple	Compound	Simple	Compound
Insured Pool									
Share of Population	100%	62.3%	68.6%	27.2%	29.8%	87.7%	91.0%	23.6%	26.0%
Risk Probability	9.6%	12.8%	12.1%	15.6%	15.0%	7.8%	7.7%	9.6%	9.5%
Risk Premium	22.1	34.5	29.9	58.5	48.3	26.6	25.1	66.3	54.7
Info Premium	2.8		5.3		10.5		3.43		11.6
CARA coef.[a]	2.9	4.7	4.2	9.8	7.8	3.3	2.9	13.0	7.8
Revealed CARA[b]	3.2		4.7		9.8		3.6		12.0
Estimation Bias			17.7%		21.7%		13.6%		21.3%
Selection Effect[c]			35.2%		78.6%		33.4%		79.3%
Consumer Welfare		21.3	19.9	6.6	4.0	23.3	22.8	5.4	2.9
Welfare Loss[d]			6.7%		39.4%		2.3%		46.4%
Selection Effect[e]			88.4%		95.1%		89.3%		95.2%
Corr(risk, coverage)		0.263	0.238	0.238	0.228	-0.312	-0.389	0.001	-0.014
risk prefs $\perp$ *risk*[f]		0.347	0.320	0.423	0.417	0.000	0.000	0.111	0.121

[a] Median CARA coefficient obtained from the WTP for insurance under simple risk. The CARA coefficient for each observation is given by the value of r satisfying $e^{rW(p)} = pe^r + (1-p)$.

[b] Median CARA coefficient obtained from the WTP for insurance under compound risk. The revealed CARA coefficient for each observation is given by the value of r satisfying $e^{rW(I)} = pe^r + (1-p)$.

[c] Difference between the average risk premium in a market with the same demand at each p as under compound risk, but in which those with the highest risk premium get insurance, and the average risk premium under compound, expressed as a fraction of the average information premium.

[d] Difference between average welfare under simple and compound risk, relative to the average welfare under simple risk.

[e] Difference between average welfare in a market with the same demand at each p as under compound risk, but in which those with the highest risk premium get insurance, and average welfare under compound risk, relative to the difference between average welfare under simple and compound risk.

[f] The correlation coefficient is the average of a sample of 1,000 correlation coefficients, each obtained by randomly assigning insurance premium $(W(I)-p)$ to risk probabilities (p) to compute agents' WTP for insurance.

Table 2 shows that while the correlation between risk and coverage is increasing in the degree of adverse selection under independence it is not monotone in our data: the correlation under monopoly is lower than under perfect competition and simple risks despite exhibiting higher adverse selection, while it is is lower under complex information than under simple risk.

Finally, the right-hand-side panel of Table 2 shows that the informational effects are quantitatively similar when insurers engage in risk-based pricing.

In the demand analysis thus far, we have exogenously imposed the information structure on the market and restricted supply-side decisions to prices only. However, as stressed in Subsection 2.2, insurers with the ability to observe or estimate the risks faced by an agent might have an incentive to withhold or share this information with the agent. We next examine the potential response of the insurers to information frictions.

Table 3 presents the information disclosure decisions of a monopolist who maximizes profits by choosing both the price schedule $\rho(p)$ and whether to reveal p to the agent. Consistent with the fact that agents exhibit on average a positive information premium at low probabilities and zero or negative at high p (see Figure 3), the monopolist chooses to disclose p to the agent at most underlying probabilities at or above 50%. Beyond increasing the profits of the monopolist, such a selective disclosure policy has also allocative implications, since it increases the average underlying risk of the insured pool. Although such implications are quantitatively small in a market like auto insurance where the risk distribution has a very thin right tail, they could be substantial in insurance markets where likely risks are more prevalent (e.g. health insurance).

Table 3: Information Disclosure under Monopoly

p	2	5	10	20	30	40	50	60	70	80	90
Disclosure	no	no	no	no	no	no	yes	no	yes	no	yes

Overall, our demand analysis highlights the need to account for the information and preference structure underlying insurance markets and, crucially, for the relationship between risk and information attitudes, since the latter can have a significant impact in the composition of the insured pool. This is especially relevant given the fact not much attention has been paid to the relationship between risk preferences and attitudes toward compound and ambiguous lotteries, which, as we show below, it does not seem to be driven by sociodemographic characteristics, financial literacy or the ability to reduce compound lotteries.

6 Covariates of the Information Premium

A preference for simple information may reflect aversion to the dispersion or perceived randomness of risk probabilities, and can have multiple causes, e.g., ambiguity aversion, inability to reduce compound risks or aversion to complexity of information about risks. Our design allows us to gauge the relative contribution of these sources, as well as look at whether information attitudes depend on sociodemographic characteristics. We can also measure the effect of the ability to reduce compound risks by looking at whether the subject correctly answered incentivized questions included in the survey about reducing compound risks. Finally, measures of cognitive ability and financial literacy can serve as proxies for attitudes toward complex information.

Figure 6 shows the results of regressing information premia $\mu(I)$ on range size, whether the information about the range is ambiguous, the error in the quiz regarding reducing compound risk (normalized by the size of the range), measures of financial literacy and cognitive ability, as well as sociodemographic variables. All the regressions control for the underlying risk p and for whether the simple risk questions were asked before the range questions or if the order was reversed (p-values are adjusted to control for multiple hypothesis testing). The first column shows the regression estimates without controlling for risk attitudes ($\mu(p)$), while the second column does control for risk attitudes.

Several conclusions emerge from these estimates. First, risk attitudes are by far the most important covariate of information premia: Risk premium accounts for about 10% of the overall variation of the information premium, while the rest of variables combined only account for a R^2 of 1%. Second, the table reflects the relationship between risk probabilities and range sizes depicted in Figure 3, namely, the wider the dispersion in risk probabilities and the lower the risk probability the higher the information premium. Once we control for range size, ambiguous information or the inability to reduce compound lotteries do not significantly increase the information premium. Third, cognitive and socio-demographic variables do not seem to significantly drive preferences for information. In contrast, gender, income, as well as cognitive ability and financial literacy are significantly associated with risk attitudes. The third column in Figure 6 shows that individuals with higher financial literacy and cognitive ability are less risk averse. Similarly, being male and earning an income above \$100k are associated with lower risk aversion. These relationships are consistent with previous studies about risk attitudes (Outreville, 2014).

Finally, it is interesting to note that there are significant order effects in the field experiment, with higher information premia associated with the reverse order, i.e., when agents were asked about WTP for range risks first. This may suggest that being exposed to simple risk may have an anchoring effect on WTP for insurance against range risks with the same underlying risk probability.[20]

7 Robustness and External Validity

7.1 Measurement Error

An important concern with the estimates of the correlation between risk and information premia presented in Subsection 4.1.1 is that they may be biased downward due to measurement error in WTP induced by the elicitation mechanism. The effect of such measurement error goes beyond the typical attenuation bias, given that the information premium is defined as the difference $W(I) - W(p)$.

To formally show the problem, let $\hat{W}(I) = W(I) + \varepsilon_I$ be the elicited WTP under information I, where ε_I is a random variable representing classical measurement error. Accordingly, the elicited risk premium is given by $\hat{\mu}(p) = \mu(p) + \varepsilon_p$ and the elicited information premium is given by $\hat{\mu}(I) = \mu(I) + \varepsilon_I - \varepsilon_p$. Assuming that measurement errors are independently drawn and that they are independent of $W(\cdot)$, the correlation between $\hat{\mu}(I)$ and $\hat{\mu}(p)$ is given by

$$corr(\hat{\mu}(I), \hat{\mu}(p)) = \frac{cov(\mu(I), \mu(p)) - Var(\varepsilon_p)}{\sqrt{(Var(\mu(I) + Var(\varepsilon_I - \varepsilon_p))(Var(\mu(p) + Var(\varepsilon_p))}}.$$

Hence, the numerator is negatively biased while the denominator is biased upwards, making both the direction and the size of the bias indeterminate.

To correct for these biases, we follow the approach proposed by Gillen et al. (2017), which is based on the idea of using additional measures of the same variable as instruments. For instance, if we have duplicate measures of the risk premium, $\hat{\mu}(p)$ and $\hat{\mu}^d(p) = \mu(p) + \varepsilon_p^d$ we can use $\hat{\mu}^d(p)$ as an instrument for $\hat{\mu}(p)$ in a regression of $\hat{\mu}(I)$ on $\hat{\mu}(p)$. Since errors are independent across measures the measurement error in $\hat{\mu}(I)$, given by $\varepsilon_I - \varepsilon_p$, is independent of the measurement error ε_p^d in $\hat{\mu}^d(p)$, making the latter a valid instrument. Accordingly, the regression coefficient $\hat{\beta}$ delivers a consistent

[20] No such order effects seem to be present in the exeriment (see Table 16 in Appendix C.4).

Figure 6: Covariates of Information Premium and Risk Premium

	$\mu(I)$	$\mu(I)$	$\mu(p)$
Risk Probability	-0.06***	-0.10***	-0.41***
	(0.01)	(0.01)	(0.01)
Probability Range	0.11***	0.12***	
	(0.01)	(0.02)	
Ambiguity	0.54	0.54	
	(0.33)	(0.38)	
Financial literacy	-0.15	-0.52	-1.71*
	(0.23)	(0.27)	(0.50)
Average Cognitive Score	0.49	0.55	-1.34*
	(0.24)	(0.23)	(0.28)
Quiz Error	-0.06	0.15	
	(0.09)	(0.12)	
$\mu(p)$		-0.10***	
		(0.01)	
Age	-0.05	-0.02	0.08
	(0.07)	(0.08)	(0.14)
Age^2/100	0.04	0.01	-0.24
	(0.07)	(0.08)	(0.13)
Female	-0.64	-0.20	3.90***
	(0.35)	(0.40)	(0.76)
Married	-0.60	-0.73	-0.59
	(0.37)	(0.42)	(0.83)
Some College	0.29	0.50	-1.22
	(0.48)	(0.55)	(1.02)
Bachelor's Degree or Higher	0.28	0.33	-2.19
	(0.54)	(0.63)	(1.16)
Hh Income: 25k-50k	0.45	0.80	0.21
	(0.54)	(0.61)	(1.16)
Hh Income: 50k-75k	0.38	0.55	-2.82
	(0.60)	(0.68)	(1.26)
Hh Income: 75k-100k	0.75	0.90	-0.97
	(0.62)	(0.72)	(1.41)
Hh Income: Above 100k	0.29	-0.33	-6.38***
	(0.62)	(0.72)	(1.33)
Non-Hispanic Black	-1.70	-2.37	2.58
	(0.75)	(0.86)	(1.53)
Spanish/Hispanic/Latino	0.31	0.33	0.04
	(0.70)	(0.80)	(1.37)
Other Race/Ethnicity	-0.12	0.13	1.23
	(0.66)	(0.77)	(1.24)
Reverse Order	4.64***	4.77***	-2.51***
	(0.33)	(0.38)	(0.71)
R^2	0.03	0.12	0.20
N	19050	10992	19432

All regressions include a constant and standard errors are clustered. Regressions including $\mu(p)$ are IV regressions with the linear interpolation of adjacent risk premia as the instrument for $\mu(p)$. Bonferroni-adjusted p-values: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

estimate of $\frac{cov(\mu(I),\mu(p))}{Var(\mu(p))}$. If, in addition, we have and additional measure $\hat{\mu}^d(I)$ of the information premium, the correlation between the risk and information premia can be consistently estimated using

$$\widehat{corr}(\mu(p),\mu(I)) = \hat{\beta}\sqrt{\frac{\widehat{cov}(\hat{\mu}(p),\hat{\mu}^d(p))}{\widehat{cov}(\hat{\mu}(I),\hat{\mu}^d(I))}}, \tag{1}$$

where $\widehat{corr}$ and $\widehat{cov}$ represent sample correlation and covariance, respectively.

Gillen et al. (2017) exploit the use of duplicate measures or *replicas* to obtain not only consistent but also efficient estimates via stacked IV regressions, one per available replica, with the remaining replicas acting as instruments. They call their approach an *obviously related instrumental variable* (ORIV) regression and show how to obtain consistent correlation estimates and bootstrapped standard errors.

To obtain replicas of risk and information premia, we take advantage of the fact that our experimental design elicits subjects' WTP for insurance for multiple loss probabilities under both simple and compound/ambiguous risks. Specifically, we use the linear interpolation of risk premium associated with the probability points adjacent to p as the second measure of $\mu(p)$. That is, if $p' < p$ and $p'' > p$ are the loss probabilities closest to p in the experimental design, the replicas of risk and information premia are given by

$$\hat{\mu}^d(p) = \mu(p')\frac{p''-p}{p''-p'} + \mu(p'')\frac{p-p'}{p''-p'},$$
$$\hat{\mu}^d(I) = \mu(I')\frac{p''-p}{p''-p'} + \mu(I'')\frac{p-p'}{p''-p'},$$

where I' and I'' represent the compound/ambiguous risks respectively associated with p' and p''. Since range sizes vary in our experiments, we normalize elicited information premium by dividing it by range size and perform the linear interpolation using the normalized premia.[21]

Table 4 shows the ORIV correlation estimates for the loss probabilities that allow for linear interpolation (column three), that is, those with adjacent probabilities on both sides. As the table shows the corrected correlations are of similar magnitude if not slightly more negative. These results are reassuring in that they suggest that the negative relationship between risk and information premia is not an artifact of measurement error.

[21] For the laboratory sample we average the normalized information premia elicited in the small range and big range treatments.

Table 4: Correlation between risk and insurance premia

p	correlation[a]	ORIV correlation[b]
2	-0.312***	-
5	-0.291***	-
10	-0.276***	-0.310***
20	-0.241***	-0.319***
30	-0.329***	-0.324***
40	-0.256***	-0.353***
50	-0.347***	-0.306***
60	-0.284***	-
70	-0.309***	-
80	-0.267***	-
90	-0.276***	-

[a] Statistical significance: *p-value < 0.10, **p-value < 0.05, ***p-value < 0.01.
[b] p-values for ORIV correlation are computed using bootstrapped standard errors.

7.2 External Validity

7.2.1 Experiment

The laboratory experiment was conducted at the BRITE Laboratory for economics research and computerized using ZTree (Fischbacher, 2007). Participants were recruited from a subject pool of undergraduate students at the University of Wisconsin-Madison. A total of 119 subjects participated in the experiment. All subjects faced 13 decisions in each treatment, covering risk probabilities from 2% to 98%. In each decision they stated their maximum willingness to pay for full insurance against binary risks. All subjects were asked for their WTP under simple risk. In addition, we randomized subjects to two different informational treatments, compound risk and ambiguous risk, both dealing with probability ranges. We also added an additional treatment for all subjects, multiplicative risk, dealing with more complex types of compound risks, which we discuss below. Elicitation mechanisms and payments were similar to those in the survey. Section C in the Appendix provides a full description of the experiment as well as detailed results.

We find that the empirical patterns unveiled by our survey are replicated are replicated in the experiment. Both risk premium and information premium are decreasing in risk probability p, as shown in Figure 7. The only major difference is that subjects in the experiment were significanlty less risk averse.

In addition, risk and information premia exhibit a negative correlation of similar

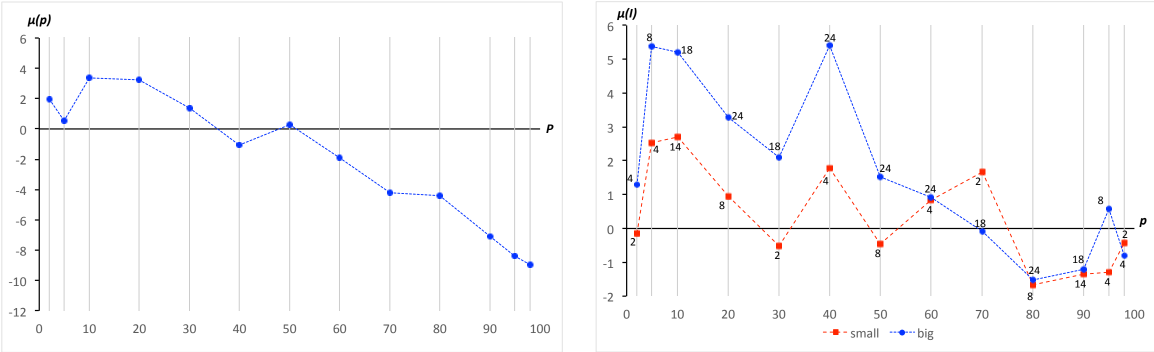

Figure 7: Average Risk and Information Premia at Different Probabilities.

magnitude: correlation coefficients consistently lie between -0.24 and -0.35, even after controlling for both measurement error and personal characteristics such as cognitive ability, financial literacy and other demographics. (see Table 15 in Appendix C).

Finally, we analyze covariates of risk and information premia with the experimental data and find that qualitatively similar results (see Appendix C.4).

7.2.2 Additional Experimental Data

As additional evidence of the external validity of our findings, we computed the correlation between risk premium and compound risk premia in the data of some of the most prominent studies looking at the relationship between ambiguity and compound risk attitudes, namely the papers by Halevy (2007), Abdellaoui et al. (2015) and Chew et al. (2017). As the bottom panel of Table 4 shows, they are consistent with our findings. Interestingly, since the data in Abdellaoui et al. (2015) includes three different probabilities we were able to calculate the ORIV correlation for $p = 1/2$, which turns out to be identical to the ORIV correlation of -0.3 in both our laboratory experiment and the UAS dataset.[22]

7.3 Other Information Environments

In our experiment we also added a treatment in which the information environment dealt with *multiplicative risks*, in which the loss is realized if an only if two independent

[22] Abdellaoui et al. (2015) design uses compound lotteries in their 'hypergeometric CR' treatment that resemble those in our multiplicative risks treatment, which prevents us from obtaining a replica of the information premium given that such compound lotteries are hard to compare across p. Nonetheless, the ORIV correction can be performed by using just a replica of the risk premium, obtained via linear interpolation of the risk premia associated with winning probability $1/2$ by using winning probabilities $1/12$ and $11/12$. Such a replica is a valid instrument since its measurement error is independent of the errors in the risk and information premia associated with $1/2$.

Table 5: Correlation between risk and insurance premia

p	Study	N	correlation	ORIV correlation
50	This paper - UAS	1,043	-0.347***	-0.306***
50	This paper - Experiment	119	-0.401***	-0.299***
50	Halevy (2007) - \$2 treatment	104	-0.557***	-
50	Halevy (2007) - \$20 treatment	38	-0.542***	-
8.33	Abdellaoui et al. (2015)[c]	115	-0.418***	-
50	Abdellaoui et al. (2015)[d]	115	-0.365***	-0.310**
91.67	Abdellaoui et al. (2015)	115	-0.518***	-
50	Chew et al. (2017)	188	-0.493***	-

[a] Statistical significance: *p-value < 0.10, **p-value < 0.05, ***p-value < 0.01.
[b] p-values for ORIV correlation are computed using bootstrapped standard errors.
[c] Correlation between the simple risk premium and hypergeometric CR premium. The hypergeometric CR treatment is similar to the multiplicative risk treatment in our experiment.
[d] ORIV correlation from the Abdellaoui et al. (2015) dataset is computed using the average risk premium under simple lotteries with winning probabilities 1/12 and 11/12 as a replica for the risk premium at probability 1/2.

binary risks with respective probabilities p_1 and p_2. Specifically, let $(p_1, p; 1 - p_1, p')$ denote the binary first-stage lottery leading to risk p with probability p_1 and risk p' with probability $1 - p_1$. The information environment we considered is $\mathcal{I}^{MR}(p) = \{I = (p_1, p_2; 1 - p_1, 0), p_1 \times p_2 = p\}$. Arguably, multiplicative risks are more complex to reduce since they require to multiply two probabilities instead of finding the midpoint of a range of probabilities. In addition, the first stage probability exhibits skewness since it leads to either no loss or a 2nd stage probability.[23]

Interestingly, the informational effects of multiplicative risks are much stronger than those associated with ranges. Figure 8 shows the comparison of information premia for multiplicative risk and range treatments. Whereas the information premium associated with multiplicative risks also declines as p goes up, it is still large at $p \leq 80\%$. A possible explanation for this disparity is that multiplicative risks are perceived as more complex and hence agents have a harder time reducing them. Using the incentivized quiz about reducing both range and multiplicative risks, Table 14 in the Appendix shows that the inability to reduce lotteries seems to increase WTP under multiplicative risks. However, they are still much larger under multiplicative risks for those who correctly reduce them. [24]

Overall, the correlation patterns observed using probability ranges continue to hold

[23] Experimental evidence shows that individuals are averse to negative skewness. See (Dillenberger and Segal, 2017) for a definition of negative skewness and for relevant references.

[24] We also find that negative skewness does not explain such disparity. Our regression estimates in Appendix C.4 show that p_1 does not significantly affect the information premium once we control for p.

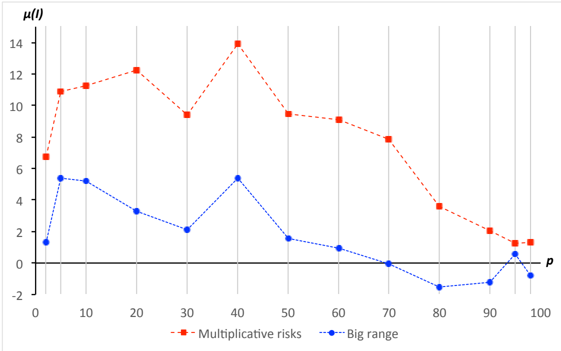

Figure 8: Information Premium of Big Range and Multiplicative Risk Treatments

under multiplicative risk: information premium is negatively related to p and the correlation between risk and information premia is significantly negative (see Table 15 in Appendix C).

8 Discussion and Conclusion

There are several takeaways from our analysis, which point to policy interventions, methodological changes and potential avenues for future research. Such implications of our analysis acquire particular relevance given the external validity of our findings.

First, the framing and perception of risks can have significant effects in the demand and allocation of insurance, partly driven by the negative correlation between risk aversion and a preference for simple information. In this context, policies aimed at regulating information disclosure can have large welfare benefits.

Second, informational effects can potentially introduce significant biases in risk preference estimates. Accordingly, it is necessary to enrich existing estimation approaches to include features of the information structure in order to obtain accurate estimates of the distribution of risk preferences in the population.

Finally, the sources of agents reaction to compound risks remain elusive. Existing theories such as ambiguity aversion, inability to reduce compound lotteries or aversion to complexity account for a small share of the variation of information premia. In addition, while preferences for simple information and risk attitudes are strongly related, most of the sociodemographic variables traditionally associated with risk attitudes, such as income or education, lack explanatory power when it comes to preferences for simple information.

References

Abdellaoui, Mohammed, Peter Klibanoff, and Lætitia Placido, "Experiments on compound risk in relation to simple risk and to ambiguity," *Management Science*, 2015, *61* (6), 1306–1322.

Barseghyan, Levon, Francesca Molinari, Ted O'Donoghue, and Joshua C Teitelbaum, "Estimating Risk Preferences in the Field," *Journal of Economic Literature*, 2016, *forthcoming.*

_ , Jeffrey Prince, and Joshua C Teitelbaum, "Are risk preferences stable across contexts? Evidence from insurance data," *American Economic Review*, 2011, *101* (2), 591–631.

Becker, Gordon M, Morris H DeGroot, and Jacob Marschak, "Measuring utility by a single-response sequential method," *Behavioral science*, 1964, *9* (3), 226–232.

Blackwell, David, "Comparison of experiments," in "Proceedings of the second Berkeley symposium on mathematical statistics and probability" The Regents of the University of California 1951.

Brown, Jeffrey R, Arie Kapteyn, Erzo FP Luttmer, Olivia S Mitchell, and Anya Samek, "Behavioral impediments to valuing annuities: Evidence on the effects of complexity and choice bracketing," Technical Report, National Bureau of Economic Research 2017.

Chew, Soo Hong, Bin Miao, and Songfa Zhong, "Partial Ambiguity," *Econometrica*, 2017, *85* (4), 1239–1260.

Chiappori, Pierre-André and Bernard Salanié, "Asymmetric information in insurance markets: Predictions and tests," in "Handbook of insurance," Springer, 2013, pp. 397–422.

Dawling, Pam, Aurélien Baillon, Laetitia Placido, and Peter P Wakker, "The rich domain of uncertainty: Source functions and their experimental implementation," *The American Economic Review*, 2011, *101* (2), 695–723.

Dillenberger, David and Uzi Segal, "Skewed noise," *Journal of Economic Theory*, 2017, *169* (C), 344–364.

Einav, Liran, Amy Finkelstein, and Jonathan Levin, "Beyond Testing: Empirical Models of Insurance Markets," *Annual review of economics*, 2010, *2*, 311.

_ , _ , Iuliana Pascu, and Mark R Cullen, "How General Are Risk Preferences? Choices under Uncertainty in Different Domains," *American Economic Review*, 2012, *102* (6), 2606–2638.

Fischbacher, Urs, "z-Tree: Zurich toolbox for ready-made economic experiments," *Experimental Economics*, 2007, *10* (2), 171–178.

Frederick, Shane, "Cognitive reflection and decision making," *The Journal of Economic Perspectives*, 2005, *19* (4), 25–42.

Gillen, Ben, Erik Snowberg, and Leeat Yariv, "Experimenting with Measurement Error: Techniques with Applications to the Caltech Cohort Study," *Journal of Political Economy*, 2017, *forthcoming.*

Grant, Simon, Atsushi Kajii, and Ben Polak, "Intrinsic Preference for Information," *Journal of Economic Theory*, 1998, *2* (83), 233–259.

Halevy, Yoram, "Ellsberg revisited: An experimental study," *Econometrica*, 2007, *75* (2), 503–536.

Handel, Benjamin R and Jonathan T Kolstad, "Health insurance for "humans": information frictions, plan choice, and consumer welfare," *The American Economic Review*, 2015, *105* (8), 2449–2500.

Harrison, Glenn W, "The Rich Domain of Uncertainty: Comment," Technical Report, Working Paper 2011 2011.

_ **and Elisabet E Rutström**, "Risk aversion in the laboratory," in "Risk aversion in experiments," Emerald Group Publishing Limited, 2008, pp. 41–196.

Jaspersen, Johannes G, "Hypothetical surveys and experimental studies of insurance demand: a review," *Journal of Risk and Insurance*, 2016, *83* (1), 217–255.

Moffatt, Peter G, Stefania Sitzia, and Daniel John Zizzo, "Heterogeneity in preferences towards complexity," *Journal of Risk and Uncertainty*, 2015, *51* (2), 147–170.

Outreville, J François, "Risk aversion, risk behavior, and demand for insurance: A survey," *Journal of Insurance Issues*, 2014, pp. 158–186.

Starmer, Chris, "Developments in non-expected utility theory: The hunt for a descriptive theory of choice under risk," *Journal of economic literature*, 2000, *38* (2), 332–382.

Sydnor, Justin, "(Over) Insuring Modest Risks," *American Economic Journal: Applied Economics*, 2010, *2* (4), 177–199.

Vieider, Ferdinand M., Mathieu Lefebvre, Ranoua Bouchouicha, Thorsten Chmura, Rustamdjan Hakimov, Michal Krawczyk, and Peter Martinsson, "Common Components of Risk and Uncertainty Attitudes Across Contexts and Domains: Evidence from 30 Countries," *Journal of the European Economic Association*, 2015, *13* (3), 421–452.

Appendix A Descriptive Statistics

Table 6 presents the summary statistics of the main sociodemographic variables of households in the UAS. Among other things, they contain measures of financial literacy, cognitive ability, education and income.

Table 6: Descriptive Statistics - UAS

Variable	Mean	Std. Dev.
Financial Literacy	0.00	1.00
Cognitive Ability	0.00	1.00
Age	48.34	15.52
Female	0.57	0.49
Married	0.59	0.49
Some College	0.39	0.49
Bachelor's Degree or Higher	0.36	0.48
HH Income: 25k-50k	0.24	0.43
HH Income: 50k-75k	0.20	0.40
HH Income: 75k-100k	0.13	0.34
HH Income: Above 100k	0.20	0.40
Black	0.08	0.27
Hispanic/Latino	0.10	0.29
Other Race	0.10	0.30
No. Individuals	4,442	

Appendix B Statistical Analysis of WTP

In this section we present the average WTP under simple risk ($W(p)$) and the information premium under compound or ambiguous risk. We report both averages for the whole sample, and also distinguishing by whether the decisions involved ambiguous ranges. Finally, we use our incentivized quiz about reducing compound risks, to contrast average WTP by subjects' ability to reduce compound lotteries.

Table 7 presents whole sample averages and reports both whether WTP are different from risk probabilities and whether information premium is significantly different from zero using one-sided paired t-tests.

Ambiguity Tables 8 and 9 show the effect of presenting agents with non-ambiguous versus ambiguous ranges. There is no clear effect of ambiguity on the information

Table 7: WTP for Insurance - UAS

	Group 1		Group 2		Group 3		Group 4	
p	$W(p)^a$	$\mu(I)^{b,c}$	$W(p)$	$\mu(I)$	$W(p)$	$\mu(I)$	$W(p)$	$\mu(I)$
2					28.2***	2.5***	28.3***	3.0***
						(2)		(4)
5	25.8***	2.8***	28.9***	4.4***				
		(4)		(8)				
10	28.5***	3.6***	31.4***	3.5***	31.4***	2.2***	30.9***	2.3***
		(18)		(14)		(8)		(4)
20	34.1***	3.5***	36.8***	2.5***	36.6***	4.6***	37.1***	2.0***
		(14)		(4)		(24)		(8)
30							42.4***	3.0***
								(18)
40			48.1***	3.5***	49.1***	1.7***		
				(24)		(4)		
50	54.7***	-0.6*						
		(8)						
60							60.3	2.2***
								(24)
70			66.5***	-0.6				
				(18)				
80	69.8***	-0.1						
		(4)						
90					77.9***	-1.1**		
						(14)		

[a] Statistical significance of one-sided paired t-test with null hypothesis $W(p) > (<)\ p$:
*p-value < 0.10, **p-value < 0.05, ***p-value < 0.01.
[b] Statistical significance of one-sided paired t-test with null hypothesis $\mu(I) > (<)\ 0$:
*p-value < 0.10, **p-value < 0.05, ***p-value < 0.01.
[c] Range sizes in parenthesis.

premium. For some probabilities it is bigger under non-ambiguity and for other ambiguity is associated with a higher information premium. Overall, effects seem to be quantitatively of the same order of magnitude.

Ability to reduce compound lotteries. Table 10 shows the average WTP associated with the range used in the incentivized question that asked subjects to compute the underlying failure probability. There are no substantial differences in information premia between those who answered correctly and those who did not correctly reduce the range, except for the last 2 ranges, in which those who reduced the range properly actually exhibit a higher WTP.

Table 8: WTP for Insurance: Non-Ambiguous Range

	Group 1		Group 2		Group 3		Group 4	
p	$W(p)^a$	$\mu(I)^{b,c}$	$W(p)$	$\mu(I)$	$W(p)$	$\mu(I)$	$W(p)$	$\mu(I)$
2					29.2***	2.3** (2)	28.5***	2.8*** (4)
5	25.3***	2.6*** (4)	29.2***	3.4*** (8)				
10	27.6***	4.1*** (18)	32.0***	2.9*** (14)	32.0***	2.1*** (8)	30.1***	3.0*** (4)
20	32.8***	3.6*** (14)	37.6***	1.7*** (4)	37.2***	4.4*** (24)	35.9***	2.7*** (8)
30							41.5***	4.0*** (18)
40			48.4***	3.9*** (24)	49.9***	1.4** (4)		
50	53.0***	0.03 (8)						
60							60.3	3.1*** (24)
70			66.8***	0.0 (18)				
80	67.7***	0.8* (4)						
90					78.2***	-0.8* (14)		

[a] Statistical significance of one-sided paired t-test with null hypothesis $W(p) > (<) \ p$:
*p-value < 0.10, **p-value < 0.05, ***p-value < 0.01.
[b] Statistical significance of one-sided paired t-test with null hypothesis $\mu(I) > (<) \ 0$:
*p-value < 0.10, **p-value < 0.05, ***p-value < 0.01.
[c] Range sizes in parenthesis.

B.1 Interpersonal Rankings of WTP

We present in this section the correlation between interpersonal rankings of WTP for insurance both across different underlying risks and information environments. Specifically, we rank individuals by their WTP for insurance for each pair of underlying risk and information (p, I) and then compute the correlation of those rankings with those under simple risk $(p, I = p)$.

Figure 9 plots the correlation coefficients as a function of the difference between underlying risk probabilities and information. The horizontal axis corresponds to the difference in underlying risk $|p - p'|$ between (p, p) and (p', I).

As the figure shows, correlation coefficients are high across environments, *for fixed underlying risks* (or close risks if one looks at the correlation between ordinal rankings of adjacent risk probabilities). However correlation substantially decreases with the

Table 9: WTP for Insurance: Ambiguous Range - UAS

	Group 1		Group 2		Group 3		Group 4	
p	$W(p)^a$	$\mu(I)^{b,c}$	$W(p)$	$\mu(I)$	$W(p)$	$\mu(I)$	$W(p)$	$\mu(I)$
2					27.2***	2.8*** (2)	28.1***	3.3*** (4)
5	26.2***	2.9*** (4)	28.7***	5.4*** (8)				
10	29.4***	3.1*** (18)	30.7***	4.1*** (14)	30.7***	2.4*** (8)	31.7***	1.6*** (4)
20	35.4***	2.9*** (14)	36.1***	3.3*** (4)	36.1***	4.7*** (24)	38.2***	1.2** (8)
30							43.3***	2.0*** (18)
40			47.8***	3.1*** (24)	48.3***	2.0*** (4)		
50	56.4***	-1.2** (8)						
60							60.3	1.2** (24)
70			66.3***	-1.2** (18)				
80	71.9***	-1.1** (4)						
90					77.5***	-1.4** (14)		

[a] Statistical significance of one-sided paired t-test with null hypothesis $W(p) > (<) p$: *p-value < 0.10, **p-value < 0.05, ***p-value < 0.01.
[b] Statistical significance of one-sided paired t-test with null hypothesis $\mu(I) > (<) 0$: *p-value < 0.10, **p-value < 0.05, ***p-value < 0.01.
[c] Range sizes in parenthesis.

difference between underlying risk probabilities, both within and across environments. The presence of informational effects tends to decrease the correlation when probability differences are not too large, but bigger ranges do not translate into significantly lower correlations than smaller ranges.

Appendix C Experiment

C.1 Design

The laboratory experiment was conducted at the BRITE Laboratory for economics research and computerized using ZTree (Fischbacher, 2007). Participants were recruited

Table 10: WTP by Ability to Reduce Compound Lotteries

		Correct			Incorrect		
Decision	p	$W(p)^a$	$\mu(I)^b$	n	$W(p)$	$\mu(I)$	n
Range							
3-7	5	22.6***	2.7***	658	34.2***	2.7**	247
3-17	10	26.3***	3.3***	484	37.3***	3.3***	417
8-32	20	30.6***	5.2***	523	42.4***	3.9***	539
21-39	30	38.7***	4.0***	655	48.5***	1.2*	406

[a] Statistical significance of one-sided paired t-test with null hypothesis $W(p) > (<) p$: *p-value < 0.10, **p-value < 0.05, ***p-value < 0.01.
[b] Statistical significance of one-sided paired t-test with null hypothesis $\mu(I) > (<) 0$: *p-value < 0.10, **p-value < 0.05, ***p-value < 0.01.

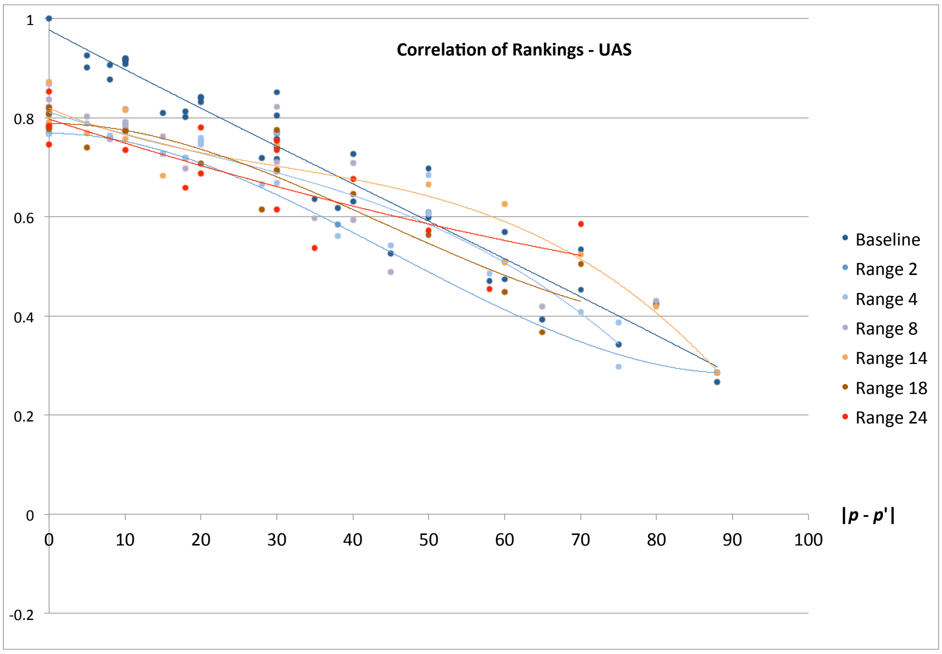

Figure 9: Correlation of interpersonal rankings by differences in risk.

from a subject pool of undergraduate students at the University of Wisconsin-Madison. A total of 119 subjects participated in 9 sessions, with an average of 13 subjects participating in each session. Upon arriving to the lab, subjects were seated at individual computers and given copies of the instructions. After the experimenter read the instructions out loud, she administered a quiz on understanding (see Appendix D for the complete instructions and quiz provided to subjects).

Each participant made 52 insurance decisions individually and in private. In each decision period, the subject was the owner of a unit called the A unit. The A unit had some chance of failing, and some chance of remaining intact. Intact A units paid out 100 experimental dollars to the subject at the end of the experiment, while failed A units paid out nothing. The probability of A unit failure, including the information available about said probability, was varied in each decision.

In each decision period, we elicited the maximum willingness to pay for full insurance using the Becker-DeGroot-Marschak mechanism. Subjects moved a slider to indicate how much of their 100 experimental dollar participation payment they would like to use to pay for insurance. Then, the actual price of insurance was drawn at random using a bingo cage from a uniform distribution on (0,100). If the willingness to pay was equal to or greater than the actual price, the subject paid the actual price, which assured that the A unit would be replaced if it failed. On the other hand, if the willingness to pay was less than the actual price, the subject did not pay for insurance and lost the A unit if there was a failure.

All subjects faced 52 different independent decisions in which they stated their maximum willingness to pay for full insurance for their A unit. We randomized subjects to two different treatments; in one, subjects received all information about probability with greater precision (which we call the No Ambiguity group) and in the other some of the probability information was ambiguous (we call this group the Ambiguity group). However, all subjects faced multiple information sets; in that sense, our design includes both within- and between- subject components.

We start by explaining the decisions faced by the No Ambiguity group. We divide the decisions into 4 different 'blocks' of 13 decisions each. In each 'block' of decisions, we asked subjects to state maximum willingness to pay for an expected rate of failure of between 2% and 98%, as described in Table 11. The four 'blocks' were as follows: 1) Probability of Loss, which provided full information about the failure rate, 2) Range Small, which provided a small range of possible probabilities of failure, 3) Range Big, which provided ranges of greater size, and 4) Compound Risk, which corresponds to multiplicative risks.[25] It was clearly explained that within the Range blocks, the actual probability of failure would be chosen from within the range with all integer numbers equally likely. The Compound Risk 'block' implies a loss only if both probabilities are realized. As can be noted from Table 11, each decision within the block has a corresponding decision with the same expected probability across multiple different information environments for ease of comparison.

Both Compound Risk and Range blocks constitute a decision that involves solving a compound risk problem. While there is no ambiguity in these decisions, we propose that in line with Halevy (2007) we may expect to see aversion from compound risk, which would manifest itself in higher willingness to pay for insurance. Along the range treatments, we chose Small and Big range in order to vary levels - Big Range is somewhat more imprecise than Small range.

The Ambiguity group faced similar decisions to the No Ambiguity group (as denoted by Table 11, except that the actual selection of the probability of failure for the Range 'blocks' was left ambiguous. Specifically, subjects were told that the actual probability is within the range but is unknown.

Subjects made decisions one at a time, but had a record sheet in front of them summarizing the ranges and probabilities for all 52 decisions. To control for any order effects, we conducted the experiment using 4 different possible orders, assigned at

[25]In the experiment itself, these were called 'Known Failure Rate' (1), 'Uncertain Failure Rate' (2 and 3), and 'Failure Rate Depends on Environmental Conditions' (4)

random to each session: (1, 2, 3, 4); (2, 3, 4, 1)' (3, 4, 1, 2) and (4, 1, 2, 3).

Following all 52 decision rounds, subjects also completed a quiz testing their ability to reduce compound lotteries and a short demographic questionnaire.[26]

At the end of the experiment, only one of the decisions was selected at random and paid out, and no feedback on outcomes was given until the end, so we consider each decision made an independent decision. At the end of the experiment, we first randomly selected one decision to be the 'decision-that-counts.' Then, we randomly selected the actual price of insurance. Finally, we used the reported probability of failure in the 'decision-that-counts' to randomly choose whether or not the A unit would fail. All random selections were carried out using a physical bingo cage and bag of orange and white balls rather than a computerized system to assure transparency.

Earnings in experimental dollars were converted to US dollars at the rate of 10 experimental dollars = $1. Participation required approximately one hour and subjects earned an average of about $29.5 each.[27]

Table 11: Experiment Treatments

Decision # (within block)	(1) Probability of Loss (%)	(2) Range Small (%)	(3) Range Big (%)	(4) Compound Risk 1st; 2nd, (%)
1	2	1-3	0-4	40; 5
2	5	3-7	1-9	10; 50
3	10	3-17	1-19	40; 25
4	20	16-24	8-32	25; 80
5	30	29-31	21-39	85; 35
6	40	38-42	28-52	50; 80
7	50	46-54	38-62	66; 76
8	60	58-62	48-72	86; 70
9	70	69-71	61-79	75; 93
10	80	76-84	68-92	95; 84
11	90	83-97	81-99	92; 98
12	95	93-97	91-99	99; 96
13	98	97-99	96-100	99; 99

C.2 Analyisis of WTP

In this section we Table 12 presents the average WTP under simple risk as well as the information premium across treatments. The table also reports both whether $W(p)$ is different from p and whether the information premium is different from zero according to one-sided paired t-tests.

[26]Other data subjects consented to provide include administrative data on math entrance exams, available at the university.

[27]In this paper, we report only on the insurance choice experiment, which was conducted at the be-

Table 12: WTP for Insurance

p	$W(p)^a$	Range				Multi-Risk
		$\mu(I)^b$	(size)	$\mu(I)$	(size)	$\mu(I)$
2	3.98**	0.14	(2)	1.29	(4)	6.74***
5	5.51	2.55**	(4)	5.37***	(8)	10.88***
10	13.38**	2.70***	(14)	5.20***	(18)	11.28***
20	23.27**	0.94	(8)	3.27***	(24)	12.23***
30	31.38	-0.51	(2)	2.11*	(18)	9.41***
40	38.94	1.78**	(4)	5.41***	(24)	13.88***
50	50.29	-0.45	(8)	1.53	(24)	9.47***
60	58.11	0.83	(4)	0.92	(24)	9.10***
70	65.80**	1.68**	(2)	-0.08	(18)	7.86***
80	75.58**	-1.66*	(8)	-1.52	(24)	3.60**
90	82.92***	-1.34*	(14)	-1.19	(18)	2.05
95	86.61***	-1.29	(4)	0.57	(8)	1.25
98	89.04***	-0.42	(2)	-0.80	(4)	1.29

[a] Statistical significance of one-sided paired t-test with null hypothesis $W(p) > (<) p$: *p-value < 0.10, **p-value < 0.05, ***p-value < 0.01.
[b] Statistical significance of one-sided paired t-test with null hypothesis $\mu(I) > (<) 0$: *p-value < 0.10, **p-value < 0.05, ***p-value < 0.01.

Ambiguity. Table 13 shows the effect of presenting agents with non-ambiguous versus ambiguous ranges. As expected ambiguity seems to elicit a somewhat stronger response from agents. Nonetheless, the effect of non-ambiguous ranges is quite large and significant at low to moderate probabilities, especially at big ranges.

Ability to reduce compound lotteries. Finally, we check whether the results might be solely driven by subjects' lack of understanding of how to reduce compound lotteries. The next table shows the WTP and risk premia of subjects that answered correctly an incentivized quiz asking them to compute the underlying failure probability of some of the above scenarios. There were six questions in the quiz, three for ranges and three regarding compound risks. Table 14 presents the results. While the magnitude of $\mu(I)$ is higher on average for those who respond incorrectly, subjects that reduce compound risks still exhibit significant information premia, especially under multiplicative risks.

ginning of the session. However, subjects stayed to participate in another risk task after the insurance task was over. The time and earnings reported above exclude the additional task time and payout.

Table 13: WTP by Ambiguity

	Compound Range					Ambiguous range				
p	$W(p)^a$	$\mu(I)^b$	(size)	$\mu(I)$	(size)	$W(p)$	$\mu(I)$	(size)	$\mu(I)$	(size)
2	3.48*	-0.45	(2)	-0.05	(4)	4.46*	0.15	(2)	2.56*	(4)
5	4.77	2.41	(4)	3.55**	(8)	6.21	2.67*	(4)	7.10***	(8)
10	12.40	3.21**	(14)	4.40***	(18)	14.31**	2.21**	(14)	5.97***	(18)
20	22.21	1.79*	(8)	2.59*	(24)	24.28**	0.13	(8)	3.92**	(24)
30	31.05	-0.21	(2)	1.28	(18)	31.69	-0.80	(2)	2.90*	(18)
40	38.05	2.55**	(4)	5.90***	(24)	39.79	1.05	(4)	4.95***	(24)
50	50.28	-0.97	(8)	0.24	(24)	50.31	0.05	(8)	2.75	(24)
60	56.84	0.62*	(4)	1.47	(24)	59.31	1.03	(4)	0.41	(24)
70	63.97**	1.97*	(2)	0.31	(18)	67.54	1.41	(2)	-0.44	(18)
80	72.72***	-0.12	(8)	-0.69	(24)	78.30	-3.13***	(8)	-2.31	(24)
90	80.14***	-1.19	(14)	-0.48	(18)	85.56**	-1.49	(14)	-1.87	(18)
95	83.26***	0.57	(4)	2.02	(8)	89.79**	-3.07**	(4)	-0.80	(8)
98	86.74***	-0.33	(2)	0.05	(4)	91.23***	-0.51	(2)	-1.61	(4)

[a] Statistical significance of one-sided paired t-test with null hypothesis $W(p) > (<)\ p$:
*p-value < 0.10, **p-value < 0.05, ***p-value < 0.01.
[b] Statistical significance of one-sided paired t-test with null hypothesis $\mu(I) > (<)\ 0$:
*p-value < 0.10, **p-value < 0.05, ***p-value < 0.01.

Table 14: WTP by Ability to Reduce Compound Lotteries - Lab

		Correct			Incorrect		
Decision	p	$W(p)^a$	$\mu(I)^b$	n	$W(p)$	$\mu(I)$	n
Range							
0-4	2	3.18**	0.31	105	10.00	8.64	14
3-17	10	13.02*	2.13**	88	14.39*	4.32**	31
61-79	70	64.56***	0.32	89	69.47	-1.24	30
Multi-Risk							
10; 50	5	4.69	9.50***	84	7.49	14.20***	35
50; 80	40	37.61	11.47***	77	41.38	18.31***	42
95; 84	80	73.88**	4.10**	50	76.81*	3.23*	69

[a] Statistical significance of one-sided paired t-test with null hypothesis $W(p) > (<)\ p$:
*p-value < 0.10, **p-value < 0.05, ***p-value < 0.01.
[b] Statistical significance of one-sided paired t-test with null hypothesis $\mu(I) > (<)\ 0$:
*p-value < 0.10, **p-value < 0.05, ***p-value < 0.01.

C.2.1 Correlation Between Risk and Information premia

Table 15 presents the correlation coefficients for different p between risk and information premia, as well as the ORIV correlation coefficients. To perform the ORIV correction we use the linear interpolation of adjacent risk premia as a replica of risk premium. We do not use replicas of the information premium given the lack of a direct comparability of information premium between different multiplicative risks.[28]

Table 15: Correlation between risk and insurance premia – Experiment

	Range		Multi-Risk	
p	correlation[a]	ORIV correlation[b]	correlation	ORIV correlation
2	-0.197**	-	-0.249**	-
5	-0.120	-0.059	-0.166**	-0.012
10	-0.214**	0.210	-0.304***	-0.333*
20	-0.394***	-0.405***	-0.315***	-0.268***
30	-0.567***	-0.499	-0.388***	-0.301***
40	-0.203**	-0.428*	-0.239***	-0.192***
50	-0.401***	-0.299***	-0.378***	-0.366***
60	-0.240***	-0.289**	-0.347***	-0.254***
70	-0.374***	-0.299***	-0.372***	-0.373***
80	-0.388***	-0.425***	-0.402***	-0.373***
90	-0.459***	-0.529***	-0.525***	-0.530***
95	-0.538***	-0.596***	-0.539***	-0.529***
98	-0.569***	-	-0.587***	-

[a] Statistical significance: *p-value < 0.10, **p-value < 0.05, ***p-value < 0.01.
[b] p-values for ORIV correlation are computed using bootstrapped standard errors.

C.3 Interpersonal Rankings of WTP

Figure 10 plots the correlation coefficients as a function of the difference between underlying risk probabilities and information treatments. The horizontal axis corresponds to the difference in underlying risk $|p - p'|$ between (p, p) and (p', I). As in the survey data, correlation coefficients are high across treatments in the lab, *for fixed underlying risks* (or close risks if one looks at the correlation between ordinal rankings of adjacent risk probabilities). However correlation substantially decreases with the difference between underlying risk probabilities, both within and across treatments. The presence of informational effects tends to decrease the correlation when probability differences are not too large, but bigger ranges do not translate into significantly lower correlations than smaller ranges. In the lab, multiplicative risks have a large negative effect on the correlation of interpersonal rankings.

[28]Information premium might depend on different attributes of the compound lottery such as skewness. Not having a replica for the information premium implies that the ORIV correlation is consistent as long as the variation in each replica of the risk premium due to measurement error is identical (Gillen et al., 2017).

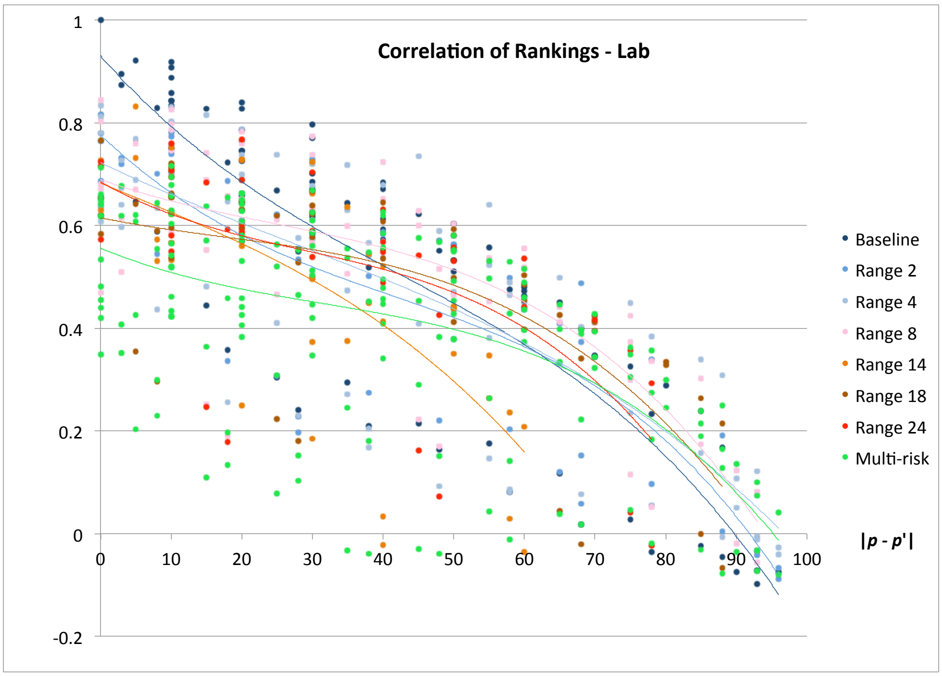

Figure 10: Correlation of interpersonal rankings by differences in risk - Experiment.

C.4 Covariates of Information Premium in the Laboratory

Table 16 presents the regression estimates from the experiment. We run separate regressions for the range and multiplicative risk treatments. In the latter regressions we include the first stage risk probability since it is associated with negative skeweness.[29] We also include as proxies for financial literacy whether the subject's major is quantitative (life sciences, natural sciences, economics and business, and engineering majors) and whether she took an economic course. GPA and the number of correct answers in the cognitive reflection test (CRT) (Frederick, 2005) are proxies for cognitive ability.

The results in terms of the explanatory power of risk premium largely replicate the findings using the UAS data. The regression R^2 goes from 0.03 to 0.14 in the range treatment and from 0.14 to 0.28 for multiplicative risks. Neither ambiguity nor skeweness seem to significantly affect information premia. Interestingly, a higher cognitive ability (CRT score) is significantly associated with a lower information premium only in the multiplicative risks treatment, potentially reflecting the fact that these risks are more complex than range risks and thus elicit a higher reaction in subjects with lower ability. In terms of demographics only age is statistically significant in the multi-risk treatment.

Unlike the field experiment, order effects are not significant. To measure them we consider whether the subjects answered the simple risk questions first or faced the reverse order, meaning that the answer questions of the respective treatment (range or multiplicative risks) first.

[29] It can be shown that lotteries with $p_1 < (>)\ 0.5$ are negatively skewed.

Table 16: Covariates of Information Premium and Risk Premium - Experiment

	$\mu(I)$				$\mu(p)$
	Range		Multi-Risk		
Risk Probability	-0.04*	-0.07***	-0.07	-0.15***	-0.12***
	(0.01)	(0.01)	(0.04)	(0.04)	(0.03)
Probability Range	0.25**	0.18			
	(0.08)	(0.08)			
(Probability Range)^2	-0.01	-0.01			
	(0.00)	(0.00)			
1st Stage Probability			-0.04	0.00	
			(0.03)	(0.03)	
Ambiguity	-0.28	0.17			
	(1.21)	(1.24)			
Quiz Score	-0.12	-0.26	0.39	0.30	
	(0.47)	(0.46)	(0.48)	(0.51)	
Quantitative Major	1.35	0.88	-2.11	-3.10	-2.84
	(1.41)	(1.49)	(2.17)	(2.34)	(3.02)
Statistics Course	1.88	1.52	-2.73	-3.11	-3.22
	(1.97)	(1.86)	(2.74)	(2.94)	(4.04)
Cumulative GPA	0.88	1.30	-0.12	0.28	1.20
	(0.96)	(0.91)	(1.53)	(1.47)	(1.59)
CRT Score	-0.46	-0.28	-3.09***	-3.35***	0.15
	(0.56)	(0.55)	(0.86)	(0.90)	(1.13)
$\mu(p)$		-0.15***		-0.31***	
		(0.04)		(0.07)	
Age	-0.20	-0.18	1.48***	1.62***	0.15
	(0.09)	(0.09)	(0.18)	(0.16)	(0.22)
Female	0.27	-0.19	3.63	1.88	-4.56
	(1.43)	(1.54)	(1.87)	(1.99)	(2.63)
Years in College	-0.18	-0.13	-0.36	-0.27	0.96
	(0.76)	(0.81)	(1.16)	(1.29)	(1.69)
Black/African American	-2.51	-2.69	-2.92	-2.12	-0.19
	(3.88)	(4.03)	(8.40)	(9.38)	(3.86)
Asian	-1.97	-2.21	-1.61	-1.44	0.94
	(1.53)	(1.40)	(2.14)	(2.20)	(3.45)
Hispanic	3.14	5.50	0.71	4.47	10.30
	(1.66)	(2.23)	(3.18)	(3.81)	(6.07)
Reverse Order	-2.21	-1.64	-1.67	-1.34	4.08
	(1.21)	(1.24)	(1.64)	(1.65)	(2.42)
R^2	0.04	0.13	0.14	0.28	0.09
N	3094	2618	1547	1309	1547

All regressions include a constant and standard errors are clustered. Regressions including $\mu(p)$ are IV regressions with the linear interpolation of adjacent risk premia as the instrument for $\mu(p)$. Bonferroni-adjusted p-values: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Appendix D Instructions

D.1 Survey

You can earn up to $10 for the next part. The amount you earn depends on the decisions you make, so you should read carefully!

We will ask you to make decisions about insurance in a few different scenarios. This time, at the end of the survey, one of the scenarios will be selected by the computer as the "scenario that counts." The money you earn in the "scenario that counts" will be added to your usual UAS payment. Since you won't know which scenario is the "scenario that counts" until the end, you should make decisions in each scenario as if it might be the one that counts.

We will use virtual dollars for this part. At the end of the survey, virtual dollars will be converted to real money at the rate of 20 virtual dollars = $1. This means that 200 virtual dollars equals $10.00.

Each Scenario

- You have 100 virtual dollars
- You are the owner of a machine worth 100 virtual dollars.
- Your machine has some chance of being damaged, and some chance of remaining undamaged, and the chance is described in each decision.
- You can purchase insurance for your machine. If you purchase insurance, a damaged machine will always be replaced by an undamaged machine.
- At the end, in the scenario-that-counts, you will get 100 virtual dollars for an undamaged machine. You will not get anything for a damaged machine.

Paying for Insurance

You will move a slider to indicate how much you are willing to pay for insurance, before learning the actual price of insurance. To determine the actual price of insurance in the "scenario that counts", the computer will draw a price between 0 and 100 virtual dollars, where any price between 0 and 100 virtual dollars is equally likely.

If the amount you are willing to pay is equal to or higher than the actual price, then:

- You pay for the insurance at the actual price, whether or not your machine gets damaged
- If damage occurs, your machine is replaced at no additional cost
- If there is no damage, your machine remains undamaged
- You get 100 virtual dollars for your machine
- That means you would earn 100 virtual dollars (what you start with) PLUS 100 virtual dollars (amount you get for machine) MINUS the price of insurance.

If the amount you are willing to pay for insurance is less than the actual price, then:

- You do not pay for the insurance
- If damage occurs, your machine is damaged and you do not get any money for your machine. That means you would earn 100 (what you start with) but you would not earn anything for your machine.
- If there is no damage, your machine remains undamaged and you get 100 virtual dollars. That means you would earn 100 virtual dollars (what you start with) PLUS 100 virtual dollars (amount you get for the machine).

This means that the higher your willingness to pay, the more likely it is that you will buy insurance.

BASELINE BLOCK: ALL TREATMENTS

Remember: You can earn up to $10 for the next part. The amount you earn depends on the decisions you make, so you should read carefully!

KNOWN DAMAGE RATE: The chance of your machine being damaged is 5% [10, 20, etc].

Please move the slider to indicate the maximum amount you are willing to pay for insurance.

Remember, if the amount you are willing to pay is higher than the actual price, then you will pay for insurance at the actual price, whether or not your machine is damaged. Should there be damage, your machine will be replaced and you will get 100 virtual dollars for it. If the amount you are willing to pay is less than the actual price, then you will not pay for insurance, but if damage occurs, your machine will not be replaced and you will not get any money for it.

[Slider moves from 0 to 100 in integer increments.]

CONFIRMATION MESSAGE

You have indicated you are willing to pay up to X for insurance. Continue? Y / N

RANGE BLOCK: AMBIGUOUS RANGE

UNCERTAIN DAMAGE RATE: The chance of your machine being damaged is between 3% and 7% [8-32 etc]. The exact rate of damage within this range is unknown.

Please move the slider to indicate the maximum amount you are willing to pay for insurance.

Remember, if the amount you are willing to pay is higher than the actual price, then you will pay for insurance at the actual price, whether or not your machine is damaged. Should there be damage, your machine will be replaced and will pay out 100 virtual dollars. If the amount you are willing to pay is less than the actual price, then you will not pay for insurance, but if damage occurs, your machine will not be replaced and will not pay out any money.

[Slider moves from 0 to 100 in integer increments.]

RANGE BLOCK: NON-AMBIGUOUS RANGE

UNCERTAIN DAMAGE RATE: The chance of your machine being damaged is between 3% and 7% [8-32 etc]. All damage rates in this range are equally likely.

Please move the slider to indicate the maximum amount you are willing to pay for insurance.

Remember, if the amount you are willing to pay is higher than the actual price, then you will pay for insurance at the actual price, whether or not your machine is damaged. Should there be damage, your machine will be replaced and will pay out 100 virtual dollars. If the amount you are willing to pay is less than the actual price, then you will not pay for insurance, but if damage occurs, your machine will not be replaced and will not pay out any money.

[Slider moves from 0 to 100 in integer increments.]

QUESTION

Before we finish, we'd like you to answer a final question. You will receive $1 for a correct answer.

Suppose a machine has a chance of being damaged between X and Y%. All damage rates in this range are equally likely. What is the average rate of damage for this machine?

The ranges to use in the question are: Group 1: range 3-7%; group 2: range 3-17%; group 3: 8-32%; group 4: 21-39%

END SCREEN

Thank you for participating!

The computer selected scenario X to be the "scenario that counts"

The computer selected the price of X virtual dollars for the insurance. Since the maximum you were willing to pay for insurance was X virtual dollars, you [bought/did not buy] insurance at the price of X.

The likelihood of damage for scenario X was [X%/between X% and Y%]. Your machine [was / was not] damaged and you got [nothing / amount] for your machine.

Based on the scenario the computer selected, your earnings for this part are X virtual dollars.

Converted to real money, your earnings are $X (X virtual dollars divided by 20).

You also earned $0 / $1 in the previous question.

A total of $X will be added to your usual UAS payment.

D.2 Laboratory Experiment: Order 1, No Ambiguity in Ranges

Note that the different orders are exactly the same, except that the order of risk scenarios (known, range, or compound) are different in both the instructions and on the subjects' screen.

In this part, we will use experimental dollars as our currency. At the end of the experiment, your experimental dollars will be converted to US dollars and paid out to you in CASH with the following conversion rate:

10 experimental dollars = $1. This means 100 experimental dollars = $10.

You will start with 100 experimental dollars - this is your participation payment for this part of the experiment ($10).

You will make a series of 52 different decisions. Once all decisions have been made, we will randomly select one of those to be the decision-that-counts by drawing a number at random from a bingo cage with balls numbered from 1 to 52. Note, that since all decisions are equally likely to be chosen, you should make each decision as if it will be the decision-that-counts. Please pay close attention because you can earn considerable money in this part of the experiment depending on the decisions you make. You should think of each decision as separate from the others.

Each Decision Period

- In each decision period, you will be the owner of a unit called an A unit. - Your A unit has some chance of failing, and some chance of remaining intact. - The probability of failure differs for different decision periods, so you should pay careful attention to the instructions in each decision period. - In each decision period, you will have the opportunity to purchase insurance for your A unit. You can use up to 100 experimental dollars from your participation payment to purchase the insurance. If you purchase insurance, a failed A unit will always be replaced for you. - At the end of the experiment, in the decision-that-counts, intact A units (those that have not failed) will pay out 100 experimental dollars. Failed A units will pay out 0 experimental dollars.

Paying for Insurance

You will indicate how much you are willing to pay for insurance in each decision by moving a slider. You will indicate your willingness to pay before learning the actual price of insurance for that round. To determine the actual price of insurance in the 'decision that counts', a number will be drawn at random from a bingo cage with numbers from 1 to 100. Any number is equally likely to be drawn.

If the maximum amount you were willing to pay for insurance is equal to or higher than the actual price of insurance, then: - You pay for the insurance at the actual price, whether or not a failure occurs - If a failure occurs, your A unit is replaced at no additional cost to you - If there is no failure, your A unit remains intact - Your A unit always pays out 100 experimental dollars

If the maximum amount you were willing to pay for insurance is less than the actual price of insurance, then: - You do not pay for the insurance - If a failure occurs, your A unit will fail and you get no experimental dollars - If there is no failure, your A unit will remain intact and pays out 100 experimental dollars

If you indicate you are willing to pay 0 experimental dollars for insurance, then you will never buy the insurance.

Failure of the A unit

After learning whether you have purchased insurance, you will find out whether your A unit has failed or not in the 'decision that counts'. The likelihood of failure depends on the specific directions in each decision. In some decisions, the likelihood of failure is known, and in some decisions, the likelihood of failure is uncertain. Let's go through some examples:

Known Failure Rate

In decisions with a known failure rate, the failure rate will be given to you. For example, suppose the failure rate is 15%. To determine whether your A unit will fail, we will place 100 balls in this bag. 15 will be orange and 85 will be white. Then, you will draw a ball at random. If the ball you drew is orange, your A unit will fail. If it is white, your A unit will remain intact (will not fail).

As another example, suppose the failure rate is 50%. To determine whether your A unit will fail, we will place 100 balls in this bag. 50 will be orange and 50 will be white. Again, if the ball you drew is orange, your A unit will fail and if it is white your A unit will remain intact (will not fail). In this type of decision, drawing an orange ball means your A unit fails.

Uncertain Failure Rate

In decisions with an uncertain failure rate, the failure rate will be given to you as a range. For example, suppose the failure rate is in the range 5% to 25%. To determine whether your A unit will fail, we will place 100 balls in this bag. Between 5 and 25 of the balls will be orange, and the remaining balls will be white. All failure rates in this range will be equally likely - a separate bingo draw will determine the number of orange balls before they are put in the bag. This means it is equally likely that there are 5, 6, 7...through 25 orange balls in the bag. Then, you will draw a ball at random. If the ball you drew is orange, your A unit will fail. If it is white, your A unit will remain intact (will not fail).

As another example, suppose the failure rate is in the range 40%-60%. To determine whether your A unit will fail, we will place 100 balls in this bag. Between 40 and 60 of the balls will be orange, and the remaining balls will be white. All numbers in this range will be equally likely. Again, if the ball you drew is orange, your A unit will fail and if it is white your A unit will remain intact (will not fail). In this type of decision, drawing an orange ball means your A unit fails.

Failure Rate Depends on Environmental Conditions

In decisions where the failure rate depends on environmental conditions, the A unit may only fail if environmental conditions are poor, but not if the environmental conditions are good. The likelihood of poor environmental conditions and the actual likelihood of failure are known and given to you. For example, suppose that the chance of poor environmental conditions is 50%. If the environment is poor, then there is a 30% chance of failure of the A unit. This means that we will have 2 bags with 100 balls each. In the first bag, we will put 50 orange balls and the remaining balls will be white. You will draw a ball at random from the first bag. If the ball is white, the environmental conditions are good and your A unit will not fail. If the ball is orange, the environmental conditions are poor and you will draw from the second bag. In the second bag, we will put 30 orange balls and the remaining balls will be white. You will draw a ball at random from the second bag. If the ball you drew from the second bag is orange, your A unit will fail. If it is white, your A unit will remain intact (will not fail).

As another example, suppose that the chance of poor environmental conditions is 70%. If the environment is poor, then there is a 50% chance of failure of the A unit. This means that the first bag will have 100 balls - 70 orange and the remaining white. You will draw a ball from the first bag at random. If it is white, your A unit will remain intact. If it is orange, we will prepare the second bag. The second bag will have 100 balls - 50 orange and the remaining white. You will draw a ball from the second bag at random. If the ball you drew from the second bag is orange, your A unit will fail. If it is white, your A unit will remain intact (will not fail). In this type of decision, both balls must be orange for your A unit to fail.

In summary:

- Each decision is equally likely to be the decision-that-counts. Therefore you should pay close attention to each decision you make. - The likelihood of failure may be different in each decision period. Pay close attention and reference the instructions if you need to. - Intact A units pay out 100 experimental dollars at the end of the experiment. Failed A units pay out nothing. - In each decision period, you will decide how much you are willing to pay for insurance. If your willingness to pay is greater than or equal to the actual price of insurance, then you will buy insurance. If your willingness to pay is less than the actual price of insurance, then you will not buy insurance. This means that the higher your willingness to pay, the more likely it is that you will buy insurance. Insurance guarantees that your A unit will be replaced at no cost and will pay out 100 experimental dollars. If you bought insurance, you pay for insurance whether or not your A unit fails.

Before you begin making decisions, you will answer the next set of questions on your screen to confirm your understanding. You may refer back to instructions at any time. Please answer the questions on your screen now.

Your decisions

You will now have 30 minutes for this part. Please take your time when making each of the 52 decisions. There will be a 5-second delay before you can submit each of your decisions on the screen. Please also record your decisions on the record sheet.

D.3 Laboratory Experiment: Order 1, Ambiguity in Ranges

Note that the ambiguity instructions are exactly the same as the instructions without ambiguity, except that for the 'uncertain failure rate' scenarios, rather than informing subjects that any probability in the range is equally likely, we say that the probability is unknown. In the below, we provide just the instructions that are different from D.2.

Uncertain Failure Rate In decisions with an uncertain failure rate, the failure rate will be given to you as a range. For example, suppose the failure rate is in the range 5% to 25%. To determine whether your A unit will fail, we will place 100 balls in this bag. Between 5 and 25 of the balls will be orange, and the remaining balls will be white. The exact number of orange balls is unknown and could be any number between 5 and 25. Then, you will draw a ball at random. If the ball you drew is orange, your A unit will fail. If it is white, your A unit will remain intact (will not fail).

As another example, suppose the failure rate is in the range 40%-60%. To determine whether your A unit will fail, we will place 100 balls in this bag. Between 40 and 60 of the balls will be orange, and the remaining balls will be white. Again, if the ball you drew is orange, your A unit will fail and if it is white your A unit will remain intact (will not fail). In this type of decision, drawing an orange ball means your A unit fails.