

On Information and the Demand for Insurance

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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 two large-scale surveys and a laboratory experiment. Across all three settings, we find an ‘information premium’ - that is, consumers are willing to pay more for insurance when there is uncertainty about underlying risks versus when risks are known. This leads to a rightward shift in demand for insurance. Importantly, we find that the information premium is negatively correlated with risk aversion. This 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. The implication is a misallocation of insurance and a reduction in consumer welfare.

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

Keywords: risk, uncertainty, ambiguity, insurance, compound risk, demand analysis, information disclosure, hypothetical survey, laboratory experiment

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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 may have difficulty estimating their own risks.

The impact of the changing information asymmetry between insurers and consumers is not well understood. This is in large part because understanding the impact requires data on two key factors that are typically unobserved in insurance claim data. The first factor is consumers' attitudes toward underlying risks when those risks are uncertain or complex. This affects the extent of information frictions (Handel and Kolstad, 2015). Laboratory experiments using lottery choices have documented that individuals are ambiguity averse and have difficulty reducing compound lotteries (Halevy, 2007). This suggests that willingness-to-pay (WTP) for insurance should be higher when underlying risks are uncertain versus when they are known (i.e., a level effect). We refer to the difference in WTP under uncertain and known risks as the 'information premium.'

The second factor is the relationship between risk preferences, measured by the risk premium an agent is willing to pay over the actuarially fair price of insurance, and the information premium. 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 uncertain, more risk averse agents will be more likely to buy insurance. On the other hand, a negative correlation implies that more risk averse agents will be *less* likely to buy insurance. The latter possibility implies 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 uncertain. Since both risk and information premia drive insurance demand, estimating them from administrative data on insurance take-up is not tractable without imposing strong assumptions on their joint distribution.

In this paper, we generate new data on these two factors using two surveys and a

¹See <https://www.iii.org/fact-statistic/facts-statistics-industry-overview>

²For 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>.

laboratory experiment. In our first survey, over 4,000 Americans representative of the U.S. population are asked their WTP to fully insure a hypothetical product that has a known value. We experimentally vary underlying risks and the risk-related information structure, including certain risks, a range of risks, and compound risks. The survey is incentivized: respondents receive a payoff (up to \$10) based partly on their insurance decision and partly on whether the product fails, whereby failure is randomly determined by our survey software based on the underlying risk distribution. The survey has several attractive features. First, the experimental variation in underlying risk and risk-related information allows us to jointly estimate risk aversion and the information premium at varying underlying risks. Second, each respondent makes decisions in a string of scenarios with varying underlying risks, which allows us to explore the inter-personal ranking of insurance take-up.

In our second survey, over 5,000 Americans representative of the U.S. population are asked their hypothetical WTP to insure a possible defect in a used car up to \$5,000. We again experimentally vary whether the underlying risks are certain or are represented by a range of probabilities and ask respondents to make decisions in multiple scenarios. An advantage of our second survey relative to the first is that we use monetary amounts that are more aligned with those that people face in existing markets; as such, the higher-stakes data from this survey is helpful to illustrate the effects of information frictions on actual insurance markets.

We conduct market equilibrium and welfare analysis by combining the data from the surveys with auto collision insurance claims data. Specifically, we sample the WTP data from our surveys using the empirical distribution of insurance claims in existing markets and construct a synthetic demand curve given by the joint distribution of risk, risk attitudes and information frictions. 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.

In both surveys, we find that WTP for insurance is significantly higher in settings with more complex or ambiguous information. The average information premium is positive for most relevant levels of underlying risk and is as high as 100% of the expected loss. Crucially, we find a negative correlation of about -0.3 between risk aversion and the information premium across individuals. This negative correlation is remarkably robust to variation in underlying risk probability and to the sources of informational

frictions. It implies that more risk averse individuals may sub-optimally under-insure when underlying risks are uncertain.

Our demand analysis points 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. First, uncertainty about underlying risks drives up the average WTP for insurance, which implies that aggregate demand is higher relative to a world where agents are fully informed about risks. Second, since the risk premium and the information premium are negatively correlated, the average risk premium is 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 them. We estimate the welfare loss associated with complex information to range between 7% under perfect competition to 40% under monopoly, with even larger effects estimated for the high-stakes survey. The results are quantitatively similar whether or not insurers are allowed to price discriminate. Further, 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.

We next conduct a laboratory experiment to evaluate the reproducibility of our survey results and link our findings to the experimental economics literature on risk preferences (e.g., [Harrison and Rutström \(2008\)](#)). In our experiment, undergraduate students are incentivized to make decisions about insuring a hypothetical product. We find the same pattern of results in our laboratory experiment: 1) average WTP is higher under uncertain underlying risks, and 2) there is a negative correlation of -0.12 to -0.57 between the risk premium and the information premium. We also demonstrate that these results can be replicated in three related laboratory experiments in the literature ([Halevy, 2007](#); [Abdellaoui et al., 2015](#); [Chew et al., 2017](#)).

Finally, we consider the drivers of heterogeneity in the information premium. First, we explore the impact of our variation in features of information uncertainty. We find that larger range probabilities result in higher information premia. The information premium decreases as underlying risks increase. However, we do not find significant differences between ambiguous and unambiguous risks. Second, we use the rich set of background data available on survey respondents, including demographic background, socio-economic status, cognitive ability and financial literacy, which allows us to explore the determinants of the information premium. We find that these individual characteristics - for example, sociodemographic characteristics, financial literacy and the ability to reduce compound lotteries - account for about 20% of the variation in

risk premia. Interestingly, 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., 2010a; Jaspersen, 2016) and to the emerging literature on the impact of information frictions on insurance markets (Handel and Kolstad, 2015; Handel et al., 2019). 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., 2010a). 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 market equilibrium analysis extends the literature on selection in markets (Einav et al., 2010b; Einav and Finkelstein, 2011; Mahoney and Weyl, 2017; Spinnewijn, 2017; Handel et al., 2019). As the model of Handel et al. (2019) emphasizes, understanding the relationship between risk, risk attitudes and information frictions is crucial to evaluate welfare and policy interventions. In this context, the use of survey data allows us to estimate their joint distribution without any structural assumptions and provide a direct measurement of selection effects associated with information frictions.

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 economics 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 individuals are averse to compound risks and that risk aversion decreases with the underlying risks - confirm the results in related work (Abdellaoui et al., 2015). However, our paper is entirely new in estimating the correlation between risk preferences and attitudes toward information about underlying risk.³

Our findings have policy relevance that is timely to the technological transformation with the advent of InsurTech. Policies that simplify underlying risk information for consumers are needed to improve the allocation of insurance. Further, our results suggest that a monopolist may have the incentive to selectively disclose risk information. A policy of mandatory disclosure of risk estimates by insurers could mitigate the selection effect and improve welfare.

In what follows, Section 2 lays out the theoretical framework. Section 3 summarizes the first (main) survey. Section 4 describes our main results. Section 5 summarizes the second survey and our demand analysis. Section 6 investigates the sources behind information attitudes. Section 7 discusses measurement error correction. Section 8 discusses reproducibility of our findings across our three settings as well as with related laboratory experiments in the literature. Section 9 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 urn. 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 scenarios.

In principle, it is reasonable to assume that the agent’s expected probability of

³Our paper is also related to research using field experiments to measure risk attitudes, for example (Harrison et al., 2007a,b). These papers use specific sub-samples of the population and tailor the design of the experiments to risks subjects are familiar with. In contrast, we use an artificial design in our survey but include a representative sample of the U.S. population.

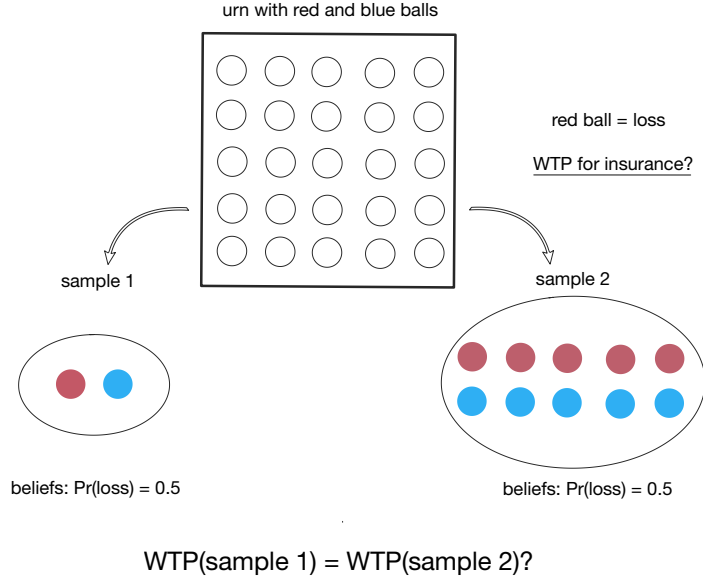


Figure 1: Urn Thought Experiment

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.

2.1 Preliminaries

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

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

different beliefs about p , even if these beliefs *reduce* to p , i.e., lead to the same expected 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 $W : \mathcal{I}(p) \rightarrow \mathbb{R}$, 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 $V : \mathcal{I}(p) \rightarrow \mathbb{R}$, 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

⁵Since 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.

⁶We 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.

⁷For instance, if we assume that the agent has EU preferences with constant absolute risk aversion

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.

2.2 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 .¹⁰

(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 $e^{-\theta(1 - WTP)} = p + (1 - p)e^{-\theta}$.

⁸Most 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 $T = \{1, \dots, N\}$ or a large market with a continuum of agents $T = [0, 1]$.

¹⁰This characterization of demand for binary risks can be expressed in terms of a joint distribution of individual surplus, costs and frictions following the approach of [Handel et al. \(2019\)](#).

following 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 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 $\text{corr}(\mu(p), \mu(I)) < 0$.*

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.

2.3 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.¹¹ 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 Survey Design

Our primary empirical evidence comes from our first survey. This was 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.¹² 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.

¹¹Similar 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.

¹²All 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.

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:

- (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),¹³ where the actual price of insurance was drawn at random by the computer from a uniform distribution on (0,100). Appendix E 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 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 questions, participants were asked a question eliciting their ability to reduce 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.¹⁴

¹³This is a common mechanism in similar experiments, for instance see Halevy (2007).

¹⁴It 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).

Table 1: Summary of Decisions Presented to Respondents, Survey 1

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.

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 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). We replicate qualitatively similar results for high stakes decisions in Survey 2 (see [Appendix B](#)) and in the laboratory experiment (see [Section 7](#)).

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 C.2](#) in [Appendix C](#) 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%.

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.¹⁵

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 $p < 50\%$.¹⁶ Information premia decrease with the underlying risk probability, which is consistent with [Abdellaoui et al. \(2015\)](#), 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](#)

¹⁵[Table C.2](#) in [Appendix C](#) shows the average information premium at each p by group.

¹⁶The 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.

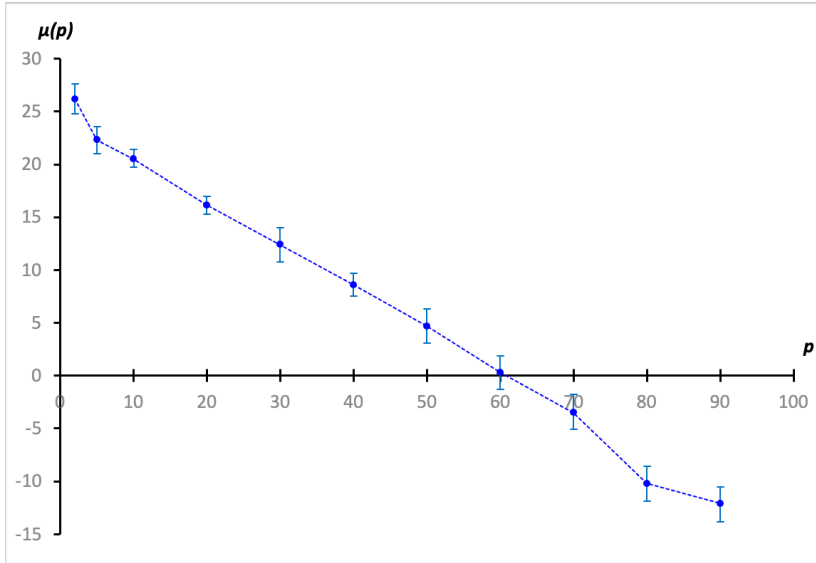


Figure 2: Average Risk Premium at Different Probabilities (bars represent 95% confidence intervals).

C, 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%.

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 information 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.

4.2 Relationship Between Risk 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

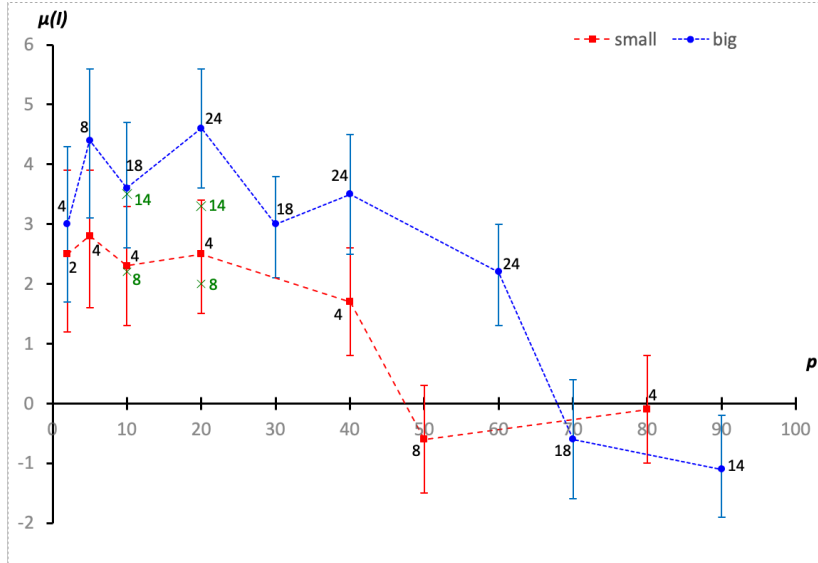


Figure 3: Information Premium at Different Probabilities (point labels represent range size and bars represent 95% confidence intervals).

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.¹⁷ 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.¹⁸

5 Demand Analysis

Our findings show that information about underlying risks has a significant impact on agents' demand for insurance. To illustrate the extent of these effects, we use our survey 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

¹⁷Table 7 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. All coefficients are significant at the 1% level.

¹⁸Appendix D.3 shows that the correlation of individual WTP rankings across information environments is high, consistent with the findings of Einav et al. (2012), but it goes down with range size due to the negative correlation.

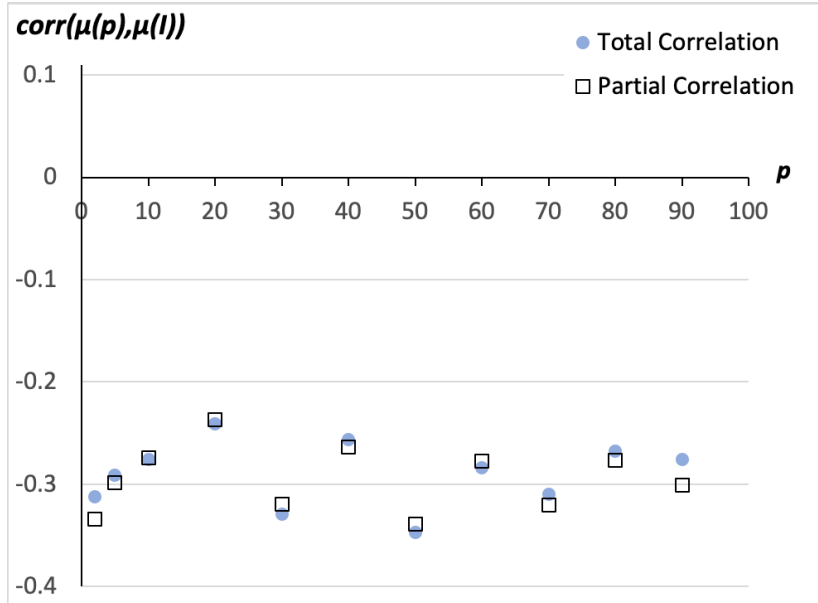


Figure 4: Correlation Coefficients between Risk Premium and Information Premium.

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 analyze market equilibrium in two different pricing 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 the spirit of Mahoney and Weyl (2017).

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.

5.1 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. \(2011\)](#).¹⁹

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.²⁰ 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} .²¹

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

¹⁹[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.

²⁰We 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 $n = 2, 3, \dots, 8$; 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 $p = 0.02$.

²¹Our 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.

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 leads to a 10 – 14% higher demand.

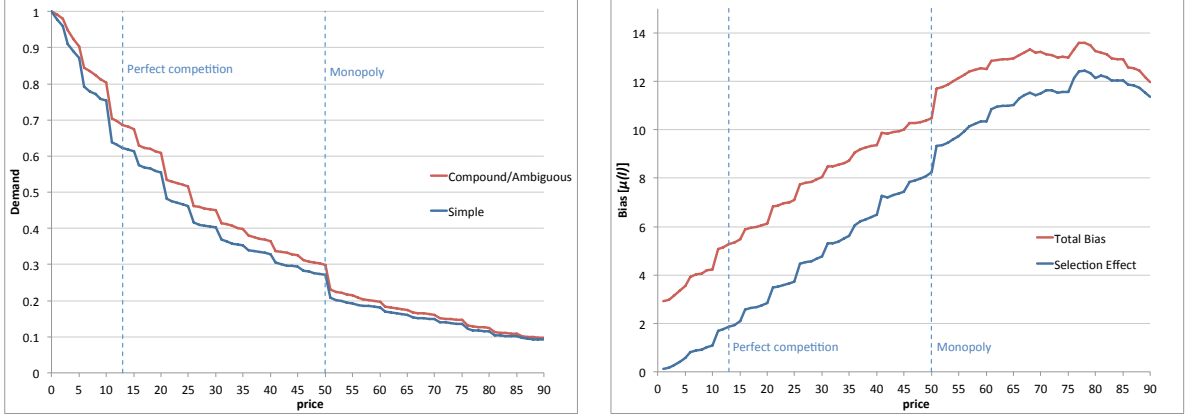


Figure 5: Demand for Insurance (left) and Bias in Risk Premium Estimates (right).

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 $1_{\{\cdot\}}$ 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 counterfactual 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

	Overall Population	<i>Uniform Price</i>				<i>Risk-based Pricing</i>			
		Perfect Competition		Monopoly		Perfect Competition		Monopoly	
		Simple	Compound	Simple	Compound	Simple	Compound	Simple	Compound
<i>Insured Pool</i>									
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
Estimation Bias			17.7%		21.7%		13.6%		21.3%
<i>Selection Effect</i> ^a			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 ^b			6.7%		39.4%		2.3%		46.4%
<i>Selection Effect</i> ^c			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
<i>risk prefs</i> \perp <i>risk</i> ^d		0.347	0.320	0.423	0.417	0.000	0.000	0.111	0.121

^aDifference 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.

^bDifference between average welfare under simple and compound risk, relative to the average welfare under simple risk.

^cDifference 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.

^dThe 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 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.

5.2 Demand for Insurance under High Stakes

One might be skeptical about constructing the demand for insurance using data from small-stakes decisions. As such, we also construct the demand analysis using Survey 2, in which individuals made hypothetical decisions over large stakes.

Survey 2 also utilized respondents from the UAS internet panel, and was conducted in the spring of 2020.²² In Survey 2, we asked respondents their hypothetical WTP to fully insure a used car against mechanical defects assessed at \$5,000 (Appendix E provides the wording of the question). Each respondent received two questions - one with a precise underlying risk and one with a range of underlying risks - in random order. We experimentally varied the underlying risks faced across respondents (generating 11 different groups). Table 3 provides a summary of decisions presented to respondents. Unlike Survey 1, Survey 2 was not incentivized.

Appendix B presents the empirical analysis of Survey 2. Overall, the data exhibits the same empirical patterns as Survey 1, with two major differences. First, individuals are significantly less risk averse at high stakes, with risk premium being significantly above zero only for $p < 0.2$. Similarly, the information premia are lower under high stakes, although still large for $p < 0.2$. For those with WTP data in both surveys (about a fifth of the sample), we find that the risk premium across the two surveys are significantly correlated (the correlation coefficient is 0.39).

Table 4 presents the market equilibrium analysis using the high-stakes data, showing qualitatively similar results with the main analysis presented in Table 2.²³ There are some slight differences. For example, the lower risk premia in Survey 2 result in a smaller share of insured agents in the population. Further, because Survey 2, relative

²²All 8,815 panel members who were in the sample in 2020 were recruited to complete the survey online, and 7,145 respondents accessed the survey. 1,826 respondents started but did not complete the survey and are excluded from our analysis.

²³Under uniform pricing, perfect competition prices were the same across simple and compound risks, given by $\rho = 13$. Monopoly prices were $\rho = 50$ under both scenarios.

Table 3: Summary of Decisions Presented to Respondents, Survey 2

Group	(1) Probability of Loss (%)	(2) Range Probability (%)
1	2	0-4
2	5	1-9
3	10	1-19
4	20	13-27
5	30	21-39
6	40	28-52
7	50	45-54
8	60	48-72
9	70	61-79
10	80	73-87
11	90	83-97

Notes: Respondents were assigned to one of 11 groups, and were presented both the probabilities described in (1) and (2), in random order.

to Survey 1, displays a larger reduction in risk premium than in information premium, we see even bigger estimation bias and welfare effects than in Survey 1.²⁴

²⁴Note that these differences may not be attributable to high stakes alone, because several factors change between Survey 1 and Survey 2, including the stakes, whether or not the survey is incentivized and the context.

Table 4: Demand for Insurance - Aggregate Outcomes under High Stakes

	Overall Population	<i>Uniform Price</i>				<i>Risk-based Pricing</i>			
		Perfect Competition		Monopoly		Perfect Competition		Monopoly	
		Simple	Compound	Simple	Compound	Simple	Compound	Simple	Compound
<i>Insured Pool</i>									
Share of Population	100%	27.0%	27.9%	9.6%	11.5%	58.5%	61.2%	15.5%	9.7%
Risk Probability	9.6%	13.2%	13%	14.1%	12.4%	4.8%	4.6%	4.1%	6.2%
Risk Premium	2.8	22.8	20.1	44.1	36.2	13.4	12.4	38.7	42.8
Info Premium	1.0		4.8		10.8		2.1		12.3
Estimation Bias			23.9%		29.8%		17.9%		28.7%
<i>Selection Effect</i> ^a			40.7%		56.8%		23.4%		53.6%
Consumer Welfare		6.2	5.6	1.8	1.0	7.8	7.6	2.8	0.6
Welfare Loss ^b			9.7%		43.9%		3.5%		77.3%
<i>Selection Effect</i> ^c			96.0%		88.5%		94.0%		28.5%
Corr(risk, coverage)		0.139	0.134	0.095	0.065	-0.371	-0.410	-0.153	-0.072
<i>risk prefs</i> \perp <i>risk</i> ^d		0.454	0.442	0.446	0.435	0.000	-0.054	0.160	0.121

^aDifference 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.

^bDifference between average welfare under simple and compound risk, relative to the average welfare under simple risk.

^cDifference 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.

^dThe 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.

5.3 Strategic Information Disclosure

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 2.3](#), 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 5](#) 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 also has 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 5: Information Disclosure under Monopoly

p	2	5	10	20	30	40	50	60	70	80	90
Survey 1 (Incentivized)	no	no	no	no	no	no	yes	no	yes	no	yes
Survey 2 (High Stakes)	no	no	no	yes	no	no	yes	no	yes	yes	no

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.

Table 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 Table 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.²⁵

7 Measurement Error Correction

An important concern with the estimates of the correlation between risk and information premia presented in [Subsection 4.2](#) 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

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

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

²⁵No such order effects seem to be present in the experiment (see [Table D.11](#) in [Appendix D.4](#)).

Table 6: Covariates of Information Premium and Risk Premium

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

be consistently estimated using

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

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

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

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.²⁶

Table 7 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.

²⁶For the laboratory sample we average the normalized information premia elicited in the small range and big range treatments.

Table 7: 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.

8 External Validity

A large literature in experimental economics has used incentivized laboratory experiments with university students to evaluate risk preferences. We next show that the pattern of results we described from our survey studies also hold in the laboratory. We first present the results of our companion laboratory experiment and then extend our discussion to evaluating the results of other laboratory experiments in the literature for which we were able to obtain data.

8.1 Laboratory Experiment

The laboratory experiment was designed to follow Survey 1 closely and included a similar set of decision questions. Approximately 100 university students at the University of Wisconsin-Madison BRITE laboratory participated. 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 to Survey 1. 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. Further, it allows us to more closely link our results to the experimental economics literature on risk preferences.

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 D 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 in the experiment. Both risk premium and information premium are decreasing in risk probability p , as shown in Figure 6. The only major difference is that subjects in the experiment were significantly less risk averse.

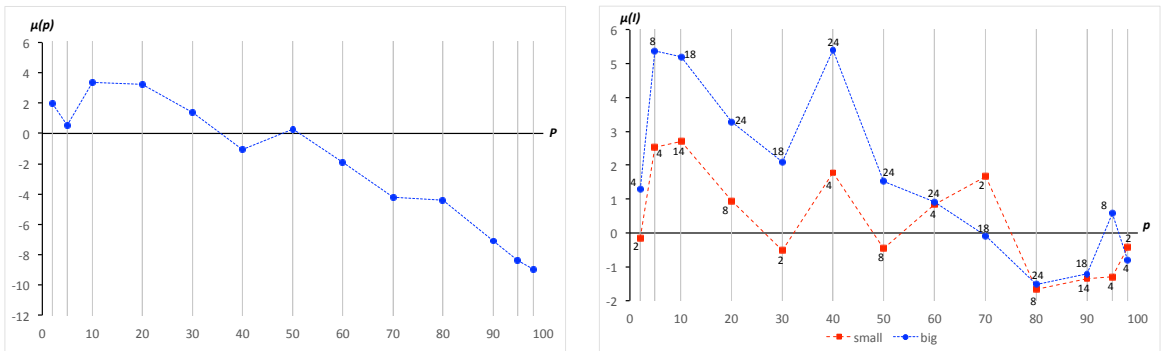


Figure 6: Average Risk and Information Premia at Different Probabilities.

In addition, risk and information premia exhibit a negative correlation of similar 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 D.10 in Appendix D).

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

8.2 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 7](#) 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.²⁷

Table 8: 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.

8.3 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 and only if two independent binary risks with respective probabilities p_1 and p_2 . Specifically, let $(p_1, p; 1 - p_1, p')$

²⁷[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.

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.²⁸

Interestingly, the informational effects of multiplicative risks are much stronger than those associated with ranges. Figure 7 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 D.9 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.²⁹

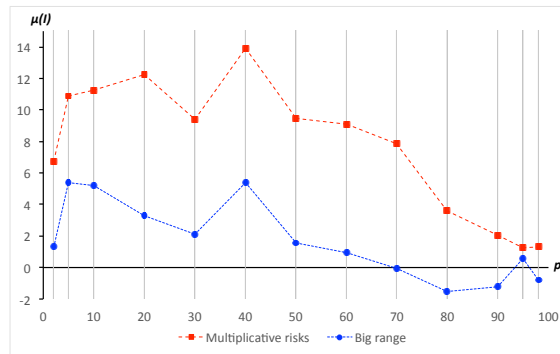


Figure 7: Information Premium of Big Range and Multiplicative Risk Treatments

Overall, the correlation patterns observed using probability ranges continue to hold under multiplicative risk: information premium is negatively related to p and the correlation between risk and information premia is significantly negative (see Table D.10 in Appendix D).

²⁸Experimental evidence shows that individuals are averse to negative skewness. See (Dillenberger and Segal, 2017) for a definition of negative skewness and for relevant references.

²⁹We also find that negative skewness does not explain such disparity. Our regression estimates in Appendix D.4 show that p_1 does not significantly affect the information premium once we control for p .

9 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.

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Appendix A Descriptive Statistics

Table A.1 presents the summary statistics of the main sociodemographic variables of households in the UAS in Survey 1.

Table A.1: Descriptive Statistics - UAS

Variable	Survey 1		Survey 2	
	Mean	Std. Dev.	Mean	Std. Dev.
Age	48.34	15.52	50.75	16.24
Female	0.57	0.49	0.58	0.49
Married	0.59	0.49	0.56	0.49
Some College	0.39	0.49	0.37	0.48
Bachelor's Degree or Higher	0.36	0.48	0.42	0.49
HH Income: 25k-50k	0.24	0.43	0.21	0.41
HH Income: 50k-75k	0.20	0.40	0.19	0.39
HH Income: 75k-100k	0.13	0.34	0.14	0.34
HH Income: Above 100k	0.20	0.40	0.27	0.44
Black	0.08	0.27	0.07	0.26
Hispanic/Latino	0.10	0.29	0.15	0.35
Other Race	0.10	0.30	0.14	0.35
Financial Literacy (range: 0-100)	67.52	22.11	69.79	21.96
No. Individuals	4,442		5,319	

Appendix B Empirical Analysis of Survey 2

This section presents the risk and information attitudes in the high stakes environment (Survey 2). As can be seen from the figures presented, the results are qualitatively similar to Survey 1.

Figure B.1 presents the average risk premium, normalized by loss size. For probabilities up to 10% agents are significantly risk averse, turning to risk seeking as loss probability goes up. In terms of magnitudes, risk premium at low probabilities are about a third of those in survey 1, but still quite large. For instance, a 2% loss probability elicits a risk premium of about 9%, i.e., over four times the actuarially fair price.

Figure B.2 presents the average information premium at each possible p , normalized by the size of the loss. On average, agents exhibit significantly large information premia at $p < 20\%$, about half the size of the information premia in survey 1.

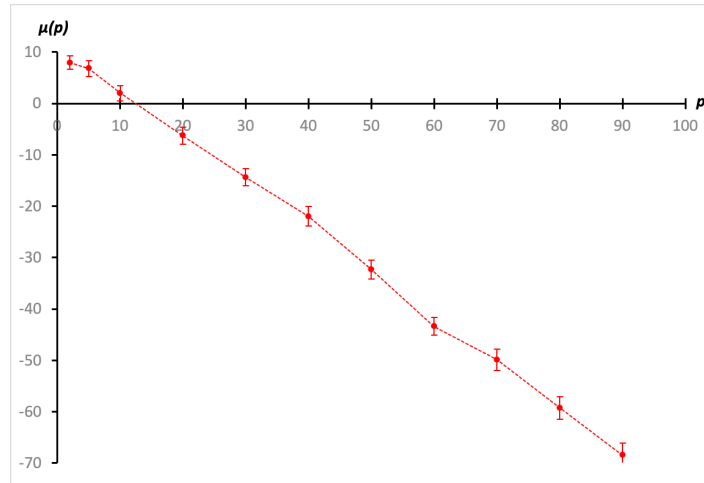


Figure B.1: Average Risk Premium (bars represent 95% confidence intervals).

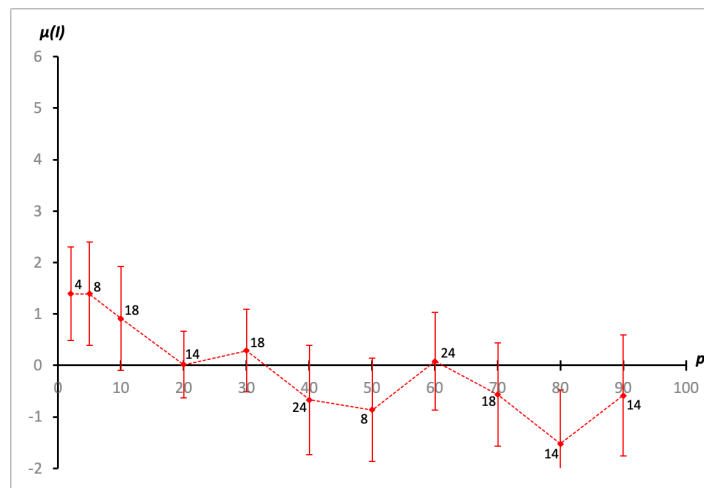


Figure B.2: Average Information Premium (labels denote range size and bars are 95% confidence intervals).

Figure B.3 plots the correlation coefficients, showing that risk and information premia are negatively correlated at all risk probabilities and of the same magnitudes as in the case of survey 1.

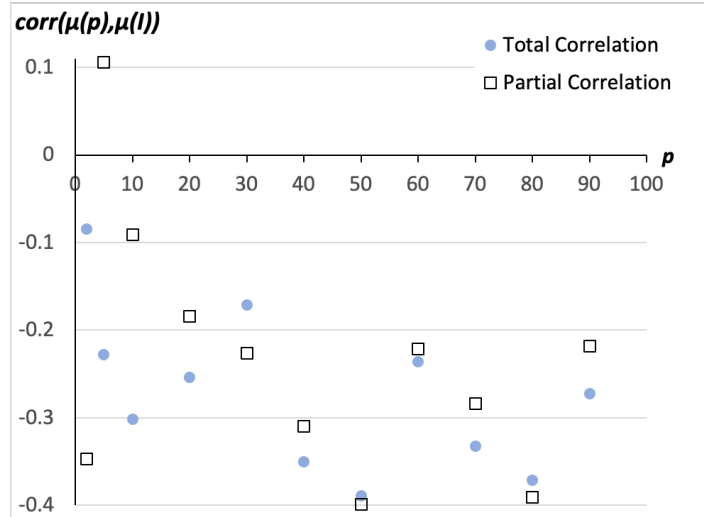


Figure B.3: Correlation Coefficients between Risk Premium and Information Premium.

Appendix C 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 C.2](#) 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 C.3](#) and [C.4](#) show the effect of presenting agents with non-ambiguous versus ambiguous ranges. There is no clear effect of ambiguity on the information 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 C.5](#) 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 C.2: WTP for Insurance - UAS

p	Group 1		Group 2		Group 3		Group 4	
	$W(p)^a$	$\mu(I)^{b,c}$	$W(p)$	$\mu(I)$	$W(p)$	$\mu(I)$	$W(p)$	$\mu(I)$
2					28.2***	2.5*** (2)	28.3***	3.0*** (4)
5	25.8***	2.8*** (4)	28.9***	4.4*** (8)				
10	28.5***	3.6*** (18)	31.4***	3.5*** (14)	31.4***	2.2*** (8)	30.9***	2.3*** (4)
20	34.1***	3.5*** (14)	36.8***	2.5*** (4)	36.6***	4.6*** (24)	37.1***	2.0*** (8)
30							42.4***	3.0*** (18)
40			48.1***	3.5*** (24)	49.1***	1.7*** (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.

C.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 C.4 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 C.3: WTP for Insurance: Non-Ambiguous Range

p	Group 1		Group 2		Group 3		Group 4	
	$W(p)^a$	$\mu(I)^{b,c}$	$W(p)$	$\mu(I)$	$W(p)$	$\mu(I)$	$W(p)$	$\mu(I)$
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.

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 D Experiment

D.1 Design

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

Table C.4: WTP for Insurance: Ambiguous Range - UAS

p	Group 1		Group 2		Group 3		Group 4	
	$W(p)^a$	$\mu(I)^{b,c}$	$W(p)$	$\mu(I)$	$W(p)$	$\mu(I)$	$W(p)$	$\mu(I)$
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.

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 E 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.

Table C.5: WTP by Ability to Reduce Compound Lotteries

Decision	p	Correct			Incorrect		
		$W(p)^a$	$\mu(I)^b$	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.

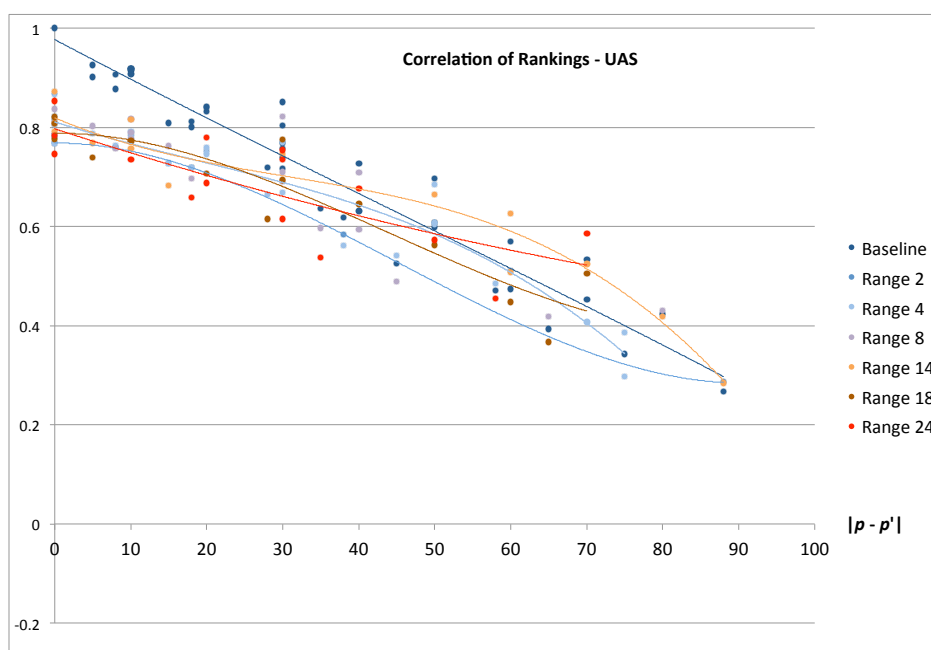


Figure C.4: Correlation of interpersonal rankings by differences in risk.

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 D.6](#). 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.³⁰ 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 D.6](#), 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 D.6](#), 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 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.³¹

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

³⁰In the experiment itself, these were called ‘Known Failure Rate’ (1), ‘Uncertain Failure Rate’ (2 and 3), and ‘Failure Rate Depends on Environmental Conditions’ (4)

³¹Other data subjects consented to provide include administrative data on math entrance exams, available at the university.

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.³²

Table D.6: 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

D.2 Analysis of WTP

In this section we [Table D.7](#) 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.

Ambiguity. [Table D.8](#) 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.

³²In this paper, we report only on the insurance choice experiment, which was conducted at the beginning 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 D.7: 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.

Table D.8: WTP by Ambiguity

p	Compound Range					Ambiguous range				
	$W(p)^a$	$\mu(I)^b$	(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.

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 D.9](#) 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.

Table D.9: WTP by Ability to Reduce Compound Lotteries - Lab

Decision	p	Correct			Incorrect		
		$W(p)^a$	$\mu(I)^b$	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.

D.2.1 Correlation Between Risk and Information premia

[Table D.10](#) 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.³³

D.3 Interpersonal Rankings of WTP

Figure [D.5](#) 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

³³Information 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](#)).

Table D.10: Correlation between risk and insurance premia – Experiment

p	Range		Multi-Risk	
	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.

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.

D.4 Covariates of Information Premium in the Laboratory

Table D.11 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 skewness.³⁴ 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 skewness seem to significantly affect information premia. Interestingly, a higher cognitive

³⁴It can be shown that lotteries with $p_1 < (>) 0.5$ are negatively skewed.

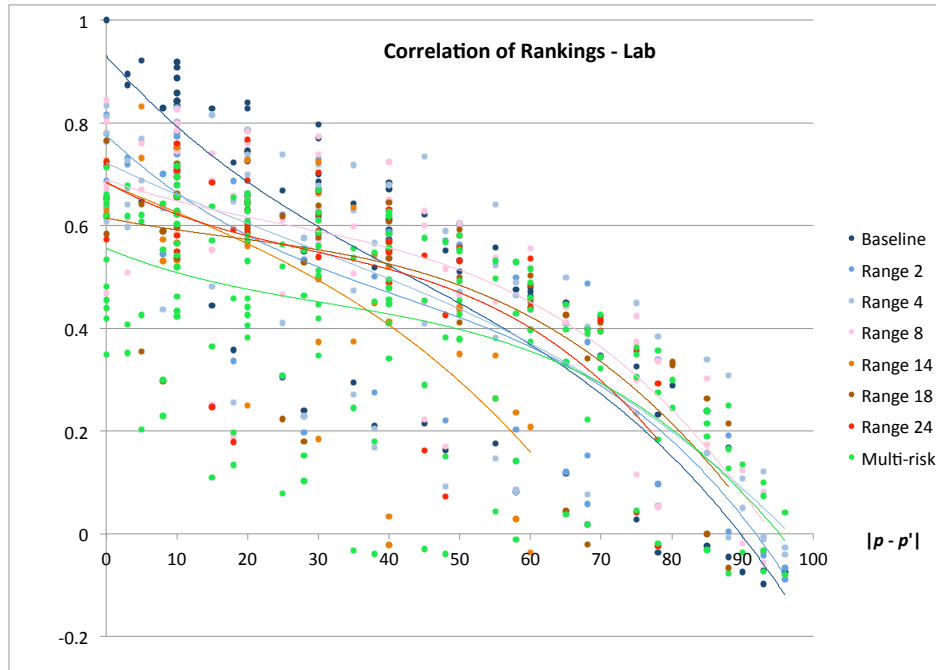


Figure D.5: Correlation of interpersonal rankings by differences in risk - Experiment.

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.

Table D.11: 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 E Instructions

E.1 Survey 1

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.

E.2 Survey 2

Our two questions were added to an existing UAS survey fielded in March, 2020, which focused mainly on perceptions and behaviors related to the Coronavirus. Given that this other survey may have induced some background risk, our questions were asked (randomly) either at the beginning or end of the survey. We do not find a significant difference in responses across the two orders; hence, we pool them in our analysis. The questions were as follows:

Question 1: Suppose you already bought a used car. After inspecting the car, an independent agency tells you that the chance the car may be defective and in the first year is **2%**. If the car is defective, your only option will be to fix it and you will need to pay \$5,000 to do this.

How much would you pay for an insurance policy that would give you back the full \$5,000 to fix the car?

[Slider moves from 0 and \$5,000 in integer increments.]

Question 2: Suppose you already bought a different used car. After inspecting the car, an independent agency tells you that the chance the car may be defective in the first year is **between 0 and 4%**. All failure rates in this range are equally likely. If the car is defective, your only option will be to fix it and you will need to pay \$5,000 to do this.

How much would you pay for an insurance policy that would give you back the full \$5,000 to fix the car?

[Slider moves from 0 and \$5,000 in integer increments.]

E.3 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.

E.4 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 [E.3](#).

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.