Uncertainty and Welfare in Insurance Markets

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Abstract

Technological advances in the insurance industry mean that insurers now may be better informed about underlying risks faced by individual consumers than consumers themselves. We evaluate the impact of these information frictions on welfare by combining demand elicitation surveys with insurance claim data. As expected, we find an 'uncertainty premium' -i.e., consumers are willing to pay more for insurance when risks are uncertain. Interestingly, we find that the uncertainty premium is negatively correlated with risk aversion at all sizes and probabilities of risks. This leads to a selection effect: individuals who purchase insurance are not necessarily the most risk averse. We show that the resulting misallocation of insurance leads to large welfare losses.

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

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1 Introduction

The insurance industry plays a central role in the economy. In the United States, insurance premiums amount to \$1.35 trillion each year, or about 6% 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. Consumers, on the other hand, may have difficulty estimating their own risks. For example, when purchasing flood insurance, consumers need to reduce the compound lottery consisting of risk of a hurricane and risk of damage to their home in the case of a hurricane. Further, in new environments, consumers may be uncertain about the precise level of risk but may be able to estimate a range of 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 'uncertainty 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 uncertainty premium. This factor is critical since it determines the allocative effect of information frictions (i.e., a selection effect). A positive correlation implies that as risk-related information becomes more uncertain, more risk averse agents will be more likely to buy insurance. On the other hand, a negative correlation implies that as risk-related information becomes more uncertain, more risk averse agents will be *less* likely to buy insurance. The latter possibility implies negative welfare consequences for

[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).

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 uncertainty premia remains unknown due to data limitations, making the study of information frictions and policy evaluation in insurance markets all but intractable 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 uncertainty 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 surveys and conduct market analysis by combining them with existing estimates on insurance claim rates from administrative data. The paper provides insights into the welfare implications of uncertainty in risk information, and highlights the impact of managerial and policy decisions about information disclosure on consumer welfare.

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 underlying risks (captured by the probability that the product loses its value) and risk-related information (including certain risks and uncertain risks such as a range of risk probabilities and compound 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 loses value. Second, the experimental variation in risk and risk-related information allows us to jointly estimate the relation between risk and uncertainty attitudes at different risks. We replicate our results in a companion survey with 5,000 individuals that uses non-incentivized hypothetical decisions over large stakes (\$5,000 losses), and in an incentivized laboratory experiment with university students. An advantage of the large-stakes survey is that it may be more relevant to decisions in actual insurance markets.

As expected, we find that WTP for insurance is significantly higher in settings with uncertain risks than in settings with certain risks. The average uncertainty 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 uncertainty premium across individuals, which is replicated in our high-stakes survey and in our laboratory experiment.[4] The magnitude of the cor-

[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

relation 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.

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 uncertainty 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 uncertainty 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 uncertainty 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 uncertainty 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

correct for potential measurement error and obtain similar correlation estimates.

[5] The uncertainty 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 uncertainty premium. The main covariate of uncertainty attitudes are risk attitudes themselves, which alone account for 10% of the variation in uncertainty premium. This implies that selection effects are predominantly driven by selection on risk preferences rather than on socio-demographic characteristics.

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.

We also analyze strategic information disclosure by a monopolist. The optimal information disclosure by a monopolist also depends on the relationship between the uncertainty and risk premia. 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. If a monopolist strategically withholds information in this way, this can further exacerbate the selection issue.

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. Our findings also have managerial implications, since they highlight the tension between optimal monopolist information disclosure policies and welfare costs to consumers.

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 concludes.

2 Related Literature

We contribute to the emerging empirical literature on the impact of information frictions and behavioral biases on consumer welfare in insurance markets (Handel and Kolstad, 2015; Bhargava et al., 2017; Handel et al., 2019; Domurat et al., 2019). Our paper is closely related to the work of Handel et al. (2019), who use health insurance data to estimate the welfare effect of information frictions regarding the perception of coverage and costs across different types of health insurance (low- and high-deductible) under the assumption that frictions are orthogonal to risk attitudes.

Different from the related work on information frictions in insurance markets, our paper focuses instead on information about underlying risks and fully captures selection effects by identifying the correlation structure between risk and uncertainty attitudes without imposing 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 market equilibrium analysis extends the literature on selection in markets (Einav et al., 2010; 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.[6]

We build on the experimental literature on ambiguity aversion. Ambiguity aversion has been documented in experiments eliciting risk and ambiguity aversion (Cohen et al., 1987; Einhorn and Hogarth, 1986; Di Mauro and Maffioletti, 2004; Chapman et al., 2020). Two related papers in this context are the experiment on ambiguity attitudes in the loss domain by Hogarth and Kunreuther (1989) and the analysis of ambiguity attitudes with lotteries on a representative sample by Dimmock et al. (2016). We are not the first to document that individuals are ambiguity averse; however, we are the first to derive implications for the relationship between risk preferences and the uncertainty premium.

Our findings also highlight the need to account for uncertainty in the estimation of risk preferences from observational data. We address the estimation of preferences under uncertainty in a companion paper (Gandhi et al., 2022).

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. 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.[7] Information I

[6]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.

[7]We implicitly assume the existence of a data generating process that maps p to a set of possible

can represent, for instance, sets of possible values of p or a probability distribution over 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, 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 $p \in [0, 1]$.*

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 uncertainty premium.

Definition 3. The *uncertainty 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.

3.1 Informational Effects on the Demand for Insurance

We decompose the impact of the information structure on aggregate demand into a level effect and a composition or selection effect. The former measures how uncertainty

I the agent may receive.

changes the *level* of aggregate demand at any given price. The latter looks at it 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,[8] 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.[9] 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 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:*

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

[9] 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).

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 uncertainty 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 uncertainty 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 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 welfare impact 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.

3.2 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.[10] 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 main 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.[11] 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 \$5 (equal to \$100 virtual dollars in the survey) 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., $I = p$.

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

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

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

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.

We elicited maximum willingness to pay for insurance using the Becker-DeGroot-Marschak mechanism (Becker et al., 1964),[12] where the actual price of insurance was 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.

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

Half of the participants under uncertain risks 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 in the insurance experiment.[13]

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 uncertainty premia and estimate their correlation structure, developing estimates that correct for potential measurement error in WTP. Next, we investigate the relationship between uncertainty 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 uncertainty 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 1 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 D.4 in Appendix D 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%.

[13]It is common in the UAS to combine multiple studies in one survey session. As such, prior to completing the experiment, participants also received a series of un-incentivized questions designed to

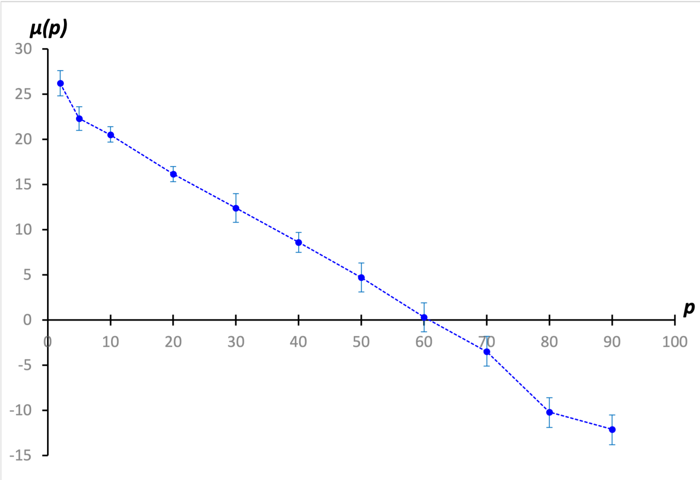

Figure 1: Average Risk Premium at Different Probabilities (bars represent 95% confidence intervals).

5.2 Uncertainty Premium

Turning to informational effects, Figure 2 presents the average uncertainty premium ($\mu(I) = W(I) - W(p)$) at each possible p. Each data point shows the range size associated with it. Since our design includes two range sizes for most of the probabilities, the graph displays two lines, respectively associated with small and big ranges.[14] As we show below, we do not find any major differences between uncertainty premium under compound and ambiguous risks. Accordingly, we pool both types of uncertain risks together.

On average, agents exhibit significantly large uncertainty 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 $p < 50\%$. uncertainty 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. The uncertainty 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 uncertainty premia at $p < 50\%$ suggests that markets where consumers face uncertain risks would exhibit greater demand due to strong level effects.

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evaluate understanding of annuity products for another project (Brown et al., 2019).

[14] Table D.4 in Appendix D shows the average uncertainty premium at each p by group.

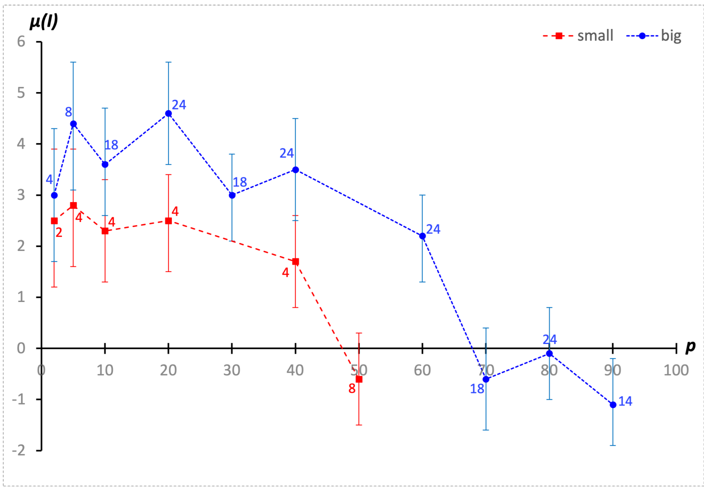

Figure 2: uncertainty premium at Different Probabilities (point labels represent range size and bars represent 95% confidence intervals).

5.3 Relationship Between Risk and Uncertainty Premium

We next look at the correlation between the risk premium and the uncertainty premium at each p, normalized by range size. Figure 3 plots the correlation coefficients, showing that risk and uncertainty premia are negatively correlated at all risk probabilities, with all coefficients significant at the 1% level. Correlation coefficients are remarkably invariant to p and consistently lie between -0.24 and -0.35. Correlations are similar when we control for individual characteristics, including cognitive ability, financial literacy, and socio-demographics (partial correlations) or not (total correlation).[15]

A concern with our estimates is that they may be biased 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 $W(p)$ enters with a positive sign in $\mu(p) = W(p) - p$ while it enters with a negative sign in $\mu(I) = W(I) - W(p)$. To correct for these biases, we follow the obviously related instrumental variable (ORIV) approach proposed by Gillen et al. (2019), which is based on the idea of using additional measures of the same variable as instruments. Appendix B describes the derivation of the ORIV estimator for $corr(\mu(p), \mu(I))$ and presents the estimates for different p. We obtain similar magnitudes and significance levels as those shown in Figure 3.

[15]Table B.2 in Appendix B reports total correlation coefficients and shows that they are statistically significant. Partial correlation coefficients are virtually identical and thus omitted.

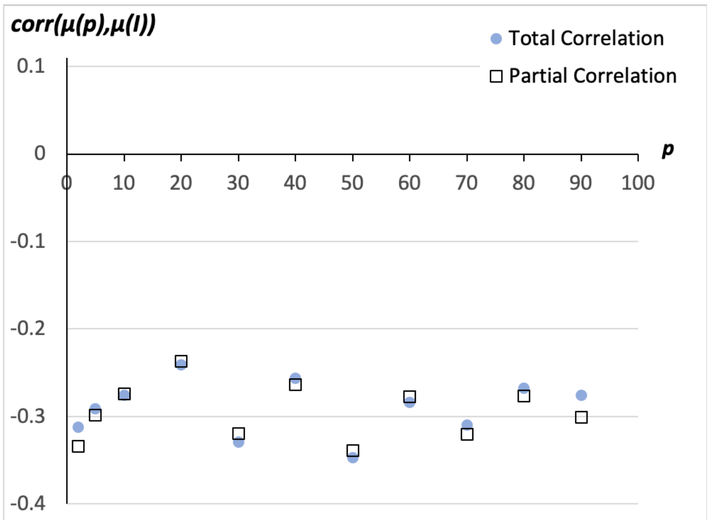

Figure 3: Correlation Coefficients between Risk Premium and Uncertainty Premium.

5.4 External Validity

Our results are confirmed by our high-stakes non-incentivized survey and our laboratory experiment. In the high-stakes survey, over 5,000 individuals from the UAS internet panel made hypothetical decisions over large stakes. Specifically, respondents report 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.[16]

Appendix C describes the survey and presents the empirical analysis. Overall, the data exhibits the same empirical patterns as the main 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 uncertainty premia are lower under high stakes, although still large for $p < 0.2$.. As in the main survey, the risk and uncertainty premia are negatively correlated with a correlation coefficients consistently between -0.2 and -0.4. About 20% of the sample participated in both the main and the high-stakes survey. We find that the risk premium across surveys are significantly correlated for these individuals (the correlation coefficient is 0.39).

The laboratory experiment design included a similar set of decision questions as the main survey. 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 main survey. Appendix E in the Appendix provides a full description of the experiment as well as detailed results.

We find that risk and uncertainty premia are decreasing in risk probability p (Fig-

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

ure E.4). In addition, risk and uncertainty premia exhibit a negative correlation of similar magnitude: estimates lie between -0.24 and -0.35 (see Table E.9 in Appendix E). The only major difference is that subjects in the experiment were less risk averse.

The remarkable invariance of our correlation estimates raises the question whether we have uncovered a robust feature of individual risk and uncertainty attitudes or whether they are just a byproduct of our specific survey design. We address this question 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).

Table 2: Correlation between risk and insurance premia

p	Study	N	correlation[a]	ORIV correlation[b]
50	This paper - main survey	1,043	-0.347***	-0.306***
50	This paper - high stakes survey[c]	804	-0.389***	-0.433**
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)[d]	115	-0.418***	-
50	Abdellaoui et al. (2015)[e]	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] ORIV correlation is computed using the sample of subjects who participated in both surveys. Replicas of the risk premium at 50 are constructed using the main survey's risk premium at 50 or at adjacent probabilities.
[d] Correlation between the certain risk premium and hypergeometric CR premium.
[e] 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.

As Table B.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 turns out to be identical to the ORIV correlation of -0.3 in our data.[17]

[17] Abdellaoui et al. (2015) use compound lotteries in their 'hypergeometric CR' treatment, preventing us from obtaining a replica of the uncertainty 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.

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 show how information frictions can create incentives to engage in selective information disclosure under imperfect competition.

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.[18] 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.[19]

[18] 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.

[19] 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 $p = 0.02$.

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 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 3 presents the main outcomes in equilibrium for the case of perfect competition and monopoly across pricing and information scenarios for both the incentivized and the high stakes surveys. 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.

Table 3: Market Outcomes

	Overall	*Uniform Price*				*Risk-based Pricing*			
		Perfect Competition		Monopoly		Perfect Competition		Monopoly	
	Population	Certain	Uncertain	Certain	Uncertain	Certain	Uncertain	Certain	Uncertain
Main Survey									
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[a]			6.7%		39.4%		2.3%		46.4%
Selection Effect[b]			88.4%		95.1%		89.3%		95.2%
High-stakes Survey									
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[a]			9.7%		43.9%		3.5%		77.3%
Selection Effect[b]			96.0%		88.5%		94.0%		28.5%

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

[b] 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.

6.2.1 Aggregate Demand

Figure 4 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 uncertainty premia.

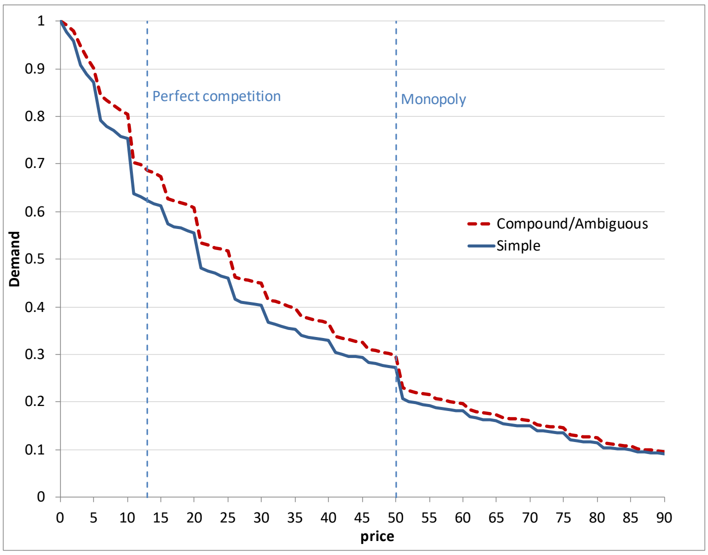

Figure 4: Demand for Insurance.

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 3 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 1.

The introduction of information frictions slightly reduces adverse selection due to the fact that the uncertainty premium is decreasing in risk (Figure 2), leading to a small drop in risk probability (5% under perfect competition and 4% under monopoly).

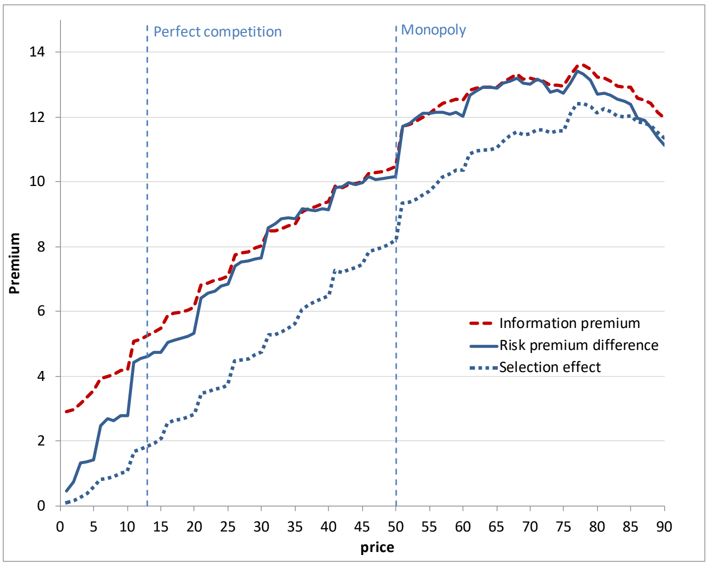

Figure 5: uncertainty premium and Differences in Risk premium.

In contrast, selection effects on risk preferences and uncertainty 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 uncertainty premium is at least twice the average uncertainty premium in the population. As Figure 5 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 uncertainty 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 5. 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. (2010) 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 uncertainty 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 uncertainty 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 3 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 uncertainty 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 Risk-Based Pricing

The right-hand-side panel of Table 3 shows that informational effects are quantitatively similar when insurers engage in risk-based pricing. The only notable difference is the presence of *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. This is driven by the risk premium being decreasing w.r.t. risk probability.

6.4 High Stakes

The bottom panel of Table 3 replicates the market analysis using the high-stakes data. The results are qualitatively similar to the ones obtained using the main survey, with several differences. First, the lower risk premia exhibited by respondents at high stakes result in a smaller share of insured agents in the population. Further, because there is a larger reduction in risk premium than in uncertainty premium relative to the main survey, we see even bigger welfare effects.[20] Finally, there is substantial advantageous selection under risk-based pricing regardless of the degree of competition.

6.5 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 3.2, insurers with the ability to observe or estimate the risks faced by an agent might have an incentive to withhold or share this information with the agent. 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 4 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 uncertainty premium at low probabilities and zero or negative uncertainty premium at high p (see Figure 2), the monopolist chooses to disclose p to the agent at

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

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 4: Information Disclosure under Monopoly

p	2	5	10	20	30	40	50	60	70	80	90
Main Survey	no	no	no	no	no	no	yes	no	yes	no	yes
High-stakes Survey	no	no	no	yes	no	no	yes	no	yes	yes	no

7 Conclusion

Our study uses surveys to uncover 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 policy interventions and methodological changes. Such implications of our analysis acquire particular relevance given that we find similar patterns across multiple survey and experimental data sources.

The paper highlights that different types of information frictions affect markets in different ways. Whereas related work shows that 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 selection effects, which reduce welfare. This suggests that friction-mitigation policies aimed at improving welfare need to be tailored to the specific frictions being targeted.

Our analysis has implications for consumers, insurers and policy-makers. For consumers, uncertainty about risks leads to mis-allocation of insurance and welfare losses. For insurers and policy-makers, the advent of InsurTech has made data about underlying risks available, and there are open questions about how such data should be used. Our results show that for insurers, there is an incentive to strategically withhold risk-related information to increase profits. For policy-makers, introducing policies of mandatory information disclosure can unambiguously improve consumer welfare.

A large body of work uses observational data to obtain estimates of risk preferences and engage in policy analysis. Methodologically, our work emphasizes the need to account for the joint distribution of the demand components to obtain unbiased risk estimates. In this context, surveys and demand simulation techniques can overcome limitations inherent to observational data. As such, our paper speaks to the point made by Stantcheva (2022) about the importance of surveys as a key tool for uncovering 'invisible' determinants of demand behavior. We explore this issue in detail in our companion paper on preference estimation (Gandhi et al., 2022).

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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 Measurement Error Correction

This section provides estimates of the correlation between risk and uncertainty premium that correct for potential biases due to measurement error. 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 uncertainty premium is given by $\hat{\mu}(I) = \mu(I) + \varepsilon_I - \varepsilon_p$. Assuming that measurement errors are independently drawn and that they are independent of $W(\cdot)$, the correlation between $\hat{\mu}(I)$ and $\hat{\mu}(p)$ is given by

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

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

However, 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 uncertainty premium, the correlation between the risk and uncertainty 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 uncertainty 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 uncertainty 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 unknown risks respectively associated with p' and p''. We normalize uncertainty premium by dividing it by range size and perform the linear interpolation using the normalized premia.

Table B.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 uncertainty premia is not an artifact of measurement error.

Table B.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.

Appendix C 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 C.3 provides a summary of decisions presented to respondents. Unlike Survey 1, Survey 2 was not incentivized.

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

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

Table C.3: 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.

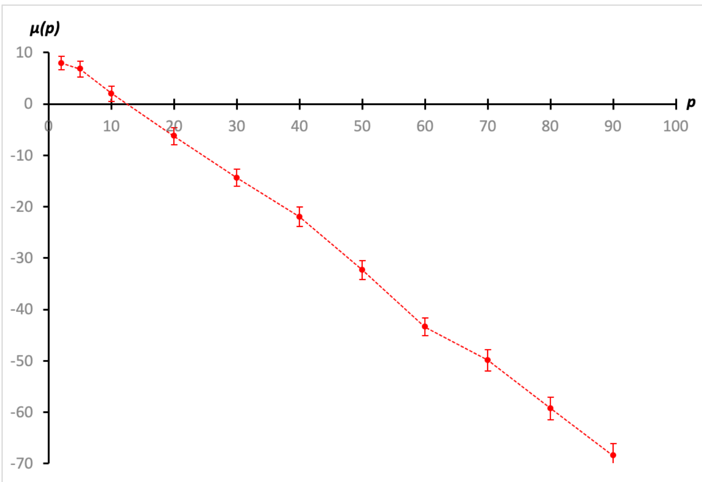

Figure C.1: Average Risk Premium (bars represent 95% confidence intervals).

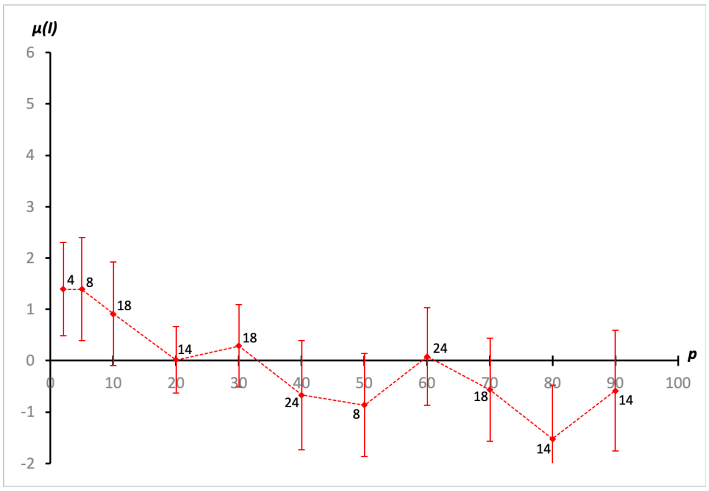

Figure C.2: Average uncertainty premium (labels denote range size and bars are 95% confidence intervals).

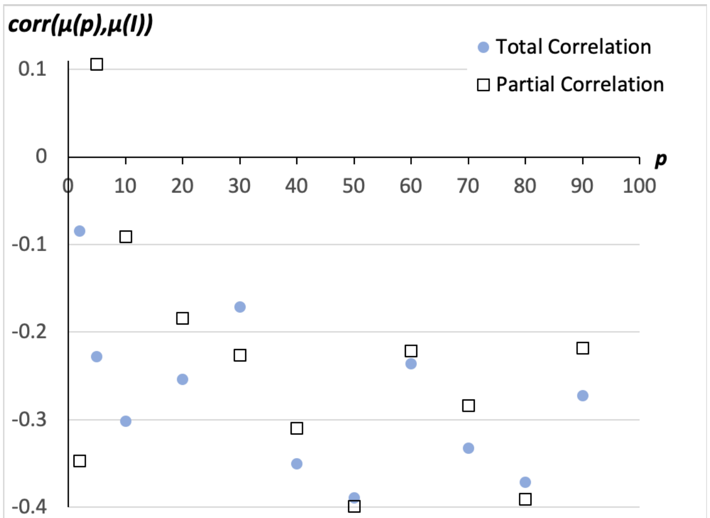

Figure C.3: Correlation Coefficients between Risk Premium and uncertainty premium.

Appendix D Statistical Analysis of WTP

In this section we present the average WTP under certain risk ($W(p)$) and the uncertainty 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 D.4 presents whole sample averages and reports both whether WTP are different from risk probabilities and whether uncertainty premium is significantly different from zero using one-sided paired t-tests.

Table D.4: 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 D.5 and D.6 show the effect of presenting agents with non-ambiguous versus ambiguous ranges. There is no clear effect of ambiguity on the uncertainty premium. Overall, effects seem to be quantitatively of the same order of magnitude.

Table D.5: 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 D.7 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 uncertainty premia between those who answered correctly and those who did not correctly reduce

Table D.6: 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.

Table D.7: WTP by Ability to Reduce Compound Lotteries

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

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.8. 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.[21] 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.8, 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.8, 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.[22]

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.[23]

[21] 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)

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

[23] 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.8: 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

E.2 Risk and uncertainty premium

The experiment confirms the results found in both surveys. Both risk premium and uncertainty premium are decreasing in risk probability p, as shown in Figure E.4. The only difference is that subjects in the experiment were significantly less risk averse.

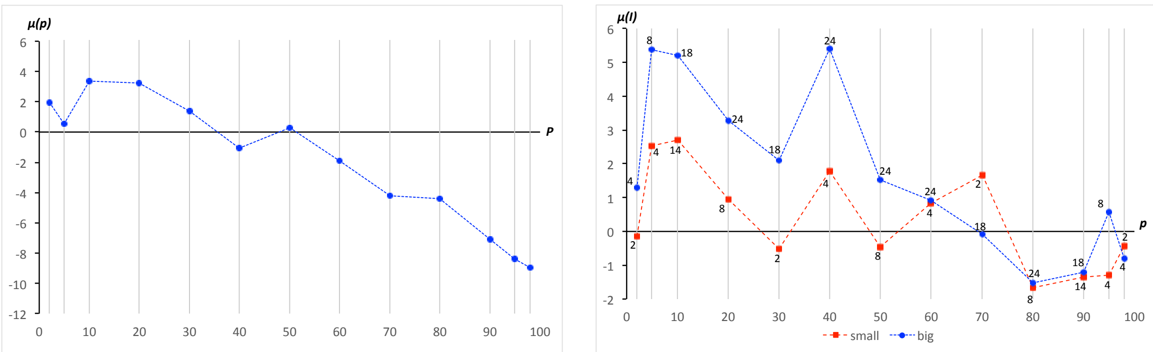

Figure E.4: Average Risk and uncertainty premia at Different Probabilities.

Informational effects of multiplicative risks are much stronger than those associated with ranges. Figure E.5 shows the comparison of uncertainty premia for multiplicative risk and range treatments. Whereas the uncertainty 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.

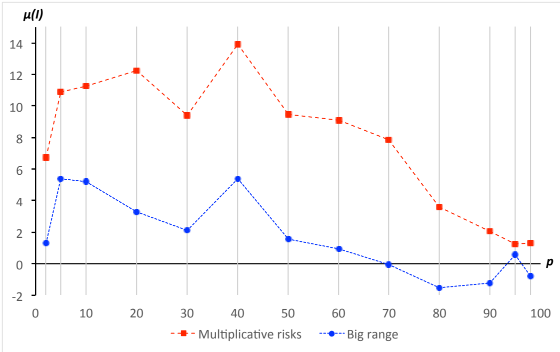

Figure E.5: uncertainty premium of Big Range and Multiplicative Risk Treatments

E.3 Relationship Between Risk and uncertainty premium

Table E.9 presents the correlation coefficients for different p between risk and uncertainty premia, as well as the ORIV correlation coefficients. To perform the ORIV correction we use the linear interpolation of adjacent risk premia as a replica of risk premium. We do not use replicas of the uncertainty premium given the lack of a direct comparability of uncertainty premium between different multiplicative risks.[24]

E.4 Analyisis of WTP

Table E.10 presents the average WTP under certain risk as well as the uncertainty premium across treatments. The table also reports both whether $W(p)$ is different from p and whether the uncertainty 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 uncertainty 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 uncertainty premia, especially under multiplicative risks.

Table E.9: 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.

Table E.10: WTP for Insurance

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

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

[24] Not having a replica for the uncertainty 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

Table E.11: WTP by Ambiguity

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

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

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

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

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

(Gillen et al., 2019).

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.