On Information and the Demand for Insurance

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Abstract

Technological advances in the insurance industry mean that insurers may be better informed about underlying risks than consumers. We evaluate the impact of these information frictions by combining demand elicitation surveys with insurance claim data. We find an 'information premium' - i.e., consumers are willing to pay more for insurance when risks are uncertain. Importantly, we find that the information premium is negatively correlated with risk aversion. This leads to a selection effect: individuals who purchase insurance are not necessarily the most risk averse. The resulting misallocation of insurance can lead to large welfare losses and biased risk preference estimates.

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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 demand 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 certain 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 relationship 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 value insurance most will be less likely to purchase it when information about underlying risks is uncertain. Despite being a key determinant of demand, the relationship between risk and information premia remains unknown due to data limitations, making the study of information frictions and policy evaluation in insurance markets all but intractable

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

[2] For an overview of recent technological trends, see the 2020 OECD report on insurance and big data (https://www.oecd.org/finance/Impact-Big-Data-AI-in-the-Insurance-Sector.pdf). Companies like Google and Amazon invested in InsurTech companies in 2018 and are considering entering insurance markets (https://www.insurancejournal.com/news/national/2019/01/02/513324.htm).

without imposing strong assumptions on their joint distribution.[3]

This paper advances our understanding of insurance demand by measuring the relationship between risks, risk preferences and information attitudes and quantifies the potential impact of information frictions on insurance markets. We overcome the inherent lack of observability of these demand determinants by generating new data using population surveys and conduct market analysis by combining them with existing estimates on insurance claim rates from administrative data.

In our main survey, over 4,000 individuals representative of the U.S. population are asked their WTP to fully insure a hypothetical product that has a known value. Respondents make a series of decisions in which we exogenously vary the underlying risks (captured by the probability that the product looses its value) and the risk-related information structure (including certain and uncertain risks). The survey has several attractive features. First, it provides incentives for truthful reporting of WTP: respondents receive up to \$10 based partly on their decision and partly on whether the product looses value. Second, the experimental variation in underlying risk and risk-related information allows us to jointly estimate risk preferences and uncertainty attitudes at different risks.

We find that WTP for insurance is significantly higher in settings with uncertain risks than in settings with certain risks. The average information premium is positive for most relevant values of risk probabilities and is as high as 100% of the expected loss. Crucially, we uncover a negative correlation of about -0.3 between the risk premium and the information premium across individuals.[4] The magnitude of the correlation is remarkably invariant to both variation in risk probability and in individual characteristics such as demographic background, socio-economic status, cognitive ability or financial literacy.[5] It implies that less risk averse individuals may sub-optimally over-insure when underlying risks are uncertain. To the best of our knowledge, we are the first to estimate the relationship between risk and information premia.[6]

[3]For instance, Handel and Kolstad (2015) and Handel et al. (2019) assume that risk preferences are independent of information frictions to estimate risk aversion from health insurance choices.

[4]We apply the *obviously related instrumental variables* (ORIV) approach of Gillen et al. (2019) to correct for potential measurement error and obtain similar correlation estimates.

[5]The information premium decreases as underlying risks increase and there is no significant difference in WTP between the two types of uncertainty that we consider - ambiguous and compound risks. Further, we find that, while individual characteristics - for example, income, gender, financial literacy and cognitive ability - account for 20% of the variation in risk premium, they only account for 3% of the variation in information premium. The main covariate of information attitudes are risk attitudes themselves, which alone account for 10% of the variation in information premium. This implies that selection effects are predominantly driven by selection on risk preferences rather than on socio-demographic characteristics.

[6]Despite this negative correlation, interpersonal rankings based on WTP for insurance exhibit a

We next conduct market equilibrium and welfare analysis by combining the survey data with auto collision insurance claims data. Specifically, we derive the distribution of risk probability from the empirical distribution of insurance claim rates estimated by Barseghyan et al. (2011), and use it to sample the WTP data from our survey. We then construct demand curves in the presence or absence of uncertainty. This approach allows us to identify the three demand determinants, namely, risks, risk preferences and information attitudes, which are crucial to study the level and selection effects of 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 and evaluate the welfare impact of mandatory disclosure policies.

Our market analysis points to a substantial misallocation of insurance. First, a positive information premium drives up the average WTP for insurance, leading to a level of aggregate demand about 10% higher relative to a world where agents are fully informed about risks. Second, the average risk premium of those who select into buying insurance is about 14% to 21% lower in the presence of information frictions due to the negative correlation between the risk premium and the information premium. Overall, we find that uncertainty about risks leads to a loss in consumer welfare ranging between 7% under perfect competition to 40% under monopoly. The results are quantitatively similar whether or not insurers are allowed to price discriminate. Importantly, roughly 90% of the welfare losses are attributable to the selection effect, highlighting the large economic impact of a correlation of -0.3 between risk and information premia relative to a world in which risk and uncertainty aversion are perfectly aligned. These effects stand in contrast to demand changes caused by other frictions studied in the literature, such as poor information about contract coverage and transaction costs (Handel and Kolstad, 2015; Handel et al., 2019), pricing/subsidies (Domurat et al., 2019) or insurance complexity (Bhargava et al., 2017). While such frictions tend to reduce demand, our results show that uncertainty about risks increases demand and leads to qualitatively different selection effects.

Our market analysis also considers strategic information disclosure by a monopolist. The data patterns that we observe imply that a monopolist with precise estimates of underlying risks should strategically withhold information about risks from low risk consumers and disclose risk information to high risk consumers. This can further

strong positive correlation, in line with existing empirical evidence (Einav et al., 2012).

exacerbate the selection issue.

We provide additional evidence for our results with our second survey. The main survey was constrained to use small-stakes risks because it was incentivized. This raises the question of whether risk premium estimates are relevant for actual insurance markets. To address this, our second survey was not incentivized and asked about 5,000 people representative of the U.S. population their WTP to insure against a hypothetical \$5,000 loss.[7] While we find significantly lower risk premium in this high-stakes survey, the effects of information frictions are quantitatively similar to those in our main survey.

Finally, we replicate our analysis in a laboratory experiment in which undergraduate students make incentivized decisions about insuring a product. We find the same pattern of results - i.e., average WTP is higher under uncertain risks relative to certain risks and there is a negative correlation of -0.12 to -0.57 between the risk premium and the information premium. This pattern of results is not only present in our work. We next use data from a series of laboratory experiments in the related literature that seek to measure ambiguity attitudes using choices framed as lotteries (Halevy, 2007; Abdellaoui et al., 2015; Chew et al., 2017). Here too, we find a negative relationship between the risk and information premium.

What type of preferences could generate the empirical patterns we uncover, especially the negative correlation between risk and information premia? We show that a particularly tractable type of multiplier preferences (Hansen and Sargent, 2001) can rationalize the data. Specifically, we prove that the class of one-parameter *second-order expected utility* preferences with risk averse CARA utility exhibit positive information premium that is negatively correlated to risk premium.

Our findings have policy relevance that is timely to the technological transformation of the insurance industry with the advent of InsurTech. Policies that simplify underlying risk information for consumers can improve the allocation of insurance. This implies that a policy of mandatory information disclosure of risk estimates by insurers unambiguously increases consumer welfare, regardless of the degree of market competition and of insurers' ability to price discriminate.

In what follows, Section 2 provides a discussion of our contribution to related work. Section 3 lays out the theoretical framework. Section 4 summarizes the first (main) survey. Section 5 describes our main empirical findings. Section 6 presents our market analysis and the main implications of our results. Section 7 identifies preferences that account for the empirical patterns. Section 8 concludes.

[7] Such loss is aligned with those that people face in existing markets: According to the Institute of Insurance Information the average amount of a auto collision insurance claim was $\$3,841$ in 2018.

2 Related Literature

This paper contributes to the literature that uses insurance take-up and claims data 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. Most of existing work assumes that consumers are perfectly able to estimate their underlying risks (Barseghyan et al., 2011; Einav et al., 2012; Sydnor, 2010), or that risk preferences are orthogonal to information frictions (Handel and Kolstad, 2015; Handel et al., 2019). However, as Spinnewijn (2017) and Handel et al. (2019) emphasize, understanding the relationship between risks, risk attitudes and information frictions is crucial to evaluate welfare and policy interventions. In this context, the use of incentivized survey data allows us to estimate their joint distribution and to study selection effects on both observables (demographics) and unobservables (preferences, underlying risks) without any structural assumptions. From a methodological perspective, we show the potential of augmenting field data with surveys aimed at eliciting preferences. This approach has been applied to measure key macroeconomic relationships, such as the impact of income shocks on consumption (Schulhofer-Wohl, 2011).

Our approach to information frictions is inspired by the theoretical and experimental literature on choice under risk and uncertainty. This literature has documented that many individuals exhibit both aversion to compound lotteries and ambiguity aversion (Halevy, 2007; Abdellaoui et al., 2015; Chew et al., 2017). Some of our findings - for example that risk premium 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 premium and information premium.[8]

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). Specifically, we provide a direct measurement of selection effects associated with information frictions about underlying risks and illustrate their potentially large negative impact on welfare.[9]

[8]A related literature uses field experiments to measure risk attitudes (Harrison et al., 2007a,b). These papers focus on specific sub-populations and tailor the experiment design to familiar risks. In contrast, we use an artefactual design but include a representative sample of the U.S. population.

[9]The paper also contributes to research measuring asymmetric information in insurance markets (Chiappori and Salanié, 2013). Specifically, our results cast doubt on using the correlation between risk and insurance coverage as a gauge of the degree of adverse selection in the market.

3 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. The agent does not know the precise proportion of red and blue balls 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.

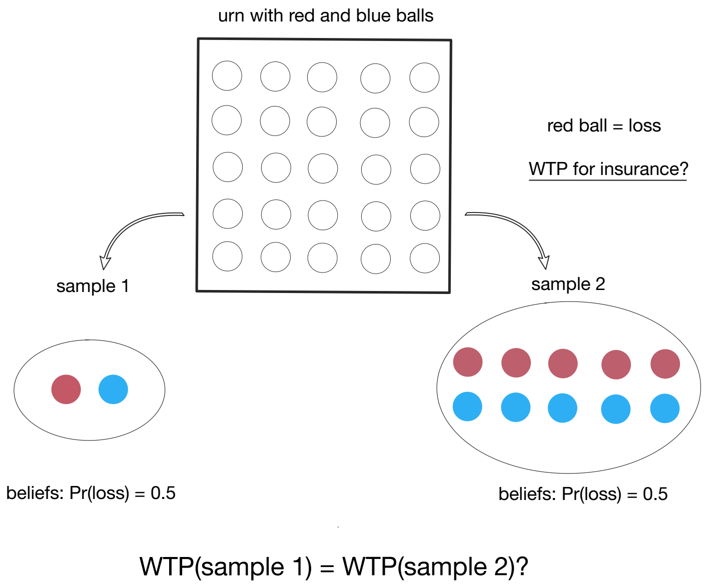

Figure 1: Urn Thought Experiment

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

3.1 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.[10] Information I can represent different things. For instance, I can represent a sample of realizations of x as in the urn example described previously. I can also represent information about the possible values or the distribution of risk p. Different I will typically lead to different beliefs about p, even if these beliefs *reduce* to p, i.e., lead to the same expected probability of a loss. For instance, if the agent's beliefs are represented by a probability distribution over possible values of p as in the urn example, an increase in the sample size would lead to a less dispersed distribution.

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

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.e., 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 $p \in [0,1]$.*

Assumption 1 implies that the agent's risk preferences can be estimated from a sample of observations $(W(p), p)$.[11] Accordingly, since the distribution of risks can be

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

[11] For instance, if we assume that the agent has EU preferences with constant absolute risk aversion (CARA) utility, given by $u(x) = -\frac{e^{-\theta x}}{\theta}$, then a single observation $(W(p), p)$ is enough to identify the CARA coefficient θ. Since $W(p)$ satisfies $u(1 - W(p)) = pu(0) + (1 - p)u(1)$, θ is the solution to $e^{-\theta(1-W(p))} = p + (1 - p)e^{-\theta}$. We refer the reader to Barseghyan et al. (2016) for a review of existing approaches to risk preference estimation using field data and of potential identification issues.

estimated from claim rate data, assuming the reduction principle allows conducting empirical analysis with insurance choice data by abstracting from information frictions that might affect demand.

The central tenet of our analysis is that violations of Assumption 1 are pervasive, implying that market demand and insurer pricing and information disclosure policies will be shaped by both risk preferences and attitudes towards information. 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, leading to a higher WTP for insurance.

Definition 2. The agent is averse to uncertain risks at p if $W(I) > W(p)$, for all $I \in \mathcal{I}(p) \setminus \{p\}$.

A preference for and neutrality with respect to uncertain risks are defined in a similar fashion. To provide a measure of the impact of information frictions about risks and how it relates to risk preferences we decompose the WTP for insurance into a risk premium and an 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 aversion to uncertain risks and to risk aversion.

3.2 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 risk attitudes 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,[12] 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.[13] Aggregate demand is given by the set of agents in T whose WTP, given by $W_t(I_t)$, is above the price for insurance $\rho(p_t)$. Price is allowed to vary with p_t to capture the

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

[13] This 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).

possibility that insurers price discriminate based on underlying risk, in line with 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 higher under uncertain risks, compared to certain risks. Let the information structure under certain risks be denoted by $\mathcal{P} = \{I_t = p_t, t \in T\}$.

Remark 1 (Level Effect)**.** *Aggregate demand is higher under $\mathcal{I}$ than under $\mathcal{P}$ 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 is that all agents are averse to uncertain risks.

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 $W_t(I_t)$, $W_t(p_t)$ 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 certain risks. 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 certain 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 misalignment is that the risk and information premia are negatively correlated.

Remark 2. *If there is a continuum of agents $T = [0,1]$ and $F_{\mathcal{P}}, F_{\mathcal{I}}$ have convex full supports then a sufficient condition for preferences to be misaligned is $corr(\mu(p), \mu(I)) < 0$.*

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

Remark 3 (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 insurance choice data. Specifically, the level effect will introduce a positive bias in risk aversion estimates while the selection effect will lead to selection bias.

3.3 Implications for information disclosure

The presence of informational effects shape 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.[14] To maximize profits the monopolist will disclose information or not depending on whether aggregate demand conditional on risk goes up or not.

Remark 4 (Information Disclosure)**.** *Disclosure of p 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 $F_{\mathcal{P}}(\cdot|p_t = p)$.*

4 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, which included rich socio-demographic information as well as measures of cognitive ability and financial literacy.[15] Appendix A provides the summary statistics of the respondents.

In the survey, we asked each participant to make a series of 10 decisions in private. Each participant was told to be the owner of a machine, which was described to have some probability p of being damaged. 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) *Certain risks*: I represents the underlying risk probability, i.e., $\mathcal{I}^C(p) = \{I = p\}$.

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

We elicited maximum willingness to pay for insurance using the Becker-DeGroot-Marschak mechanism (Becker et al., 1964),[16] where the actual price of insurance was

[14] Similar arguments apply to the case in which the monopolist can choose to obfuscate information.

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

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

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	68-92
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.

drawn at random from the uniform distribution on $(0, 100)$. Appendix F contains the survey instructions. We divided participants into four groups, as described in Table 1. Participants received a block of decisions with 5 risk probabilities under certain risk, and a block of decisions with 5 range probabilities under uncertain 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. Hence, the former group received a compound risk, while the latter group received an ambiguous risk. This design feature allowed us to check for potential differences in attitudes towards two common sources of information frictions, namely, the perception of risks as the realization of a series of bad shocks (compound risk) and the lack of precise information about the distribution of shocks (ambiguous risk).

At the end of the survey 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.[17]

5 Empirical Analysis

This section presents the main empirical patterns of determinants of insurance demand under information frictions. First, we illustrate the magnitude of risk and information premia and estimate their correlation structure, developing estimates that correct for potential measurement error in WTP. Next, we investigate the relationship between information premium and sociodemographic variables and the external validity of our findings. 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).

5.1 Risk Premium

Figure 2 displays the average risk premium ($\mu(p) = W(p) - p$) 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.3 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%.

5.2 Information Premium

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.[18] As

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

[18] Table C.3 in Appendix C shows the average information premium at each p by group.

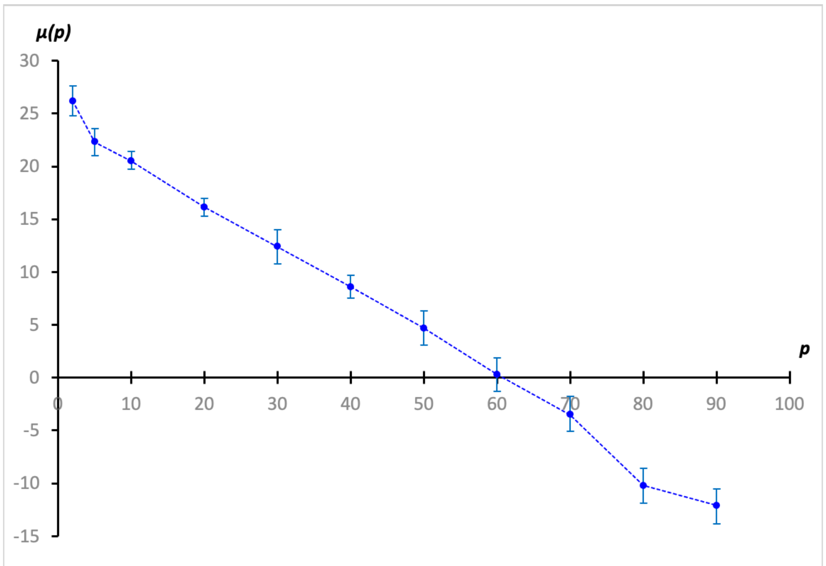

Figure 2: Average Risk Premium at Different Probabilities (bars represent 95% confidence intervals).

we show below, we do not find any major differences between information premium under compound and ambiguous risks. Accordingly, we pull both types of uncertain risks together in the empirical estimation and the market analysis.

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 $p < 50\%$. Information premium decreases with risk probability, which is consistent with the finding by Abdellaoui et al. (2015) that aversion to compound and ambiguous lotteries increases as winning probability goes up. Information premium is somewhat less heterogeneous than risk premia, with a standard deviation between 14% and 20%.

Since the typical probability of filing an insurance claim is substantially lower than 50%, the fact that we observe large information premia at $p < 50\%$ suggests that markets where consumers face uncertain risks would exhibit greater demand due to strong level effects.

5.3 Relationship Between Risk and Information Premium

We next look at the correlation between the risk premium and the information premium, normalized by range size. We do so for each probability p separately to control for the negative relationship between p and both $\mu(p)$ and $\mu(I)$.

Figure 4 plots the correlation coefficients, showing that risk and information premia

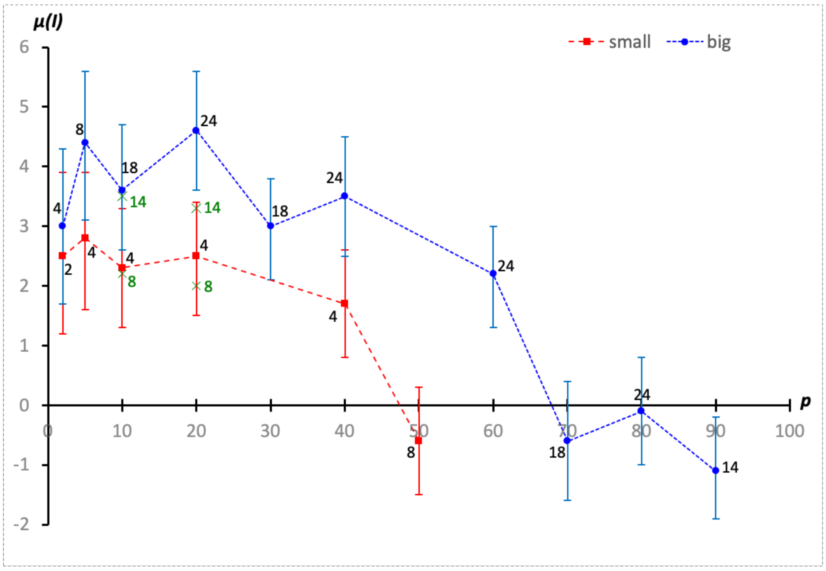

Figure 3: Information Premium at Different Probabilities (point labels represent range size and bars represent 95% confidence intervals).

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.[19] Despite the negative correlation, there is a positive association between individual WTP rankings across information environments, consistent with the findings of Einav et al. (2012) (see Appendix E.6).

5.3.1 Measurement Error Correction

An important concern with the estimates of the correlation between risk and information premia 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

[19] Table 2 in Subsection 5.3.1 reports the total correlation coefficients in columns two and four and shows that they are highly significant. The partial correlation coefficients are virtually identical and therefore omitted. All coefficients are significant at the 1% level.

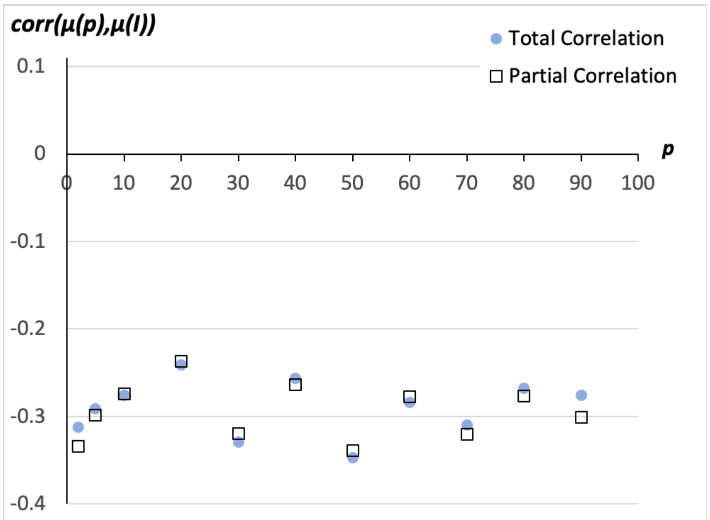

Figure 4: Correlation Coefficients between Risk Premium and Information Premium.

errors are independently drawn and that they are independent of $W(\cdot)$, the correlation between $\hat{\mu}(I)$ and $\hat{\mu}(p)$ is given by

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

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

To correct for these biases, we follow the approach proposed by Gillen et al. (2019), 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 $\dfrac{cov(\mu(I), \mu(p))}{Var(\mu(p))}$. 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 be consistently estimated using

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

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

Gillen et al. (2019) 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 risk probabilities. Specifically, we use the linear interpolation of risk premium associated with the probability points adjacent to p as the second measure of $\mu(p)$. That is, if $p' < p$ and $p'' > p$ are the loss probabilities closest to p in the experimental design, the replicas of risk and information premia are given by

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

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

where I' and I'' represent the uncertain risks respectively associated with p' and p''. We normalize information premium by dividing it by range size and perform the linear interpolation using the normalized premia.

Table 2 shows the ORIV correlation for probabilities with adjacent probabilities on both sides (column three). The estimates are of similar magnitude if not slightly more negative. These results indicate that the negative relationship between risk and information premia is not an artifact of measurement error.

5.3.2 Correlation in Existing Experimental Data

The remarkable invariance of our correlation estimates raises the question whether we have uncovered a robust feature of individual risk and information attitudes or whether they are just a byproduct of our specific survey design. We address this question by replicating our analysis in our companion laboratory experiment, which is described below, and by computing 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 Table 2 shows, correlation coefficients are significantly negative in all the datasets. 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

Table 2: 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.

turns out to be identical to the ORIV correlation of -0.3 in our data.[20]

Table 3: 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 certain risk premium and hypergeometric CR premium.
[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.

[20] Abdellaoui et al. (2015) use compound lotteries in their 'hypergeometric CR' treatment, preventing us from obtaining a replica of the information premium given that such lotteries are hard to compare across p. Nonetheless, the ORIV correction can still be performed by using a replica of the risk premium at 1/2, obtained via linear interpolation with probabilities 1/12 and 11/12.

5.4 Covariates of the Information Premium

Our survey design allows us to gauge the relative impact on WTP of features of the information structure, such as the degree of ambiguity or the perceived complexity of compound risks, as well as to look at whether information attitudes depend on sociodemographic characteristics.

Table 4 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 range size), measures of financial literacy and cognitive ability, as well as sociodemographic variables. All the regressions control for risk probability p and for whether the certain risk scenario was presented before uncertain risks 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 premium: Risk premium accounts for about 9% of the overall variation of the information premium, while the rest of variables combined only account for a R^2 of 3%. Second, the table reflects the relationship between risk probabilities and range sizes depicted in Figure 3, namely, the wider the range and the lower the risk probability the higher the information premium. In contrast, whether the range is ambiguous or not does not lead to significant differences in the information premium. Information attitudes do not seem to be driven by misperception of risks, as measured by the error in the incentivized quiz about reducing compound risk (normalized by range size). Third, cognitive and socio-demographic variables do not seem to significantly drive information attitudes. In contrast, gender, income, as well as cognitive ability and financial literacy are significantly associated with risk attitudes. The third column in Table 4 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, we find significant order effects, with higher information premia associated with the reverse order, i.e., when agents were asked about WTP for uncertain risks first. This may suggest that being exposed to certain risk may have an anchoring effect on WTP for insurance against uncertain risks.[21]

[21] No such order effects seem to be present in our lab experiment (see Table E.9 in Appendix E.4).

Table 4: Covariates of Information Premium and Risk Premium

	$\mu(I)$	$\mu(I)$	$\mu(p)$
Risk Probability	-0.06***	-0.14***	-0.41***
	(0.01)	(0.01)	(0.01)
Range Size	0.11***	0.11***	
	(0.01)	(0.01)	
Ambiguity	0.54	0.50	
	(0.33)	(0.32)	
$\mu(p)$		-0.19***	
		(0.01)	
Financial literacy	-0.15	-0.45	-1.71**
	(0.23)	(0.23)	(0.50)
Average Cognitive Score	0.49	0.30	-1.34*
	(0.24)	(0.23)	(0.48)
Quiz Error	-0.06	0.22	
	(0.09)	(0.09)	
Age	-0.05	-0.04	0.08
	(0.07)	(0.06)	(0.14)
$\text{Age}^2/100$	0.04	-0.01	-0.24
	(0.07)	(0.06)	(0.13)
Female	-0.64	0.11	3.90***
	(0.35)	(0.35)	(0.76)
Married	-0.60	-0.73	-0.59
	(0.37)	(0.36)	(0.83)
Some College	0.29	0.01	-1.22
	(0.48)	(0.47)	(1.02)
Bachelor's Degree or Higher	0.28	-0.15	-2.19
	(0.54)	(0.54)	(1.16)
Hh Income: 25k-50k	0.45	0.53	0.21
	(0.54)	(0.53)	(1.16)
Hh Income: 50k-75k	0.38	-0.11	-2.82
	(0.60)	(0.58)	(1.26)
Hh Income: 75k-100k	0.75	0.59	-0.97
	(0.62)	(0.62)	(1.41)
Hh Income: Above 100k	0.29	-0.85	-6.38***
	(0.62)	(0.62)	(1.33)
Non-Hispanic Black	-1.70	-1.21	2.58
	(0.75)	(0.71)	(1.53)
Spanish/Hispanic/Latino	0.31	0.30	0.04
	(0.70)	(0.70)	(1.37)
Other Race/Ethnicity	-0.12	0.10	1.23
	(0.66)	(0.63)	(1.24)
Reverse Order	4.64***	4.13***	-2.51***
	(0.33)	(0.32)	(0.71)
R^2	0.03	0.13	0.20
N	19,050	19,050	19,432

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: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

5.5 External Validity

Our empirical results are confirmed by our companion laboratory experiment. The experiment design included a similar set of decision questions. We also added an additional treatment for all subjects, *multiplicative risks* to check the robustness of our results to alternative forms of compound risks. Elicitation mechanisms and payments were similar to those in the survey. Appendix E in the Appendix provides a full description of the experiment as well as detailed results.

We find that both risk and information premia are decreasing in risk probability p (Figure E.5). The only major difference is that subjects in the experiment were significantly less risk averse. In addition, risk and information premia exhibit a negative correlation of similar magnitude: estimates lie between -0.24 and -0.35, even after controlling for both measurement error and personal characteristics (see Table E.8 in Appendix E). Finally, we analyze covariates of information premium with the experimental data and find that qualitatively similar results (see Appendix E.4).

6 Market Analysis

The empirical analysis shows that information about underlying risks is a significant determinant of insurance demand. To illustrate its potential impact on insurance markets, we combine our survey with existing claim rate data to simulate the demand for full insurance against binary risks and evaluate the change in market outcomes due to information frictions across different pricing and competition scenarios. We focus on three main aspects of market performance, namely, aggregate insurance take up, selection effects and welfare. In addition, we illustrate the extent to which information frictions can lead to estimation biases in the analysis of insurance market data. Finally, we show how information frictions can create incentives to engage in selective information disclosure in imperfectly competitive markets.

6.1 Constructing the Demand for Insurance

We construct the demand for insurance by drawing from our sample of (W_t, p_t, I_t) data using the empirical distribution of risk probabilities derived from claim rate data in existing insurance markets. Specifically, we use the distribution of semiannual claim rates for auto-collision insurance estimated by Barseghyan et al. (2011) to generate a distribution of risk probabilities. We then discretize this distribution using as a support the eleven risk probabilities (from 0.02 to 0.90) covered by our survey. Finally, we calculate aggregate demand for insurance, given by the share of agents with WTP above market prices, by weighting each observation (W_t, p_t, I_t) according to the likelihood of p_t given by the discretized distribution.

To construct the distribution over p_t, we first assume that the need of agent i to file 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 $p_i = 1-e^{-\lambda_i}$. Next, we assume that λ_i follows a gamma distribution with (annualized) mean $\bar{\lambda} = 0.116$ and standard deviation 0.272.[22] 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.[23]

6.2 Market Equilibrium

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 (*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 risk probability p_t (*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 compare outcomes in the absence of information frictions (certain risk) to those under information frictions (uncertain risk).

We determine the equilibrium allocation for insurance under uniform pricing by considering the set of prices, up to the monopoly price, that yield non-negative profits to insurers. Let ρ denote the price for insurance and $s(\rho) = 1 - \hat{F}(\rho)$ the fraction of agents in the population with $W_t(I_t) > \rho$ where $\hat{F}$ denotes the cdf of $W_t(I_t)$ in our weighted dataset. That is, $s(\rho)$ is the share of agents who buy insurance when the

[22] 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.

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

price is ρ. Taking into account the presence of adverse selection, profits are given by

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

In the case of risk-based pricing, we restrict our analysis to perfect competition and monopoly. In the former, prices are actuarially fair, i.e., $\rho(p) = p$, while in the latter the monopolist chooses $\rho(p)$ to maximize profits.

Table 5 presents the main outcomes in equilibrium for the case of perfect competition and monopoly across pricing and information scenarios. Since the impact of information frictions on market outcomes are qualitatively similar across pricing scenarios we focus our discussion on uniform pricing and briefly discuss any differences under risk-based pricing at the end of this section.

6.2.1 Aggregate Demand

Figure 5 depicts the proportion of insured agents ($s(\rho)$) for simple and range risks. In both cases the set of prices associated with non-negative profits is the interval $[13, 50]$, where $\rho = 13$ is the price under perfect competition and $\rho = 50$ is the monopoly price, both represented by dashed blue lines. The level effect on aggregate demand is substantial: information frictions lead to a 10-14% higher demand, driven by the higher WTP of agents with positive information premia.

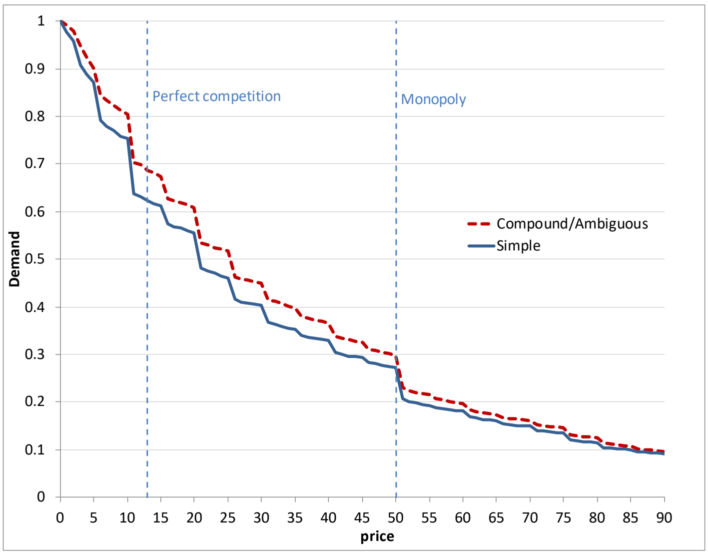

Figure 5: Demand for Insurance.

Table 5: Market Outcomes

		Uniform Price				*Risk-based Pricing*			
	Overall	Perfect Competition		Monopoly		Perfect Competition		Monopoly	
	Population	Certain	Uncertain	Certain	Uncertain	Certain	Uncertain	Certain	Uncertain
Insured Pool									
Share of Population	100%	62.3%	68.6%	27.2%	29.8%	87.7%	91.0%	23.6%	26.0%
Risk Probability	9.6%	12.8%	12.1%	15.6%	15.0%	7.8%	7.7%	9.6%	9.5%
Risk Premium	22.1	34.5	29.9	58.5	48.3	26.6	25.1	66.3	54.7
Info Premium	2.8		5.3		10.5		3.43		11.6
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%
Selection Effect[c]			88.4%		95.1%		89.3%		95.2%
Estimation Bias			17.7%		21.7%		13.6%		21.3%
Selection Effect[a]			35.2%		78.6%		33.4%		79.3%
Corr(risk, coverage)		0.263	0.238	0.238	0.228	-0.312	-0.389	0.001	-0.014
risk prefs $\perp$ *risk*[d]		0.347	0.320	0.423	0.417	0.000	0.000	0.111	0.121

[a]Difference between the average risk premium in a market with the same demand at each p as under uncertain risk, but in which those with the highest risk premium get insurance, and the average risk premium under uncertain risk, expressed as a fraction of the average information premium.
[b]Difference between average welfare under simple and compound risk, relative to the average welfare under certain risk.
[c]Difference between average welfare in a market with the same demand at each p as under uncertain risk, but in which those with the highest risk premium get insurance, and average welfare under uncertain risk, relative to the difference between average welfare under simple and uncertain risk.
[d]The correlation coefficient is the average of a sample of 1,000 correlation coefficients, each obtained by randomly assigning insurance premium $(W(I) - p)$ to risk probabilities (p) to compute agents' WTP for insurance.

6.2.2 Selection Effects

In addition to increasing aggregate demand, information frictions lead to changes in the risk profile of agents who buy insurance and, especially, in their level of risk aversion.

Regarding the risk profile of insurance buyers, there is adverse selection in equilibrium, which gets exacerbated as the market becomes less competitive. Specifically, Table 5 shows that the risk probability is 25% higher than the population average when the market is competitive (12.8% versus 9.6%), and 50% higher under monopoly. Adverse selection is nonetheless mitigated by the fact that the risk premium is decreasing in risk as shown by Figure 2.

The introduction of information frictions slightly reduces adverse selection due to the fact that the information premium is decreasing in risk (Figure 3), leading to a small drop in risk probability (5% under perfect competition and 4% under monopoly).

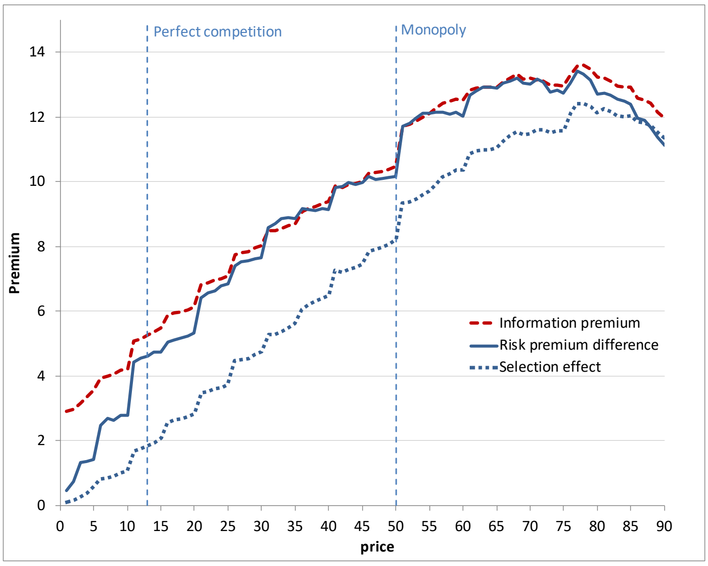

Figure 6: Information Premium and Differences in Risk premium.

In contrast, the selection effect on risk preferences and information attitudes are substantial. The average risk premium of insured agents is between 13% and 17% higher under certain risk than under uncertain risk, while their information premium is at least twice the average information premium in the population. As Figure 6 illustrates, these differences grow significantly with market price, i.e., as the market becomes less competitive. Importantly, while these differences are partly driven by the fact that information frictions increase WTP and thus we should expect risk premium of insurance buyers to be lower on average, the selection effect induced by the negative correlation between risk and information premia accounts for a large fraction of the change in risk premium. To quantify the selection effect we fix the level of aggregate demand under uncertain risk and reallocate insurance to those with the highest risk premium. We then compute the change in average risk premium caused by the reallocation, which is depicted by the dotted line in Figure 6. The figure shows that the selection effect accounts for 40% of the differences in risk premium under perfect competition and its contribution increases to 81% under monopoly.

6.2.3 Welfare

The presence of information frictions leads to changes in consumer welfare. To assess these changes, we follow the approach of Einav et al. (2010b) to measure the welfare from being insured as the difference between the WTP for insurance under certain risks and the price for those who buy insurance. In line with the existing literature (Spinnewijn, 2017; Handel et al., 2019), we do not include the information premium since the underlying risks covered by the policy are not altered by the information available to agents. Nonetheless, it can be shown that this welfare measure would differ from one that takes into account information attitudes 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

$$E\left((W_t(p_t) - \rho)1_{\{W_t(I_t)>\rho\}}\right),$$

where $1_{\{.\}}$ is the indicator function.

Information frictions operate through three main channels. First, they affect the size of the insured population (level effect). Second, they impact market prices by changing the risk profile of insurance buyers (adverse selection). Finally, they change the risk preference profile of insured agents (selection effect).

The bottom panel in Table 5 shows the welfare estimates. The introduction of uncertain risks leads to welfare losses ranging from 7% to about 40%, depending on how competitive the market is. Importantly, they are almost entirely driven by the selection effect, with roughly 90% of overall welfare losses caused by the negative correlation between risk and information premia. The reasons for the predominance of the preference selection channel are twofold. First, the adverse selection channel is muted since the drop in risk probability is too small to trigger noticeable price changes. Second, once we control for the selection effect, the increase in aggregate demand is concentrated among agents whose surplus from acquiring insurance is negative but close to zero, accounting for a small fraction of overall welfare losses ($\sim$10%).

The magnitude of consumer welfare losses suggests that regulation aimed at providing simple information about underlying risks, such as the estimated probability of filing a claim, would be beneficial for consumers regardless of the degree of market competition. Our welfare results stand in contrast to the analysis by Handel et al. (2019) showing that mitigating information frictions leads to welfare losses. The reasons behind the apparent contradiction lie in the fact that we focus on a different kind of frictions and that they assume that risk preferences are independent of frictions. In their setting there are two types of contracts, low- and high-deductible health insurance, and the main information friction roughly involves a lack of understanding of the high-deductible insurance shifting demand away from it. As frictions are reduced riskier consumers buy insurance pushing prices up via a significant increase in adverse selection, and these welfare losses are not compensated by a selection of more risk averse agents since preferences are assumed to be independent of frictions. Our analysis focuses instead on information about underlying risks and fully captures selection on both risks and risk preferences.

6.3 Implications for Estimation with WTP Data

In the presence of information frictions, using data on (W_t, p_t) from the pool of insured agents to estimate risk attitudes would lead to significant biases. Figure 6 and Table 5 show the size of the bias, given by the average information premium. On average, risk premium estimates would be 18-22% higher than the actual level of risk premium in the pool of insured agents. The selection effect accounts for about 35% of the bias under perfect competition and 79% of the bias under monopoly.

In addition, the negative relationship of both risk and information premia with risk probability depicted in Figures 2 and 3 has implications for measuring the extent of adverse selection in insurance markets. Existing research emphasizes the positive correlation between risk (p) and coverage ($1_{\{W(I)\geq\rho\}}$) as evidence of adverse selection (Chiappori and Salanié, 2013). In particular, a higher correlation coefficient should be associated with a higher degree of adverse selection. However, as the bottom panel of Table 5 shows, the correlation between risk and coverage is lower while adverse selection is higher under monopoly than under perfect competition. To show that this is due to $W(I) - p$ and risk probability p being negatively correlated (about -0.4 in our data), 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. The last row in Table 5 shows that the counterfactual correlation between risk and coverage is in fact increasing in the degree of adverse selection.

6.4 Risk-Based Pricing

The right-hand-side panel of Table 5 shows that informational effects are quantitatively similar when insurers engage in risk-based pricing, except for two notable exceptions. First, the negative correlation between risk probability and risk premium creates *advantageous* selection under perfect competition ($\rho(p) = p$), i.e., the average risk probability of the insured pool is lower than that of the population as a whole. Second, unlike under uniform pricing, the correlation between risk and coverage increases with average risk probability, implying that its use as a gauge of adverse selection may also be sensitive to insurers' ability to price discriminate.

6.5 High Stakes

One might be skeptical about constructing the demand for insurance using data from small-stakes decisions. As such, we reproduce our analysis using a second survey, in which over 5,000 individuals from the UAS internet panel made hypothetical decisions over large stakes. Specifically, we asked respondents their hypothetical WTP to fully insure a used car against mechanical defects assessed at $5,000, which is roughly in line with average claims in auto collision insurance.[24]

Appendix B describes the survey and presents the empirical analysis. Overall, the data exhibits the same empirical patterns as the first survey, with two major differences. First, individuals are 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 participants in both surveys (about a fifth of the sample), we find that the risk premium across surveys are significantly correlated (the correlation coefficient is 0.39).

Table 6 replicates the market analysis using the high-stakes data, showing qualitatively similar results to those in Table 5, with some slight differences. For example, the lower risk premia result in a smaller share of insured agents in the population. Further, because there is a larger reduction in risk premium than in information premium relative to the first survey, we see even bigger welfare effects and estimation bias under high stakes.[25] Finally, there is substantial advantageous selection under risk-based pricing regardless of the degree of competition.

[24] According to the Institute of Insurance Information, the average claim was $3,574 in 2018.

[25] These differences may also be due to differences in survey incentives and framing of insurance.

Table 6: Demand for Insurance - Aggregate Outcomes under High Stakes

	Overall	*Uniform Price*				*Risk-based Pricing*			
		Perfect Competition		Monopoly		Perfect Competition		Monopoly	
	Population	Certain	Uncertain	Certain	Uncertain	Certain	Uncertain	Certain	Uncertain
Insured Pool									
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
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%
Selection Effect[c]			96.0%		88.5%		94.0%		28.5%
Estimation Bias			23.9%		29.8%		17.9%		28.7%
Selection Effect[a]			40.7%		56.8%		23.4%		53.6%
Corr(risk, coverage)		0.139	0.134	0.095	0.065	-0.371	-0.410	-0.153	-0.072
risk prefs $\perp$ *risk*[d]		0.454	0.442	0.446	0.435	0.000	-0.054	0.160	0.121

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

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

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

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

6.6 Strategic Information Disclosure

In our 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 3.3, 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. These informational asymmetries might affect crucial elements of insurers' decisions, such as contract design, information acquisition and disclosure policies. While exploring these issues is beyond the scope of the paper, we provide a glimpse of the potential insurer response to information frictions by examining the information disclosure decisions of a monopolist under risk-based pricing.

Table 7 presents the profit maximizing disclosure policy of the monopolist as a function of underlying risk p. 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 high risk probabilities. Beyond increasing the profits of the monopolist, such a selective disclosure policy also has allocative implications, since it increases the average risk of the insured pool by inducing higher risk consumers to buy insurance, compared to the case of no disclosure. Although such implications are quantitatively small in a market where the risk distribution has a very thin right tail, they could be substantial in insurance markets where larger risks are more prevalent (e.g. health insurance).

Table 7: 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

7 Preferences that Rationalize the Data

The empirical patterns in Section 5 can be explained by *second order expected utility* (SOEU) preferences (Neilson, 1993, 2010; Ergin and Gul, 2009) with respect to ambiguous and compound risks I. Let X be the finite set of final outcomes and $\Delta(X)$ the set of probability distributions over X. SOEU preferences imply that there is a probability distribution q over risks p such that the value of I to the agent is given by

$$U(I) = \int_{p \in \Delta(X)} \phi \left(\sum_{x \in X} u(x) p(x) \right) dq(p),$$

where u is increasing and represents utility over final outcomes, while ϕ is an increasing function that captures utility over certainty equivalents of certain risks.

We prove that a single parameter SOEU with identical CARA utility over both final outcomes and certainty equivalents can produce (i) risk and information premia that are positive at small p and typically decreasing in p, and (ii) a negative relation between risk and information premia. Strzalecki (2011) has shown that such SOEU preferences belong to the family of multiplier preferences commonly used in macroeconomics and asset pricing (Hansen and Sargent, 2001). We relegate the proofs to Appendix D.

Let ϕ and u be given by CARA utility with risk aversion coefficient θ:

$$\phi(z) = u(z) = \left(1 - e^{-\theta z}\right) / \theta. \tag{2}$$

The next result characterizes the risk premium under CARA SOEU and shows that if the agent is risk averse ($\theta > 0$) then $\mu(p)$ is decreasing in p above some lower bound that goes down with the degree of risk aversion.[26]

Proposition 1. *The risk premium of full insurance against binary risk p is given by*

$$\mu(p) = 1 - p + \frac{1}{\theta} \log \left(p + (1-p)e^{-\theta}\right). \tag{3}$$

If $\theta > 0$ then there exists $\underline{p}(\theta) \in (0,1)$ such that $\mu(p)$ is strictly decreasing for all $p > \underline{p}(\theta)$. Furthermore, $\underline{p}(\theta)$ is strictly decreasing in θ and $\lim_{\theta \to \infty} \underline{p}(\theta) = 0$.

Turning to the information premium, Proposition 2 states that $\mu(I)$ is decreasing in p and, importantly, it is negatively related to the risk premium. To keep things simple we focus on uncertain risks I in which the risk probability takes on two values, $p - \varepsilon$ and $p + \varepsilon$ for $\varepsilon \in (0, \min\{p, 1-p\})$ and assume that $q(p-\varepsilon) = q(p+\varepsilon) = 0.5$.

Proposition 2. *The information premium is increasing in ε and given by*

$$\mu(I) = 1 - p - \mu(p) - \frac{1}{\theta}\left(1 - e^{-\theta(1-p-\mu(p))}\right) + \frac{1}{\theta} \log \left(\frac{1}{2} e^{\varepsilon\left(1-e^{-\theta}\right)} + \frac{1}{2} e^{-\varepsilon\left(1-e^{-\theta}\right)} \right). \tag{4}$$

If $\theta > 0$ then $\mu(I)$ is positive and decreasing in p for all $p \in (0,1)$. Moreover, for any fixed $p \in (0,1)$, if $\theta > 0$ then $\mu(I)$ is decreasing in $\mu(p)$.

[26]Since the risk premium should be zero at $p = 0$, it must be initially increasing in p.

8 Conclusion

Our study uncovers key systematic relationships between the determinants of insurance demand, such as the negative correlation between risk aversion and uncertainty aversion, and quantifies the impact of information frictions on insurance markets. There are several takeaways from our analysis, which point to methodological changes, policy interventions and potential avenues for future research. Such implications of our analysis acquire particular relevance given that we find similar patterns across multiple survey and experimental data sources.

Methodologically, our work emphasizes the need to account for the joint distribution of the different demand components in order to obtain unbiased estimates and engage in policy analysis. In this context, the use of surveys and demand simulation techniques can help overcome limitations inherent to field data. We also illustrate that tractable models of uncertainty preferences, such as second order expected utility, can be used to explain the relationship between risk preferences and information frictions.

In addition, our results challenge the traditional view that consumers enjoy informational advantages over insurers. As the latter become more sophisticated than the former in acquiring and processing information about risks, informational asymmetries between them might be reversed, potentially leading to significant changes in welfare and in the nature of competition in insurance markets.

The paper highlights that different types of information frictions affect markets in different ways. Whereas frictions about insurance contracts (e.g., information about coverage, pricing, transaction costs) tend to depress demand for those contracts (Handel and Kolstad, 2015; Bhargava et al., 2017; Handel et al., 2019; Domurat et al., 2019), we show that frictions about risks increase insurance demand and lead to distinct selection effects. These differences imply that friction-mitigation policies aimed at improving welfare need to be tailored to the specific frictions being targeted. In particular, policies aimed at regulating disclosure of certain risk estimates can have large welfare benefits.

Finally, the sources of agents' reaction to uncertain risks remain elusive. Most of the sociodemographic variables traditionally associated with risk attitudes, such as income or education, lack explanatory power when it comes to uncertainty preferences. This implies that information frictions cannot be controlled for in empirical work by simply conditioning on observable characteristics.

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[For Online Publication]

Appendix A Descriptive Statistics

Table A.1 presents the summary statistics of the main sociodemographic variables of households in the UAS in Surveys 1 and 2.

Table A.1: Descriptive Statistics - UAS

	Survey 1		Survey 2	
Variable	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 High Stakes

This section briefly describes the details of our second survey design and uses it to replicate the empirical analysis of Section 5.

All 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. Each respondent received two questions – one with a precise risk probability and one with a probability range – in random order. The specific wording of the questions is detailed in Appendix F.2. We randomly varied risk probability across respondents (generating 11 different groups). Table B.2 provides a summary of decisions presented to respondents. Unlike Survey 1, Survey 2 was not incentivized.

Table B.2: Summary of Decisions Presented to Respondents, Survey 2

Group	(1) Probability (%)	(2) Range (%)
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 (1) and (2), in random order.

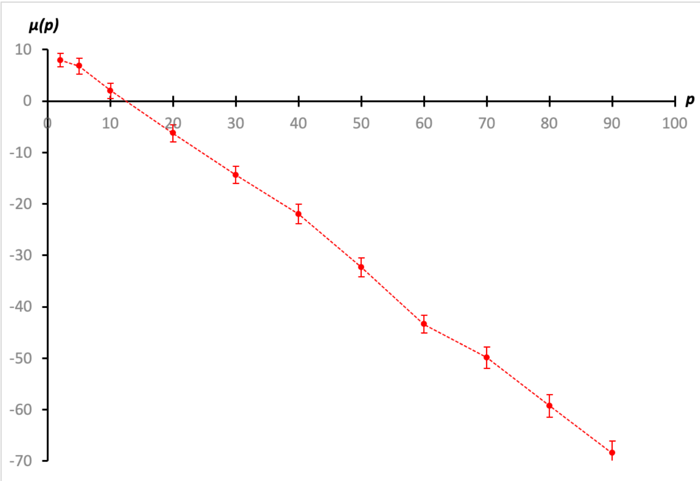

Figure B.1: Average Risk Premium (bars represent 95% confidence intervals).

Figure B.1 presents the average risk premium, normalized by loss size ($5,000). For probabilities up to 10% agents are significantly risk averse, turning to risk seeking as risk 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%, over four times the actuarially fair price.

The average information premium at each possible p, normalized by loss size, is significantly positive at $p < 20\%$, as shown in Figure B.2.

Figure B.3 presents total and partial correlation between risk and information premia at each risk probability, which are negative and of similar magnitude to those found in first survey.

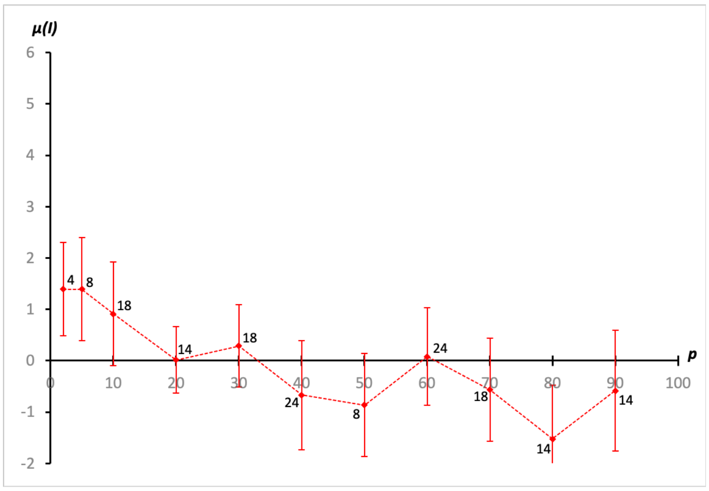

Figure B.2: Average Information Premium (labels denote range size and bars are 95% confidence intervals).

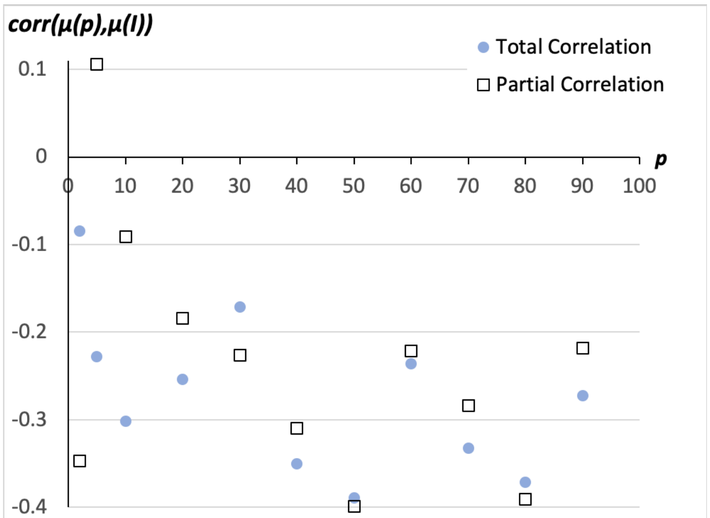

Figure B.3: Correlation Coefficients between Risk Premium and Information Premium.

Appendix C Statistical Analysis of WTP

In this section we present the average WTP under certain risk ($W(p)$) and the information premium under uncertain risk. We report both averages for the whole sample, and also distinguishing by whether 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.3 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.

Table C.3: WTP for Insurance - UAS

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

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

Ambiguity Tables C.4 and C.5 show the effect of presenting agents with non-ambiguous versus ambiguous ranges. There is no clear effect of ambiguity on the information premium. Overall, effects seem to be quantitatively of the same order of magnitude.

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

	Group 1		Group 2		Group 3		Group 4	
p	$W(p)^a$	$\mu(I)^{b,c}$	$W(p)$	$\mu(I)$	$W(p)$	$\mu(I)$	$W(p)$	$\mu(I)$
2					29.2***	2.3**	28.5***	2.8***
						(2)		(4)
5	25.3***	2.6***	29.2***	3.4***				
		(4)		(8)				
10	27.6***	4.1***	32.0***	2.9***	32.0***	2.1***	30.1***	3.0***
		(18)		(14)		(8)		(4)
20	32.8***	3.6***	37.6***	1.7***	37.2***	4.4***	35.9***	2.7***
		(14)		(4)		(24)		(8)
30							41.5***	4.0***
								(18)
40			48.4***	3.9***	49.9***	1.4**		
				(24)		(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.

Ability to reduce compound lotteries. Table C.6 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

Table C.5: WTP for Insurance: Ambiguous Range - UAS

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

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

the range, except for the last 2 ranges, in which those who reduced the range properly actually exhibit a higher WTP.

C.1 Interpersonal Rankings of WTP

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

Table C.6: WTP by Ability to Reduce Compound Lotteries

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

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

underlying risks (or close risks if one looks at the correlation between WTP rankings of adjacent risk probabilities). However, correlation substantially decreases with the difference in risk probabilities, both within and across information environments. The presence of informational effects decreases the correlation when probability differences are not too large, but bigger ranges do not translate into substantially lower correlations than smaller ranges.

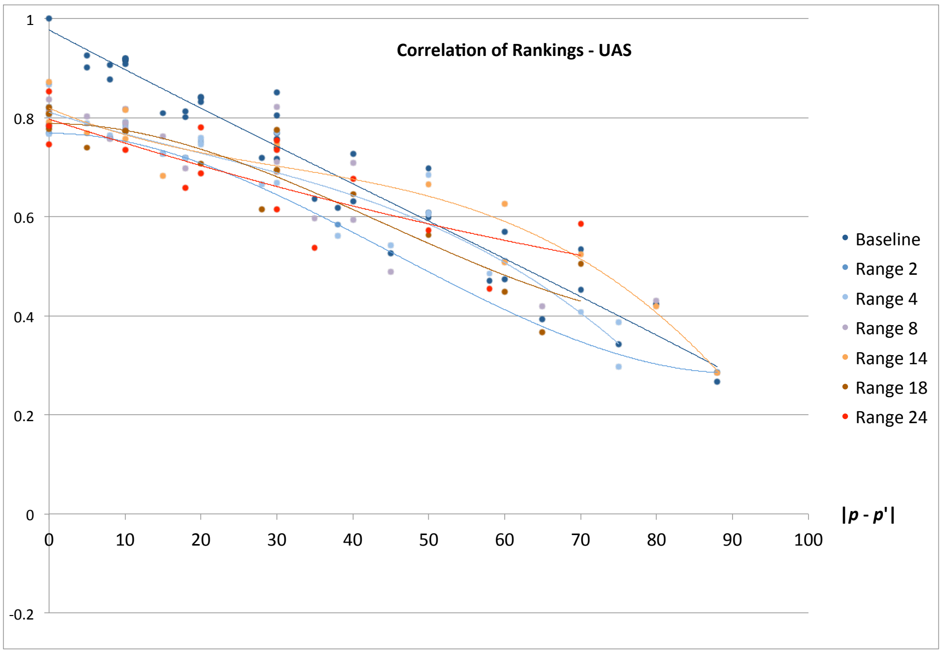

Figure C.4: Correlation of interpersonal rankings by differences in risk.

Appendix D Omitted Proofs

Proof of Proposition 1. The risk premium satisfies

$$u(1-p-\mu(p)) = pu(0) + (1-p)u(1),$$

which yields

$$\mu(p) = 1 - p - u^{-1}(pu(0) + (1-p)u(1)). \tag{5}$$

Under CARA utility we have that $u^{-1}(y) = -\frac{1}{\theta}\log(1-\theta y)$, $u(0) = 0$ and $u(1) = \frac{1-e^{-\theta}}{\theta}$. Plugging these expressions into (5) yields expression (3). To show the existence of lower bound $\underline{p}(\theta)$ we first differentiate (3) w.r.t p:

$$\frac{d\mu(p)}{dp} = -1 + \frac{1}{\theta}\frac{1-e^{-\theta}}{p+(1-p)e^{-\theta}}. \tag{6}$$

If $\theta > 0$ then $e^{-\theta} < 1$ so the numerator of the last term is positive and the denominator is increasing in p. Hence, $\frac{d\mu(p)}{dp}$ is decreasing in p. In addition,

$$\left.\frac{d\mu(p)}{dp}\right|_{p=0} = -1 + \frac{1}{\theta}(e^{\theta}-1) > 0$$

for all $\theta > 0$, given that $\frac{1}{\theta}(e^{\theta}-1)$ is increasing in θ and $\lim_{\theta\to 0}\frac{1}{\theta}(e^{\theta}-1) = 1$.[27] We also have that

$$\left.\frac{d\mu(p)}{dp}\right|_{p=1} = -1 + \frac{1}{\theta}(1-e^{-\theta}) < 0$$

for all $\theta > 0$, since the last term is decreasing in θ and $\lim_{\theta\to 0}\frac{1}{\theta}(1-e^{-\theta}) = 1$. Hence, there exists a unique $\underline{p}(\theta) \in (0,1)$ such that $\left.\frac{d\mu(p)}{dp}\right|_{p=\underline{p}(\theta)} = 0$, and $\frac{d\mu(p)}{dp} < 0$ for all $p > \underline{p}(\theta)$. Such a lower bound on p is given by

$$\underline{p}(\theta) = \frac{1}{\theta} - \frac{1}{e^{\theta}-1}.$$

To see that $\underline{p}(\theta)$ is decreasing in θ notice that

$$\frac{d\underline{p}(\theta)}{d\theta} = -\frac{1}{\theta^2} + \frac{e^{\theta}}{(e^{\theta}-1)^2} = -\frac{(e^{\theta}-1)^2 - \theta^2 e^{\theta}}{\theta^2(e^{\theta}-1)^2}.$$

The denominator in the RHS is positive so we need to prove that the numerator is also positive. Notice that the numerator is zero at $\theta = 0$, so it suffices to show that it is increasing in θ. The derivative of the numerator is $e^{\theta}\left(2(e^{\theta}-1-\theta)-\theta^2\right)$, which is positive if $2(e^{\theta}-1-\theta)-\theta^2 > 0$. This function is equal to zero at $\theta = 0$ and increasing in θ (its derivative is $2(e^{\theta}-1-\theta)$) so it must be positive for all $\theta > 0$.

[27] The derivative of $\frac{1}{\theta}(e^{\theta}-1)$ is $\frac{1+(\theta-1)e^{\theta}}{\theta^2}$. This expression is increasing in θ since the numerator is increasing in θ (its derivative is θe^{θ}) and equal to zero at $\theta = 0$, i.e., the numerator must be positive for all $\theta > 0$. To show that the limit is zero we apply L'Hopital's rule: $\lim_{\theta\to 0}\frac{1}{\theta}(e^{\theta}-1) = \lim_{\theta\to 0}\frac{e^{\theta}}{1} = 1$.

Finally, $\lim_{\theta\to\infty}\underline{p}(\theta)=\lim_{\theta\to\infty}\frac{1}{\theta}-\frac{1}{e^{\theta}-1}=0$. $\square$

Proof of Proposition 2. The information premium satisfies

$$u(1-p-\mu(p)-\mu(I))=\frac{1}{2}\phi((p-\varepsilon)u(0)+(1-p+\varepsilon)u(1))+\frac{1}{2}\phi((p+\varepsilon)u(0)+(1-p-\varepsilon)u(1)).$$

Since $u(0)=0$ and $u(1-p-\mu(p))=(1-p)u(1)$ we can rewrite the above expression as

$$u(1-p-\mu(p)-\mu(I))=\frac{1}{2}\phi(u(1-p-\mu(p))+\varepsilon u(1))+\frac{1}{2}\phi(u(1-p-\mu(p))-\varepsilon u(1)),$$

which implies that

$$\mu(I)=1-p-\mu(p)-u^{-1}\left(\frac{1}{2}\phi(u(1-p-\mu(p))+\varepsilon u(1))+\frac{1}{2}\phi(u(1-p-\mu(p))-\varepsilon u(1))\right).$$

Substituting ϕ, u and u^{-1} using CARA utility (2) and $u^{-1}(y)=-\frac{1}{\theta}\log(1-\theta y)$ leads to

$$\begin{aligned}\mu(I)&=1-p-\mu(p)\\&\quad+\frac{1}{\theta}\log\left(1-\frac{\theta}{2}\left[\frac{1-e^{-\theta\left(\frac{1-e^{-\theta(1-p-\mu(p))}}{\theta}+\varepsilon\frac{1-e^{-\theta}}{\theta}\right)}}{\theta}+\frac{1-e^{-\theta\left(\frac{1-e^{-\theta(1-p-\mu(p))}}{\theta}-\varepsilon\frac{1-e^{-\theta}}{\theta}\right)}}{\theta}\right]\right)\\&=1-p-\mu(p)+\frac{1}{\theta}\log\left(e^{-\left(1-e^{-\theta(1-p-\mu(p))}\right)}\left[\frac{1}{2}e^{-\varepsilon\left(1-e^{-\theta}\right)}+\frac{1}{2}e^{\varepsilon\left(1-e^{-\theta}\right)}\right]\right),\end{aligned}$$

which yields expression (4). Notice that only the last term in (4) depends on ε, and it is equal to $\frac{1}{\theta}\log\left(cosh(\varepsilon|1-e^{-\theta}|)\right)$. Hence, $\mu(I)$ is increasing in ε since $\cosh(y)$ is positive and increasing for $x>0$ and log is an increasing function.

We next argue that $\mu(I)$ is positive for $\theta>0$. We can rewrite (4) as follows:

$$\mu(I)=1-p-\mu(p)-u(1-p-\mu(p))+\frac{1}{\theta}\log\left(cosh(\varepsilon|1-e^{-\theta}|)\right).$$

The last term is positive since $\cosh(y)\geq 1$. In addition, CARA utility with $\theta>0$ satisfies $u(z)\leq z$ for $z\in[0,1]$, since $u(0)=0$ and $\frac{du}{dz}=e^{-\theta z}$, which is decreasing in z and equal to one at $z=0$. Hence, $\mu(I)$ must be positive.

To show that $\mu(I)$ is decreasing in p we differentiate (4) w.r.t. p to obtain

$$\frac{d\mu(I)}{dp}=-\left(1+\frac{d\mu(p)}{dp}\right)\left(1-e^{-\theta(1-p-\mu(p))}\right).$$

It is easy to check by looking at (6) that $\frac{d\mu(p)}{dp}>-1$ if $\theta>0$. In addition, $1-e^{-\theta(1-p-\mu(p))}>0$ since $1>p+\mu(p)$ for $p\in(0,1)$, implying that the RHS of the above expression is negative. The last fact also implies that $\mu(I)$ is decreasing in $\mu(p)$ for fixed $p \in (0,1)$ when $\theta > 0$. This is because the partial derivative of $\mu(I)$ w.r.t. $\mu(p)$ is given by

$$\frac{\partial \mu(I)}{\partial \mu(p)} = -1 + e^{-\theta(1-p-\mu(p))} < 0.$$

□

Appendix E Experiment

E.1 Design

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 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 F for the complete instructions and quiz provided to subjects).

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

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

We randomized subjects to two different treatments; No Ambiguity group and Ambiguity group. All subjects faced multiple information environments; 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 their maximum WTP for an expected rate of failure of between 2% and 98%, as described in Table E.7. 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) Multiplicative Risks.[28] 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. Multiplicative Risks imply a loss only if both probabilities are realized. As can be noted from Table E.7, each decision within the block has a corresponding decision with the same expected probability across information environments for ease of comparison.

Both Multiplicative Risks and Range blocks constitute a decision that involves solving a compound risk problem. 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 E.7, 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.[29]

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

Earnings in experimental dollars were converted to US dollars at the rate of 10 experimental dollars = \$1. Participation required approximately one hour and subjects earned an average of about \$29.5 each.[30]

E.2 Risk and Information Premium

The experiment confirms the results found in both surveys. Both risk premium and information premium are decreasing in risk probability p, as shown in Figure E.5. The only difference is that subjects in the experiment were significantly less risk averse.

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

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

[30] In 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 E.7: Experiment Treatments

Decision # (within block)	(1) Probability of Loss (%)	(2) Range Small (%)	(3) Range Big (%)	(4) Multiplicative Risks 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

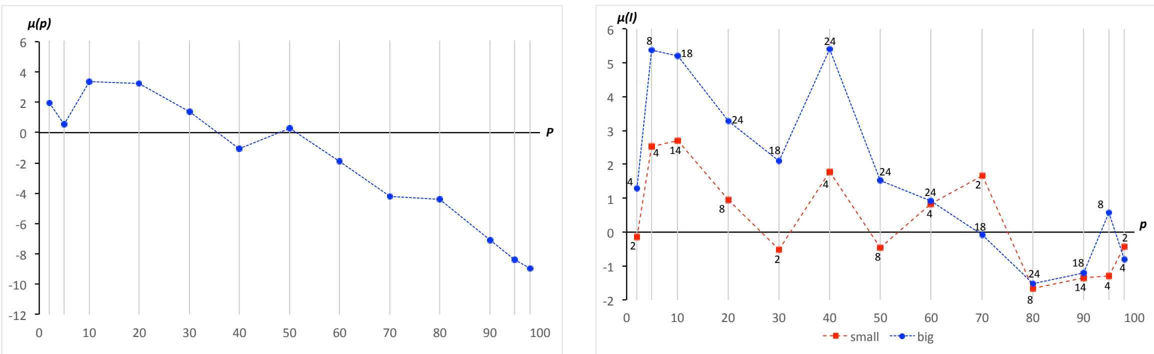

Figure E.5: Average Risk and Information Premia at Different Probabilities.

Informational effects of multiplicative risks are much stronger than those associated with ranges. Figure E.6 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 E.12 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.

E.3 Relationship Between Risk and Information Premium

Table E.8 presents the correlation coefficients for different p between risk and information premia, as well as the ORIV correlation coefficients. To perform the ORIV

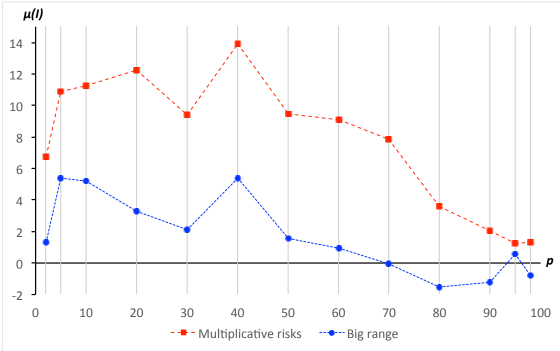

Figure E.6: Information Premium of Big Range and Multiplicative Risk Treatments

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.[31]

Table E.8: Correlation between risk and insurance premia – Experiment

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

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

[31]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., 2019).

Table E.9: 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: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

E.4 Covariates of Information Premium in the Laboratory

Table E.9 presents the regression estimates from the experiment. We run separate regressions for the range and multiplicative risk treatments. In the latter regressions we include the first stage risk probability since it is associated with negative skeweness (Dillenberger and Segal, 2017).[32] We also include as proxies for financial literacy whether the subject's major is quantitative (life sciences, natural sciences, economics and business, and engineering majors) and whether she took an economic course. GPA and the number of correct answers in the cognitive reflection test (CRT) (Frederick, 2005) are proxies for cognitive ability.

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

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

E.5 Analyisis of WTP

Table E.10 presents the average WTP under certain 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.

Table E.11 shows the comparison of presenting agents with non-ambiguous versus ambiguous ranges. No clear pattern emerges, with information premium being sometimes smaller and other times larger under ambiguity.

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 E.12 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 E.10: WTP for Insurance

p	$W(p)^a$	Range $\mu(I)^b$	(size)	$\mu(I)$	(size)	Multi-Risk $\mu(I)$
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 E.11: WTP by Ambiguity

p	Non-ambiguous Range $W(p)^a$	$\mu(I)^b$	(size)	$\mu(I)$	(size)	Ambiguous range $W(p)$	$\mu(I)$	(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.

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

Table E.12: WTP by Ability to Reduce Compound Lotteries - Lab

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

E.6 Interpersonal Rankings of WTP

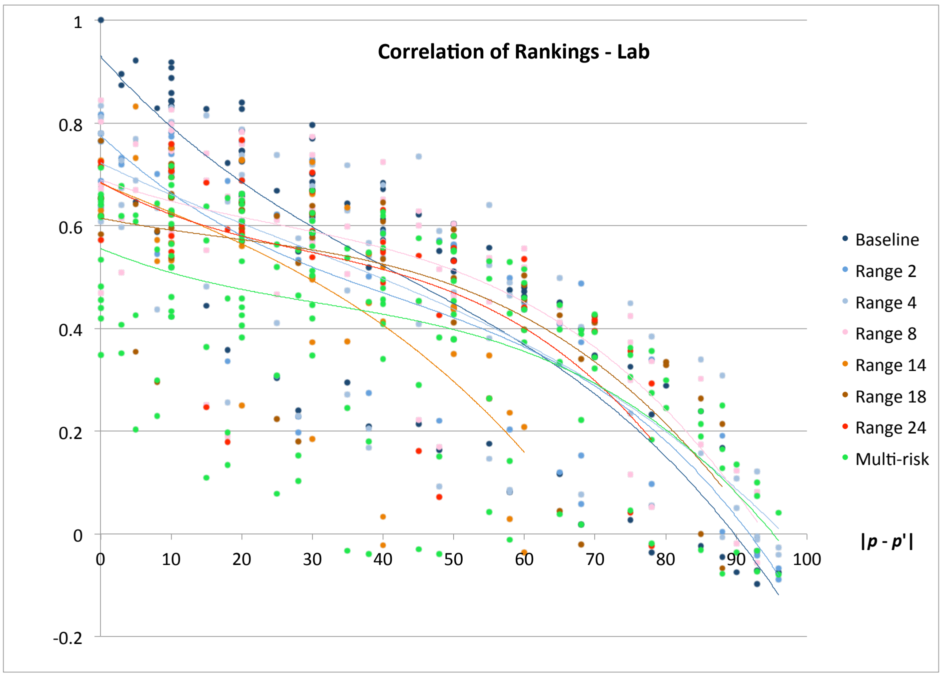

Figure E.7: Correlation of interpersonal rankings by differences in risk - Experiment.

Figure E.7 plots the correlation coefficients across different risk probabilities and information treatments. The horizontal axis corresponds to the difference in underlying risk $|p - p'|$ between (p, p) and (p', I). As in the survey data, correlation coefficients are high across treatments for close risk probabilities but they substantially decrease with the difference between underlying risk probabilities. Multiplicative risks have exhibit the lowest correlation of interpersonal rankings.

Appendix F Instructions

F.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.

F.2 Survey 2

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.]

F.3 Laboratory Experiment: Order 1, No Ambiguity

Instructions for different orders are the same, except for the order of presentation.

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.

F.4 Laboratory Experiment: Order 1, Ambiguity in Ranges

Instructions are the same as those without ambiguity, except for the 'uncertain failure rate' scenario. We provide just the instructions that are different from Appendix F.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.