Information and Risk Preferences: The Case of Insurance Choice

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Abstract

Despite standard economic models that assume stability of preferences, empirical work on insurance choice has documented a surprising lack of stability of risk preferences across domains. We hypothesize that informational differences can partly explain the observed empirical regularities, and test our hypothesis by conducting lab and field experiments with over 4,000 participants. We exogenously vary the information subjects receive about the underlying risk they face and elicit willingness to pay for insurance. We have three major findings: 1) information plays a significant role - willingness to pay for insurance is higher in settings with more complex or ambiguous information; 2) both risk aversion and aversion to complex or ambiguous information are decreasing in the underlying risk probability; and 3) risk aversion and aversion to complex or ambiguous information are negatively correlated, with the correlation coefficient being remarkably invariant to underlying risk and sociodemographic characteristics. Using demand simulation techniques, we illustrate how informational effects can bias the empirical estimation of risk preferences and have a large impact on the allocative efficiency of insurance markets.

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1 Introduction

The insurance industry plays a major role in the economy. In the United States, insurance premiums totaled more than \$1.1 trillion in 2015, or about 7% of gross domestic product. A large literature is devoted to understanding the choice patterns of the demand side of the insurance market. One of the goals of this literature is to estimate risk preferences, which factor into insurance related decision-making. A series of studies do this using field data (Barseghyan et al., 2011; Einav et al., 2012). In contrast to standard economic models that assume stability of preferences, a surprising finding from this literature is that there is a lack of stability in risk preferences across domains. For example, Barseghyan et al. (2011) finds that households exhibit greater risk aversion in home than auto deductible choices.[1] Interestingly, this literature also shows that, despite the apparent instability of risk attitudes, individuals can be ranked across contexts based on revealed risk preferences.

The empirical literature often relies on the critical assumption that people make their insurance decisions as if they are able to perfectly estimate their risks - that is, that they can come up with a probability distribution over potential outcomes. And, the ability to estimate risk is assumed to be unaffected by the complexity of risks faced or by the information that people have about their risks. These assumptions are problematic given evidence from experimental economics showing that people have difficulty understanding risk. In particular, experimental work shows that elicited risk preferences are affected by factors such as the presence of compound risk (i.e., multi-stage lotteries over outcomes) and ambiguity. More broadly, there is empirical evidence showing that informational frictions, e.g. about risk coverage, affect insurance choice and bias the estimation of risk preferences based on those choices (Handel and Kolstad, 2015). This literature underscores the need to understand the effect of information on revealed risk preferences, and the impact of such informational effects on the demand for insurance and their implications for the estimation of risk preferences from insurance choice data.

We propose that the informational context in which insurance decisions are made matters. For example, suppose that people know the precise probability of an adverse event in one context, but in another context can only estimate the probability imprecisely. Sources of informational differences could include compound risks, ambiguity and differences in complexity or framing. All these highlight different violations of the reduction principle, i.e., the ability to reduce information about risks to distributions

[1] Einav et al. (2012) uses data on employer-provided insurance choice and finds that only about 30% of the sample exhibits consistent risk preferences across all 6 domains tested.

over final outcomes, which lead to preferences not being invariant to information. Taking the example from Barseghyan et al. (2011), people may have a better understanding of the probability of a car crash versus an adverse event happening to a home, since they have more experience seeing or hearing about car crashes. These differences in information could explain why Barseghyan et al. (2011) find that people are willing to pay as much as 50% more in premiums for home insurance versus the equivalent insurance on an automobile, leading to an apparent instability in preferences.

It is important to understand the relationship between risk attitudes over final outcomes and information attitudes, and how this relationship varies with underlying risks. Understanding this relationship is necessary to assess the impact that information about risk may have on the allocation of insurance and on the estimation of risk preferences using data from insurance markets. For instance, whether risk aversion and a preference for simple information are positively or negatively related partly determines the allocative efficiency of insurance markets. In the presence of informational effects, a positive correlation means that, given the same underlying risk, the more risk averse agents tend to acquire insurance. However, this is not necessarily the case when risk aversion and a preference for simple information are negative correlated, since the latter can induce agents who are less risk averse to buy insurance, while more risk averse agents abstain from doing so.

In this paper, we provide an analysis of the relationship between risk and information preferences and argue that attitudes toward information associated with violations of the reduction principle could explain the surprising findings in the field data regarding the instability of risk preferences. We also illustrate how informational effects can significantly bias the estimation of risk preferences and generate large welfare effects in insurance markets.

We conducted a laboratory experiment (N=119 university student subjects) and an artefactual field experiment (Harrison and List, 2004) (N=4,000 respondents from a representative online panel) to understand how willingness to pay for insurance varies with information. In our experiments, we compared maximum willingness to pay (WTP) for insurance under different probability of a loss in different information environments: precisely stated risk (which we refer to in the paper as simple information), ranges of risk probabilities (generating ambiguity), and compound risks (which we call multiplicative risks). Each subject was exposed to a series of decisions with different expected loss probabilities ranging from 0.02 to 0.98, which allows us to evaluate how responses to information about risk differ by the expected loss probability.

Our methodological approach has several attractive features. Experiments allow us a level of control and ability to systematically change the informational environment that is not possible with naturally occurring data (Smith, 1994). Existing estimates of risk preferences from insurance data, such as Barseghyan et al. (2011), Einav et al. (2012) or Sydnor (2010), assume that agents know their risk probabilities, which in turn are estimated using claim frequency data conditional on a limited set of observable characteristics. We can experimentally vary this assumption. Second, we can investigate potential sources of information attitudes, both in terms of features of the information structure and in terms of individual characteristics such as the ability to reduce compound lotteries, financial literacy, cognitive ability or other sociodemographic characteristics.

We find that, although risk and information attitudes are widely heterogeneous, individuals tend to insure more when information about risk is complex or ambiguous as long as the underlying risk probability is not too high. Both experiments show similar large responses to compound or ambiguous risks at risk probabilities below 50%, leading to average 'information premium', defined as the difference in WTP under compound risks and under simple risks, as high as 100% of the expected loss. In both experiments, information premia and risk aversion, measured as the insurance premium agents are willing to pay to insure against simple risk over the actuarially fair price, are decreasing in the underlying risk probability. Crucially, our experiments reveal that preferences for simple information are negatively correlated with risk aversion, a surprising finding that is extremely robust to variation in underlying risk probability or in the sources of informational effects (complexity or ambiguity). In both experiments, the information and the insurance premium exhibit a correlation between -0.2 and -0.4 at most risk probabilities. Such a negative relationship turns out to be the driver of welfare effects associated with information and significantly bias risk preference estimates in our demand simulation exercise. Despite this negative correlation, interpersonal rankings based on willingness to pay for insurance exhibit a strong positive correlation as long as underlying risk probabilities are similar, in line with existing empirical evidence (Einav et al., 2012).

The lack of simple information can have two different effects on the aggregate demand for insurance: a *level* effect and a *selection* or composition effect. First, information premium drives up average WTP at low and moderate risk probabilities, which essentially represent the relevant ranges of risks in most insurance markets. The level effect thus implies that aggregate demand will be higher in a market without simple information ($I \neq p$) than in a market where all agents receive simple information ($I = p$). The selection effect is related to which agents end up buying insurance in the market. Since risk and information premium are negatively correlated, the average risk premium will be lower in a market where agents are exposed to compound or ambiguous risks than in a market where agents face equivalent simple risks. To quantitatively assess these effects we use our experimental data as well as estimates of actual insurance claim rates from Barseghyan et al. (2011) to construct an aggregate demand curve. We then identify the range of possible equilibrium prices, ranging from perfect competition to monopoly, and the pool of insured agents in the market at each of these prices. We find that risk premium estimates based on data on WTP and underlying risk probabilities from the pool of insured agents are biased upward by about 20%, of which at least a third is due to the selection effect. In addition, the welfare loss associated with the absence of simple information about risks ranges between 7% and 40%, which is almost solely driven by the selection effect (about 90% of the overall welfare loss).

Our findings lend support to the theory on the role of information in affecting risk preferences - and suggest that informational differences can allow for unstable revealed risk preferences in empirical data, without necessarily implying unstable preferences. Our analysis reveals that the features of compound risks, i.e., the size of the range of probabilities or whether they correspond to multiplicative risks, have a significant impact on information premia. In contrast, whether the range of probabilities is ambiguous or not does not seem to matter. In terms of sociodemographic characteristics, financial literacy and the ability to reduce compound lotteries are significantly related to lower risk premia. However, none of these individual characteristics are significantly associated with the information premium. Moreover, while individual characteristics and information attributes account for about 20% of the variation in risk premia, they only account for about 1% of the variation in information premia. The main covariate of information attitudes are risk attitudes, which alone account for 10% of the variation in information premium.

There are two main implications of our work. First, researchers using naturally occurring data to assess risk preferences need to incorporate informational differences as an omitted variable in their estimations. In this context, the negative correlation between information and risk preferences, by introducing selection bias, highlights the need for their joint estimation. That is, we need to not only account for the presence of information frictions, as emphasized by Handel and Kolstad (2015), but also to understand the relationship between these frictions and risk preferences. Second, the need to account for the joint relationship between risk, risk attitudes and information attitudes applies to the empirical analysis of insurance markets, given that, as

Einav et al. (2010) emphasize, the inferences on welfare, competition or the presence of asymmetric information can be very sensitive to the specification of risk preferences and the correlation structure between risk and preferences. For instance, an important part of this literature focuses on the positive correlation between risk and insurance coverage as evidence of asymmetric information (Chiappori and Salanié, 2013). Our findings about both risk and information premium being decreasing in risk and the negative correlation between risk and information premia thus affecting the relationship between risk and coverage. In particular, they can attenuate or even reverse the correlation between risk and coverage even if asymmetric information is pervasive. Our demand simulation exercise shows that the correlation is between risk and coverage can be much smaller than when risk preferences are independent of the underlying risk.

Our findings also yield policy recommendations regarding information in insurance markets. Specifically, policies aimed at simplifying the information conveyed to potential insurance buyers, such as simple risk assessments associated with individual socio-demographic profiles may lead to significant welfare gains by reducing the misallocation of insurance caused by the negative correlation of risk and information premia. Finally, from a decision theoretic perspective, the negative correlation between risk aversion and aversion to compound or ambiguous risks is somewhat of a puzzle, since our intuition is that the same primitive sources behind risk aversion should be at work when it comes to aversion to compound and ambiguous risks.

In what follows, Section 2 lays out the theoretical framework, Section 3 provides an overview of the experimental design, Section 4 describes our results, Section 5 presents our demand simulation results, Section 6 investigates the sources behind information attitudes and Section 7 concludes.

1.1 Literature Review

Our work is related to three strands of literature, respectively focused on the estimation of risk preferences, violations of the reduction principle, and empirical analysis of the demand for insurance. Given the sheer size of these literatures, rather than attempting to provide a detailed overview we focus on research closest to this paper and refer the reader to the various excellent literary surveys for further sources on each of the three topics.

Existing research on the estimation of risk preferences has a long tradition in economics. These include experimental studies as well as emprirical work with survey and field data. Excellent surveys include Harrison and Rutström (2008) for experimental work on risk attitudes and Barseghyan et al. (2016) and Outreville (2014) for studies using field data. Recent papers have been on the use of data from individual insurance choices to estimate risk preferences. However, while several experimental studies have looked at the invariance of risk preferences to the choice domain (Dawling et al., 2011; Harrison, 2011; Vieider et al., 2015), it has not have been analyzed by the empirical literature, with the exception of Barseghyan et al. (2011) and Einav et al. (2012). Both papers exploit data from different insurance and investment decisions to gauge the extent to which intra- and inter-personal comparisons of risk preferences are stable across contexts.

There is a large body of research on violations of the reduction principle, both using experimental and field data (see Starmer (2000) for a review). Our paper is closer to the laboratory experiments of Halevy (2007) and Abdellaoui et al. (2015), who look at the relationship between attitudes towards compound lotteries and ambiguity attitudes. In the context of lotteries Abdellaoui et al. (2015) find that risk aversion goes up with the probability of winning, which is consistent with our finding that risk premium goes down in both the lab and the field with the probability of a loss. In contrast to these papers, we focus on the relationship between risk preferences and preferences over compound or ambiguous lotteries. To the best of our knowledge, our paper is the first to uncover a negative correlation between the two. In addition, our field experiment provides validity to our findings in the lab. Also related to our paper is the innovative analysis of Handel and Kolstad (2015), who show, in the context of health insurance plan choice, the importance of controlling for information frictions and search and hassle costs when estimating risk preferences from choice data. Our finding that risk aversion and preferences for simple information are negatively correlated suggests that their identifying assumption of informational frictions being orthogonal to risk preferences may not hold, a point raised theoretically by Freixas and Kihlstrom (1984) and Cabrales et al. (2017).

Our analysis is related to the empirical analsysis of the demand for insurance (see Einav et al. (2010) and Jaspersen (2016) for a review). Our demand simulation exercise tries to illustrate the potential pitfalls of conducting demand and welfare analysis while ignoring the relationship between between risk, risk preferences and, from their dependence on the information structure.

Finally, our paper is also related to research relying on field experiments to estimate risk attitudes such as Harrison et al. (2007a,b). These papers use specific subsamples of the population (e.g., card dealers in Harrison et al., 2007b) and tailor the experimental design to the risks subjects are familiar with or exposed to so as to get more accurate estimates of risk preferences. In contrast, we use an artifactual design for our field sample that is identical to the laboratory experiment, which allows for the comparison of lab and field estimates. Despite the potential drawback of having subjects face somewhat unfamiliar insurance questions, the fact that we have a representative sample of individuals make tailoring the insurance scenarios impractical and would prevent us from developing reliable interpersonal rankings of risk aversion. Such interpersonal rankings are essential to conduct our analysis of the demand for insurance.

2 Framework

We consider an insurance framework as follows. A decision maker (DM) is exposed to some objective risk, defined as a probability distribution $F : X \to [0, 1]$ over the set of outcomes $X \in \mathbb{R}$. We assume that X is compact and denote its highest element by $\bar{x}$, which represents the absence of a loss, and its lowest element by $\underline{x}$. For instance, $X = [0, 1]$ may represent residual values of an asset exposed to different perils, e.g., a home or a car, relative to its original value. Likewise, $X = \{0, 1\}$ can refer to binary risks in which either the risk is realized ($x = 0$) or not ($x = 1$). Alternatively, it can represent different wealth or income levels. The set of probability distributions over X is denoted by $\Delta(X)$.

The DM has access to information $I \in \mathcal{I}$ about risk F, where $\mathcal{I}$ is the set of possible I that the DM may posses. We define an information environment $\mathcal{I}(F) \subset \mathcal{I}$ as the subset of possible I when the risk is F.[2] Information I can represent different things. For instance, it can be a set of noisy signals about F. Likewise, it could represent a sample of observed realizations of risks the individual has been exposed to in the past or experienced by a set of other agents. We can think of I as the DM's *perceived risk*. In our experiment we will focus on three particular cases:

(i) the DM knows her objective risk, i.e., $I = F$.

(ii) I represents *compound risks* or probability distributions over risks in $\Delta(X)$. That is, I is an element of $\Delta(\Delta(X))$. I reduces to F if $F(x) = \int_{G \in \Delta(X)} dI(G(x))$ for all $x \in X$. We denote $\mathcal{I}^{CR}(F) \subset \Delta(\Delta(X))$ the set of probability distributions I over risks that reduce to F.

(iii) The DM has *ambiguous information* about F, in which I is a subset of potential risks in $\Delta(X)$ the DM deems possible but she lacks information about the likelihood of each of them. We denote $\mathcal{I}^{A}(F) \subset 2^{\Delta(X)}$ the set of subsets I of $\Delta(X)$

[2] We implicitly assume the existence of a data generating process that maps F to a set of possible I the DM may receive.

such that, if the DM were to use a uniform prior over elements of I, I reduces to F (if I is finite, then it reduces to F if $F(x) = \frac{1}{|I|}\sum_{G\in I} G(x)$ for all $x \in X$.)[3]

Case (i) is the traditional approach to analyzing decision making under risk. Case (ii) represents situations in which the DM perceives risks as the combination of multiple random events. For example, her home may get flooded if there is unusually heavy rain *and* the sewage system is clogged by debris. Finally, case (iii) represents the standard approach to modeling ambiguity.

We consider the DM's demand for insurance, expressed as the willingness to pay (WTP) for an insurance policy that ensures the DM gets $\bar{x}$ after risks are realized, i.e., after a draw from F takes place. To do so we assume that the DM is endowed with well-defined preferences $\succcurlyeq$ over $\mathcal{I}$ represented by a mapping $W : \mathcal{I} \to \mathbb{R}$, where $W(I)$ represents the willingness to pay for insurance under information I. That is, since the DM observes I and not necessarily F, we consider information as the primitive over which risk preferences are defined, in a similar spirit as in Blackwell (1951).[4] We assume that the preference relation is complete and stable.

The representation of preferences over perceived risks given I in terms of WTP is equivalent to representing them in terms of utility. Specifically, if DM's utility associated with I is given by $V : \mathcal{I} \to \mathbb{R}$, then $V(\delta_{(\bar{x}-W(I))}) = V(I)$, where δ_x is the degenerate distribution that yields x with probability one. That is, $\bar{x} - W(I)$ is the certainty equivalent of I. Since our definition revolves around the notion of insurance against losses, let $l_F = \bar{x} - E_F(x)$ be the expected loss from risk F, where E_F denotes expectation w.r.t. F.

Definition 1. The DM is risk averse (loving) w.r.t. objective risks if $\delta_{(\bar{x}-l_F)} \succ (\prec)\ F$, i.e., if $W(F) > (<)\ l_F$, for all $F \neq \delta_{\bar{x}}$. The DM is risk neutral if $W(F) = l_F$ for all F.

Existing approaches to estimating risk preferences from field data involve either individual- or market-level analysis. Individual-level studies use observed choices from a menu of insurance policies. If the menu is sufficiently rich, this amounts to roughly observing WTP (Barseghyan et al., 2016). In addition, objective risk F is estimated using empirical insurance claim frequencies and loss size (which can be conditional on some socio-demographic variables). In order to estimate risk preferences, the following critical assumption about the link between information and risk is imposed:

[3]The use of a uniform prior is usually justified by appealing to the principle of insufficient reason.

[4]We have in mind a situation in which the agent has intrinsic preferences for information, as defined by Grant et al. (1998). That is, the agent may experience different utility depending on which I he has, even if he cannot act upon I to affect their risks. Nonetheless, the above definitions imply that W also reflects the instrumental value of I in environments where actions contingent on I that affect F are unobserved by the econometrician.

Assumption 1 (Reduction Principle). *$W(I) = W(F)$ for all $I \in \mathcal{I}(F)$ and all F.*

The reduction principle establishes that, given the information at hand, the DM acts as if she perfectly learns F from I and, given this knowledge, the specific attributes of I do not affect her demand for insurance.[5] Special versions involve the reduction of compound lotteries (Samuelson, 1952) and ambiguous lotteries, i.e., $W(I) = W(F)$ for all $I \in \mathcal{I}^{CR}(F)$ and all $I \in \mathcal{I}^{A}(F)$.[6,7]

Under Assumption 1, a sample of (WTP, F) allows for the estimation of the DM's risk preferences, while ignoring the information environment faced by the DM.[8] This is because, under the reduction principle, as long as the underlying risk does not change, elicited preferences over risk are invariant to information.

Proposition 1 (Stability of Risk Preferences). *Let Assumption 1 be satisfied. For any $I \in \mathcal{I}(F)$ and $I' \in \mathcal{I}(F')$, $I \succcurlyeq I'$ if and only if $W(F) \leq W(F')$.*

An important consequence of the stability of risk preferences is that a sample of observations (WTP, F) from different insurance contexts can be used to estimate individual risk preferences $W(F)$, regardless of informational differences likely present across contexts. For instance, home insurance policies typically cover many different risks (over 10 types of perils), some of which the homeowner might be unfamiliar with or have little data about, thus making the inference of the probability of filing a claim quite difficult. In contrast, assessing risks covered by auto insurance is arguably more straightforward for many drivers.

Often times the focus is on the estimation of the distribution of risk preferences in the population using a cross section of (WTP, F), with the goal of analyzing outcomes in insurance markets and policy evaluation. This approach hinges upon assuming that individuals can be globally ranked with respect to their risk aversion and, crucially, that these rankings are unaffected by information. The existence of a global ranking of risk translates into an index θ such that an agent with a higher θ is globally more

[5]Assumption 1 implies that $\{\mathcal{I}(F)\}_{F \in \Delta(X)}$ represents a partition of the set $\mathcal{I}$. Since I can only be reduced to one F, the intersection of $\mathcal{I}(F)$ and $\mathcal{I}(F')$ must be empty for any $F \neq F'$.

[6]Popular models of ambiguity aversion proposed in the decision theory literature imply that the reduction principle applies to $\mathcal{I}^{CR}(F)$ for all F but not to $\mathcal{I}^{A}(F)$, although Halevy (2007) finds a strong relationship between the two.

[7]Note that here the focus is on the reduction to objective risks, i.e., on whether the DM infers the actual risks she faces. In contrast, one could think of many preference classes that exhibit aversion to 2-stage or ambiguous lotteries, such as minmax expected utility, as reducing them to some $F' \neq F$.

[8]For instance, if we assume that the DM has EU preferences with constant absolute risk aversion (CARA) utility, given by $u(x) = -\frac{e^{-\theta x}}{\theta}$, and F represents a binary risk in which the probability of a loss is p, then a single observation of WTP is enough to identify the CARA coefficient θ. Since WTP satisfies $u(1 - WTP) = pu(0) + (1-p)u(1)$, θ satisfies $e^{-\theta(1-WTP)} = p + (1-p)e^{-\theta}$.

risk averse than agent with lower θ. One way to formalize this global comparative risk is by having a family of preferences W_θ satisfying the following assumption:

Assumption 2 (Global Ranking)**.** *$W_\theta(F) \le W_{\theta'}(F)$ for all $\theta' > \theta$ and all $F \in \Delta(X)$.*

Assumption 2 states that the WTP to insure against risk F goes up with θ, since a more risk averse agent has a lower certainty equivalent of F.[9]

The reduction principle and the global ranking assumption imply the stability of interpersonal comparisons across informational contexts.

Proposition 2 (Stability of Interpersonal Risk Rankings)**.** *Under Assumptions 1 and 2, for any $I, I' \in \mathcal{I}(F)$ and any F, $W_\theta(I) \le W_{\theta'}(I')$ if and only if $\theta' \ge \theta$.*

The stability of interpersonal rankings is instrumental to the estimation of the distribution of risk preferences and for demand analysis since it implies that, if we fix underlying risks, those exhibiting a higher WTP and hence those who acquire insurance in the market are more risk averse than those who do not buy insurance, irrespective of the information environment.

Even when individual-level data is not available, under Assumptions 1-2, it is still possible to estimate the distribution of risk preferences using information about market shares and prices of a menu of available lotteries. This is because the existence of a global ranking of risk preferences allows us to assign each risk type θ to a particular preferred lottery in the menu, and market shares are then informative of the relative presence of the set of types associated with each lottery. We refer the reader to Barseghyan et al. (2016) for a review of existing approaches to estimate risk preferences using field data and of potential identification issues.

2.1 Informational Effects

Experimental evidence shows that violations of the reduction principle are pervasive.[10] This has important consequences, since both the stability of risk preferences and the invariance of interpersonal rankings is no longer warranted. In particular, the individual demand for insurance, embodied in $W(I)$, may no truly reflect an agent's risk preferences, given by $W(F)$, and furthermore the interpersonal ranking of $W(I)$ may differ from the ranking of $W(F)$. In this context, information may alter both the *level* of aggregate demand for insurance and the *composition* of demand in terms of the distribution of risk preferences of those acquiring insurance, thus affecting the estimation

[9] CARA utility is an example of a family of preferences that satisfies the global ranking assumption.

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

of risk preferences from data on insurance buyers and the analysis of insurance markets based on demand estimates.

In what follows, we call $I = F$ *simple information*, in the sense that the DM does not need to process I to infer objective risks and acts as if he understands such objective risks.

Definition 2. The DM prefers simple information (SI) at F if $F \succ I$, i.e., if $W(I) > W(F)$, for all $I \in \mathcal{I}(F) \setminus \{F\}$,

Aversion to SI and SI-neutrality are defined in a similar fashion. Special cases of SI-preferences include compound risk aversion ($\mathcal{I}(F) = \mathcal{I}^{CR}(F)$) and ambiguity aversion ($\mathcal{I}(F) = \mathcal{I}^{A}(F)$). The former has been theoretically linked to a preference for one-shot resolution of uncertainty in environments where information is gradually revealed to the DM (Dillenberger, 2010).

To discuss the informational effects on demand, we decompose an individual's insurance premium $W(I) - l_F$ into a risk premium and an information premium.

Definition 3. The *information premium* of $I \in \mathcal{I}(F)$ is defined as $\mu(I) = W(I) - W(F)$. The *risk premium* is $\mu(F) = W(F) - l_F$.

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

The presence of informational effects ($\mu(I) \neq 0$) implies that the demand for insurance at both the individual and the aggregate level is not invariant to the information structure, i.e., Proposition 1 does not hold. In such a case, risk preference estimates based (WTP, F) data are unstable: Keeping F fixed, *unobserved* differences in information across environments can lead to different WTP. Hence, in markets where agents do not have access to simple information, a positive (negative) information premium biases upward (downward) risk preference estimates.

In addition, informational effects can introduce instability of interpersonal rankings, meaning that Proposition 2 does not hold. As a consequence, the ranking of individuals w.r.t. their elicited risk aversion ($\mu(I) + \mu(F)$) may not coincide with the ranking of individuals according to their actual risk aversion ($\mu(F)$). This can affect the composition of demand since, controlling for risk F, those acquiring insurance at a given price are not necessarily those that the highest risk premia.

The lack in invariance of interpersonal rankings may come from heterogeneity of information (agents have different I) and/or from heterogeneity in information preferences (agents have different $\mu(I)$). In this context, not only the magnitude and heterogeneity of $\mu(I)$ but also the relationship between $\mu(I)$ and $\mu(F)$ in the population affect the correlation of rankings based on $\mu(I) + \mu(F)$ and those based on $\mu(F)$. For instance, as the next results states, rankings will be preserved if a higher preference for SI (higher $\mu(I)$) is always aligned with higher risk aversion (higher $\mu(F)$)[11] Let $\theta^i(I)$ be the ranking of individual i's $W(I)$ when every agent in the population has information I, and let μ^i denote the information and insurance premia of individual i.

Proposition 3. *If $\mu^i(I) \geq \mu^j(I)$ implies $\mu^i(F) \geq \mu^j(F)$ for all i, j and all $I \in \mathcal{I}(F)$, then $\theta^i(I) = \theta^j(I')$ for all $I, I' \in \mathcal{I}(F)$.*

In contrast to Proposition 3, if $\mu^i(I)$ and $\mu^i(F)$ exhibit a negative correlation then the pairwise rankings under I and F can be reversed, leading to the aforementioned compositional changes in demand, impacting the allocative efficiency of insurance markets and introducing an additional selection bias in risk preference estimates.

The following simple example illustrates the potential impact of information on the demand for insurance.

Example 1. *There are three agents, $n = 1, 2, 3$, facing the same probability $p = 10\%$ of losing \$100. Their respective WTP when $I = p$ are $W^n(p) = 9, 8$ and 7. The insurance market is competitive, i.e., the price for insurance is 10. Consider the following two scenarios:*

1. *Aligned preferences: information premia are $\mu^n(I) = 4, 2$ and 0, respectively.*

2. *Negative Correlation: information premia are $\mu^n(I) = 0, 2$ and 4, respectively.*

In this example, no agent would acquire insurance under simple information. In the 'positive correlation' scenario, agents 1 and 2 buy insurance at the market price. In the 'negative correlation' scenario, agents 2 and 3 buy insurance. Hence, the *level effect* involves raising demand from 0 to 2 agents. However, under positive correlation it is the two most risk averse agents who buy insurance (Proposition 3 holds), while under negative correlation the two least risk averse agents end up acquiring insurance. Hence, while aggregate demand is the same, the composition or *selection effect* implies an average WTP for simple risks of 8.5 in the positive correlation scenario, while only 7.5 in the negative correlation scenario.

These effects can have important implications for both the estimation of risk preferences, and for allocative efficiency and welfare in insurance markets. Regarding the

[11] This is also the case when reaction of information is homogeneous across agents, regardless their individual risk preferences.

estimation of risk preferences, the level effect implies that risk premia estimates based on WTP will be biased upwards since they include also the information premium. For instance, in both scenarios of the example the average WTP is \$3 higher than the average risk premium of those buying insurance. In addition, the selection effect can introduce bias by affecting the distribution of risk preferences of those who buy insurance. From a welfare perspective, the availability of simple information not only increases welfare by preventing agents from buying insurance for purely informational reasons but also by ensuring that the agents valuing insurance the most do acquire it.

2.2 Information Environments

In order to measure informational effects and better understand their impact on the demand for insurance and the estimation risk preferences we focus on information environments dealing with either compound risks ($\mathcal{I}^{CR}$) or ambiguous risks ($\mathcal{I}^{A}$), for two reasons. First, both have been extensively studied in the decision theory and experimental literatures, which shows that a majority of subjects violate the reduction principle in these environments. Second, in the environments we consider, the application of Bayes' rule represents a focal method to reduce I to F (in the ambiguity case this is done by imposing a uniform prior over the set of possible risks).

Our experiment deals with binary risks $X = \{0, 1\}$, with $x = 0$ indicating a loss, and $x = 1$ the absence of it. Hence, a risk $F \in \Delta(X)$ is fully characterized by $p := Prob(x = 0)$. Given this, with an slight abuse of notation we use p instead of F. We look at three different environments, two dealing with compound risks and one with ambiguous risks.

1. *Unambiguous Range*: $\mathcal{I}^{UR}(p)$ is the subset of compound risks given by the uniform distribution on a range of probabilities centered around p, i.e.,

$$\mathcal{I}^{UR}(p) = \{I \in \mathcal{I}^{CR}(p) : I = U[p - \varepsilon, p + \varepsilon], \varepsilon \in (0, \min\{p, 1 - p\}]\}$$

2. *Ambiguous Range*: $\mathcal{I}^{AR}(p)$ is similar to the unambiguous range, except that no distribution over loss probabilities in the range is specified, i.e.,

$$\mathcal{I}^{AR}(p) = \{I \in \mathcal{I}^{A}(p) : I = [p - \varepsilon, p + \varepsilon], \varepsilon \in (0, \min\{p, 1 - p\}]\}$$

3. *Multiplicative risks*: $\mathcal{I}^{MR}(p)$ is the subset of compound risks in which the loss is realized if an only if two independent binary risks with respective probabilities

p_1 and p_2 are realized, that is, $p = p_1 \times p_2$. Let $(p_1, p; 1 - p_1, p')$ denote the binary first-stage lottery leading to risk p with probability p_1 and risk p' with probability $1 - p_1$. Then,

$$\mathcal{I}^{MR}(p) = \{I \in \mathcal{I}^{CR}(p) : I = (p_1, p_2; 1 - p_1, 0), p_1 \times p_2 = p\}$$

In both range treatments, I is completely characterized by (p, ε), and they can be ranked in terms of dispersion: a higher ε leads to a mean-preserving spread of the first-stage lottery, which has been associated with bigger informational effects (Halevy, 2007; Miao and Zhong, 2012). There are two other aspects of range environments worth emphasizing. The first one is that the first-stage lotteries in $\mathcal{I}^{UR}(p)$ are symmetric (as those in $\mathcal{I}^{AR}(p)$ under the uniform prior), in contrast to skewed first-stage lotteries. There is some experimental evidence associating negative skeweness to aversion to compound risks (Boiney, 1993). The second one is that the application of Bayes rule is fairly straightforward, p is just the midpoint of the range. Hence, we conjecture that violations of the reduction principle in this case should not be driven primarily by the complexity associated with reducing these risks. Nonetheless, we test for such possibility by explicitly asking individuals to reduce lotteries in $\mathcal{I}^{UR}(p)$.

Our interest in the multiplicative risks (MR) treatment stems from the fact that the most prevalent forms of insurance tend to cover risks that could be perceived as multiplicative in nature. For instance, the probability of a car accident may depend on independent events like driving conditions (driven by random events like weather or road and traffic conditions), and how alert the driver is. Likewise, the probability of a house suffering flood damage can be seen as the outcome of both heavy rain and poor house insulation. Multiplicative risks can also be interpreted as the result of mixing a risk more likely than p (since $p_2 > p$) with the absence of risk. Accordingly, the MR treatment allow us to introduce skeweness in the first stage lotteries. Multiplicative risks exhibit negative skeweness if $p_1 < 0.5$ and positive skeweness if $p_1 > 0.5$ (see Appendix E for details). In addition, multiplicative risks arguably exhibit higher complexity, since reduction requires knowledge that $p = p_1 \times p_2$, which might be less intuitive than identifying p with the midpoint of a range of probabilities, and computationally more involved.

3 Experiment Design

We conducted a laboratory experiment with university students and a complementary artefactual field experiment with a representative online panel of Americans. There are complementarities between our laboratory experiment and our field experiment. The laboratory experiment has a smaller and more homogeneous sample size, but the session is longer so we elicit a greater number of decisions to obtain more precise estimates. The artefactual field experiment has a larger and more diverse sample, allowing us to explore external validity and includes a richer set of demographics. However, the field experiment is more costly, so we include fewer elicitations. We find consistent results across both experiments, despite differences in experimental protocols and subject pools. This is an additional contribution given the replication crisis in the social sciences.

3.1 Laboratory Experiment

The laboratory experiment was conducted at the BRITE Laboratory for economics research and computerized using ZTree (Fischbacher, 2007). Participants were recruited from a subject pool of undergraduate students at the University of Wisconsin-Madison. A total of 119 subjects participated in 9 sessions, with an average of 13 subjects participating in each session. Upon arriving to the lab, subjects were seated at individual computers and given copies of the instructions. After the experimenter read the instructions out loud, she administered a quiz on understanding (see Appendix D for the complete instructions and quiz provided to subjects).

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

In each decision period, we elicited the maximum willingness to pay for full insurance using the Becker-DeGroot-Marschak mechanism (henceforth BDM) (Becker et al., 1964)[12] Subjects moved a slider to indicate how much of their 100 experimental dollar participation payment they would like to use to pay for insurance. Then, the actual price of insurance was drawn at random using a bingo cage from a uniform distribution on (0,100). If the willingness to pay was equal to or greater than the actual price, the

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

subject paid the actual price, which assured that the A unit would be replaced if it failed. On the other hand, if the willingness to pay was less than the actual price, the subject did not pay for insurance and lost the A unit if there was a failure.

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

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

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

The Ambiguity group faced similar decisions to the No Ambiguity group (as denoted by Table 1, 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

[13] 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)

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 [14].

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.[15]

Table 1: Laboratory Experiment Treatments

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

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

[15] 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.

3.2 Artefactual Field Experiment

The artefactual field experiment was conducted with participants 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. A key benefit of conducting research on the UAS is that the sample includes adults ages 18+ from many different backgrounds and educational levels. Another advantage is that we have interesting information on this sample regarding their real-world insurance decisions. Over four thousand respondents participated in the survey.[16] Appendix B provides the summary statistics.

Each participant made a series of 10 decisions. We simplified the instructions relative to the instructions in the laboratory. Each participant was the owner of a machine, which was described to have some probability of being damaged and some probability of remaining undamaged. Undamaged machines paid out $10 to the subject at the end of the survey, while damaged machines paid out nothing. The probability of damage, including information available about said probability, was varied in each decision.

Similar to the laboratory experiment, we elicited the maximum willingness to pay for full insurance using the BDM, where the actual price of insurance was drawn at random by the computer from a uniform distribution on (0,100). Since we did not have enough time in the session to ask questions about all probabilities, we divided participants into four groups, as described in Table 2. All participants received a block of decisions with 5 risk probabilities, and a block of decisions with 5 range probabilities. The order of blocks was randomized, but the order of probabilities within each block was kept constant (ordered from smallest to largest). In addition, half of the participants received a range noting that 'all numbers within this range are equally likely' while the other half did not receive this information. Hence, the former group received a complex lottery, while the latter group received an ambiguous range.

Earnings were in virtual dollars, which were translated to US dollars at the rate of 20 virtual dollars = $1. Prior to completing the experiment, participants also received a series of questions about understanding annuities (non-incentivized) for another project. After the experiment, participants were asked a question eliciting their ability to solve compound lotteries, and received $1 for a correct answer. Participation in all parts of the survey required approximately 15 minutes, and participants earned

Table 2: Field Experiment Treatments

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

\$10 for survey completion, in addition to \$8.6 on average on the insurance experiment.

4 Results

We next present the experiment results regarding risk attitudes and preferences for simple information in both the lab and the UAS sample. First, we illustrate the magnitude risk and information premia and how they change with the underlying risk probability. Next, we explore the relationship between risk attitudes and preference for simple information by focusing on the correlation structure, controlling for risk probabilities. Finally we look at whether informational effects impact the interpersonal comparison of WTP for insurance. In what follows, to facilitate comparisons, we report risk probabilities, WTP, as well as risk and information premia in percentages (e.g., $\mu(10) = 15$ means that the risk premium of full insurance against a 0.1-likely loss is 0.15).

4.1 Risk Attitudes and Preferences for Simple Information

Figure 1 displays the risk preferences of respondents when the probability of failure is known (i.e., simple information). The risk preferences are reported as willingness to pay (WTP) for insurance minus the probability of failure *WTP*-p. The 0 line represents risk neutrality. Both the lab (left panel) and the field (right panel) show that risk aversion decreases with p. Subjects were risk averse at small probabilities and risk loving at large probabilities, which is in line with related work (Abdellaoui et al., 2015). Figure 1 also shows that field respondents are substantially more risk averse than lab subjects, although the pattern of being risk averse on average at low p and risk loving at high p is present in both samples. In both cases risk premia are widely heterogeneous: in the lab the standard deviation ranged 10% from to 22%, depending on the underlying risk probability p; in the field it ranged from 25% to 30%.

Turning to informational effects, Figure 2 presents the average differences in WTP between each of the range treatments and the baseline ($WTP_{range} - WTP_0$). Each data point shows the range size associated with it. We also report the results of paired t-tests about the significance of these differences in Tables 5 and 8 in Appendix A.

Both the lab and the UAS sample show similar large responses at $p < 50\%$ when range sizes are big, leading to an increase in WTP as high as 100% of the expected loss.

[16] 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.

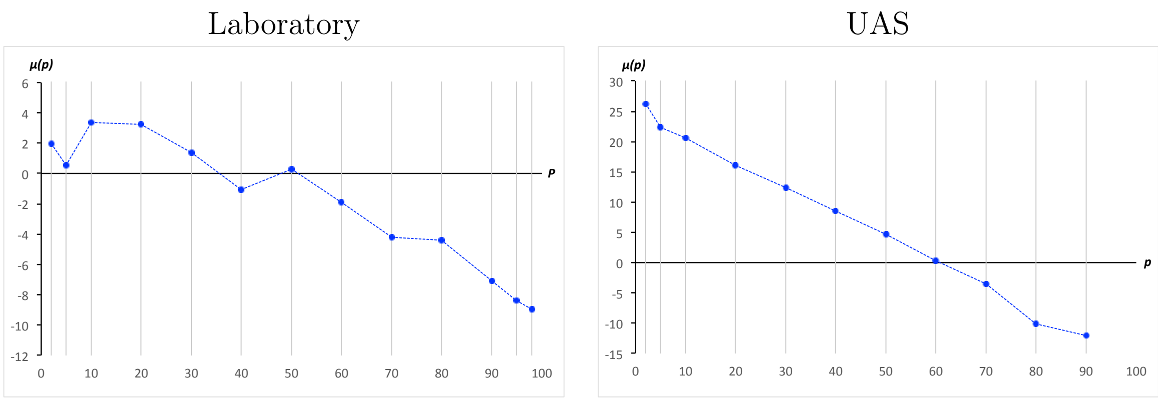

Figure 1: Average Risk Premium at Different Probabilities.

Smaller range sizes still elicit a strong response in the field for $p < 50\%$, whereas in the lab this is only true for probabilities 5% and 10%. Information premia decrease with the underlying risk probability, which is consistent with Abdellaoui et al. (2015), who find that aversion to compound and ambiguous lotteries increases with the probability of getting a high outcome. However, as we show in Appendix A and in Section 6, the presence of large information premia does not seem to be driven by ambiguity or by the inability to reduce compound lotteries. In terms of heterogeneity, information premia are somewhat more homogeneous than risk premia: they exhibit a standard deviation between 10% and 14% in the lab and between 14% and 20% in the field.

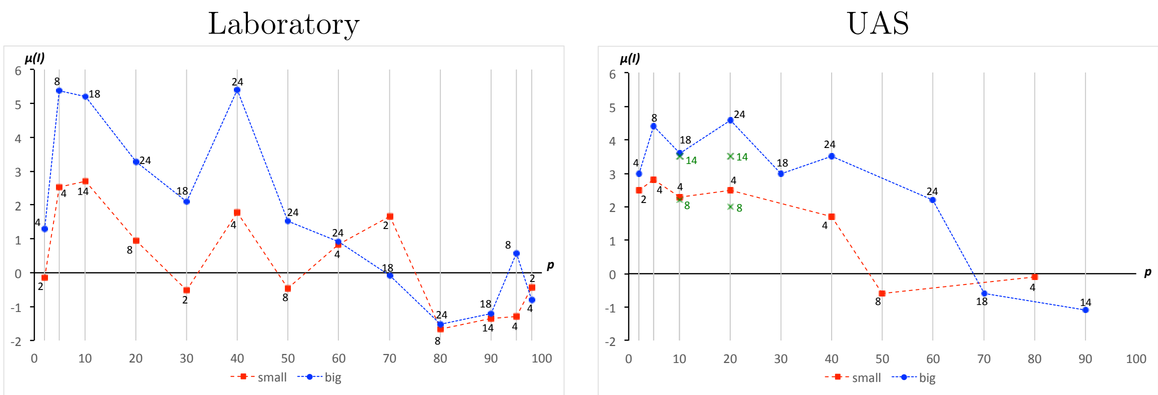

Figure 2: Information Premium at Different Probabilities (point labels represent range size).

Interestingly, the informational effects of multiplicative risks are much stronger than those associated with ranges. Figure 3 shows the comparison of information premia $\mu(I)$, given by the difference between WTP in the treatment and the baseline, for multiplicative risk and big range treatments in the lab. Whereas the information premium associated with multiplicative risks also declines as p goes up, it is still large at $p \leq 80\%$. A possible explanation for this disparity is that multiplicative risks are perceived as more complex and hence agents have a harder time reducing them. Using our incentivized quizzes about reducing both range and multiplicative risks, Table 7 in the Appendix shows the WTP associated with the ranges and multiplicative risks used in the quiz. While the inability to reduce lotteries seems to increase WTP under multiplicative risks, they are still much larger under multiplicative risks for those who correctly reduce them. This is consistent with Wolf and Pohlman (1983), who show that dealers in treasury auctions exhibit more risk aversion when they bid than what their own probability assessments would predict.

An alternative explanation for the higher information premia for multiplicative risks could be aversion to negative skewness of the first-stage lottery (Dillenberger and Segal, 2017). Roughly speaking, negative skeweness means that the right tail area below the cdf of the first stage lottery is bigger than the left tail area. In our experiment, range risks are not skewed while multiplicative risks are negatively skewed when $p_1 < 0.5$, i.e., for $p \in \{2\%, 5\%, 10\%, 20\%\}$. Our results indicate that, while negative skeweness might contribute to the much higher information premia of multiplicative risks at low probabilities, it does not explain the large differences in information premium between range and multiplicative risks at probabilities $p = 30\%$ and between 50% to 80%.[17]

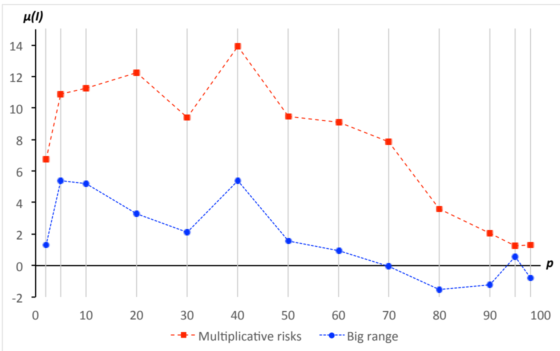

Figure 3: Information Premium of Big Range and Multiplicative Risk Treatments - Lab.

4.1.1 Relationship Between Risk and Information Premia.

A pattern that emerges in our analysis of risk and information attitudes is that both risk aversion and a preference for simple information are prevalent at low risk probabilities. It is important to understand whether these traits are related once we control for

[17] Actually, our regression estimates in Appendix C show that p_1 does not significantly affect the information premium once we control for p.

the underlying risk probabilities to understand the impact of information attitudes on insurance markets and on the estimation of risk preferences in the field. We do so by looking at the correlation between the insurance premium and the information premium for each probability point separately.

Figure 4 plots the correlation coefficients for both the lab (left graph) and the field (right graph) and shows that risk and information premia are negatively correlated at all risk probabilities. Furthermore, in the field, the correlation coefficient is remarkably invariant to the underlying risk regardless of whether we control for individual characteristics (partial correlation) or not (unconditional correlation): it consistently lies between -0.27 and -0.35, even after controlling for cognitive ability, financial literacy and other demographics (they are all significant at the 1% level). In the lab, while correlation coefficients exhibit more variation—which may be due in part to the smaller sample size, roughly range between -0.2 and and -0.4 for probabilities between 10% and 80%.[18] At very low p the correlation is smaller (between -0.1 and -0.25), while it is very negative (below -0.5) at $p \geq 90\%$. This is true regardless of whether risks are given by ranges or by multiplicative risks, although the latter induce somewhat more negative correlation than the former.

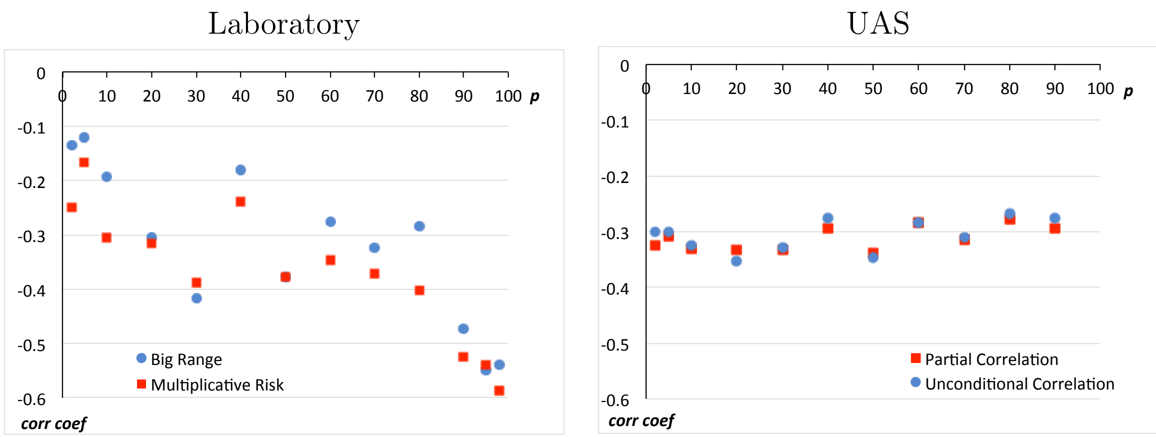

Figure 4: Correlation Coefficients between Risk Premium and Information Premium.

The fact that risk averse agents tend to exhibit a lower preference for simple information has several implications. First, empirical estimates of risk preferences that do not control for information will tend to underestimate the degree of risk aversion of those who are more risk averse and overestimate the degree of risk aversion of those that

[18]All of coefficients in the lab are significant at the 1% or 5% level, except for the coefficients associated with risk probabilities $p = 2\%$ and $p = 5\%$ for the range treatment and $p = 5\%$ for multiplicative risks.

are less risk averse. Hence, in order to get an accurate picture of how risk preferences are distributed in the population we need to account for the presence of informational effects and their relationship with risk attitudes. Second, this negative correlation can have significant allocative effects in insurance markets, since those who buy insurance may not necessarily exhibit higher risk aversion than those who do not buy insurance, after controlling for the underlying risk. Hence, policies aimed at regulating information in insurance markets can have interesting distributional effects. We provide a quantitative exploration of these issues in the next section. Finally, from a decision theory perspective, it is unclear what are the potential sources of this negative correlation. Intuitively, if risk aversion is a manifestation of aversion to random outcomes, a more risk averse individual should react more to the introduction of compound risks, given that they add an extra layer of randomness. We briefly discuss this issue when we explore potential determinants of information premium in Section 6.

4.1.2 Interpersonal Rankings of Demand for Insurance

The presence of strong informational effects and the negative correlation between risk and information premia can affect the interpersonal comparison of risk attitudes. To gauge how stable are those interpersonal rankings we rank individuals by their WTP for insurance, for each pair of underlying risk and information (p, I) and then compute the correlation of those rankings with the baseline $(p, I = p)$.

Figure 5 plots the correlation coefficients as a function of the difference between underlying risk probabilities and information treatments. The horizontal axis corresponds to the difference in underlying risk $|p-p'|$ between (p, p) and (p', I). In addition, Figure 6 presents a correlation matrix both within and across treatments for underlying probabilities in the laboratory sample $p \in \{10, 50, 90\}$, while Figure 7 presents the same information for the UAS sample (rankings are within group).[19]

As the figures show, correlation coefficients are high across treatments in the lab, *for fixed underlying risks* (or close risks if one looks at the correlation between ordinal rankings of adjacent risk probabilities). However correlation substantially decreases with the difference between underlying risk probabilities, both within and across treatments. The presence of informational effects tends to decrease the correlation when probability differences are not too large, but bigger ranges do not translate into significantly lower correlations than smaller ranges. In the lab, multiplicative risks have a large negative effect on the correlation of interpersonal rankings.

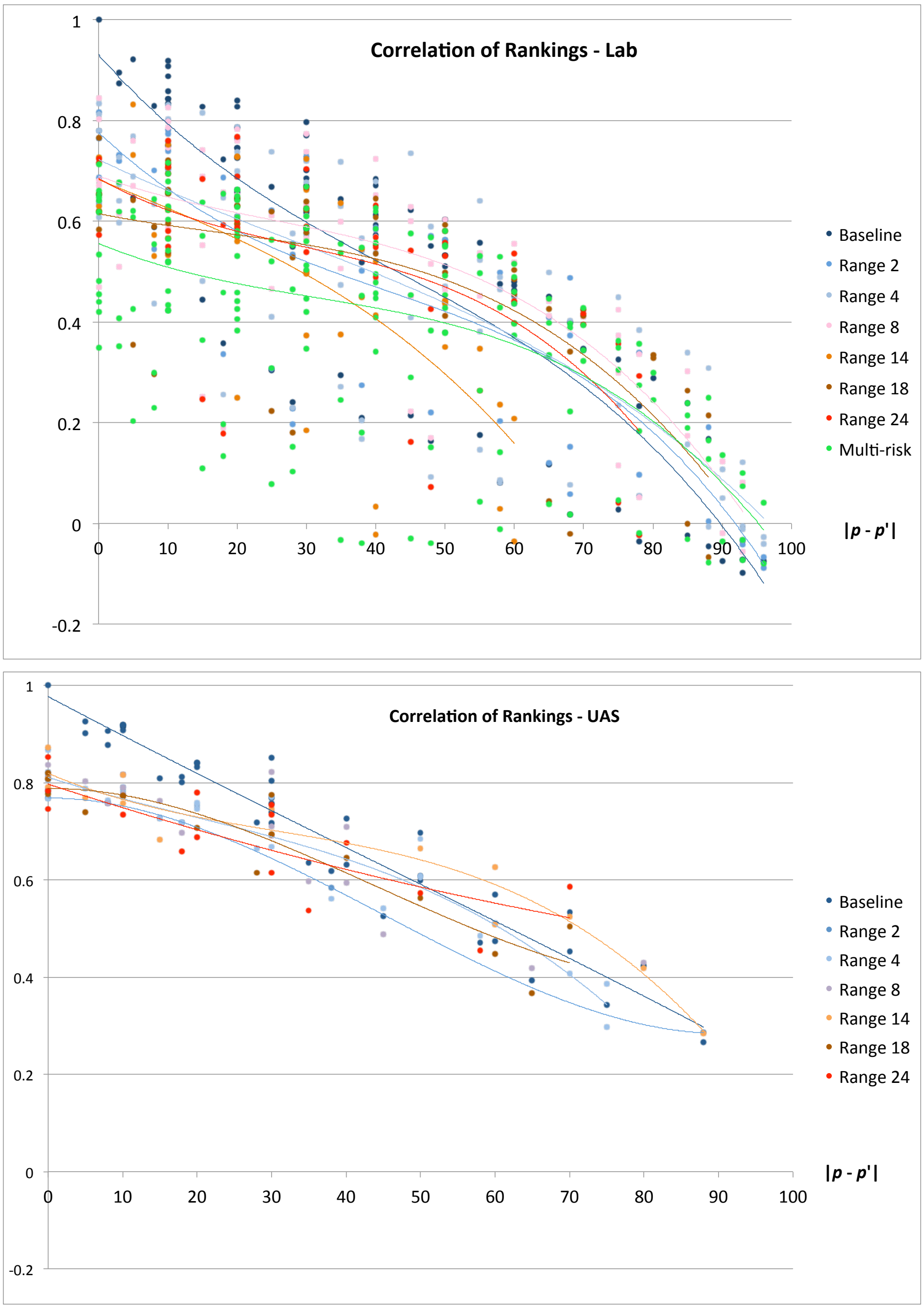

Figure 5: Correlation of interpersonal rankings by differences in risk.

Despite the relatively high correlation between rankings in the baseline and the treatments, the lack of invariance of these rankings can have large selection effects on demand, as we illustrate in the next section.

[19]Notice risk probabilities differ across groups. This is why we look for correlations of within group rankings.

		Baseline			Small Range			Big Range			Compound Risks		
	p	5	50	90	5	50	90	5	50	90	5	50	90
Baseline	5	1											
	50	0.593	1										
	90	0.289	0.684	1									
Small Range	5	0.712	0.5	0.263	1								
	50	0.57	0.844	0.651	0.593	1							
	90	0.348	0.724	0.792	0.392	0.744	1						
Big Range	5	0.655	0.536	0.329	0.769	0.632	0.379	1					
	50	0.489	0.724	0.568	0.527	0.79	0.699	0.652	1				
	90	0.336	0.608	0.653	0.433	0.653	0.731	0.453	0.731	1			
Compound Risks	5	0.44	0.456	0.3	0.489	0.467	0.348	0.56	0.402	0.277	1		
	50	0.341	0.619	0.495	0.38	0.61	0.577	0.467	0.63	0.613	0.638	1	
	90	0.245	0.585	0.617	0.4	0.58	0.715	0.392	0.569	0.682	0.443	0.592	1

Figure 6: Correlation of interpersonal rankings for selected risk probabilities - Laboratory.

5 Informational Effects on the Demand for Insurance

Our experiments show that information about underlying risks has a significant impact on agents' WTP for insurance and can lead to changes in market demand. To better understand these changes, we consider a market for full insurance in the context of our experiment. Aggregate demand in this context is equal to the share of agents with WTP higher than the price of insurance. As we discuss in Section 2 the lack of simple information can have two different effects on aggregate demand: a *level* effect and a *selection* or composition effect. First, information premium drives up average WTP at low and moderate risk probabilities, which essentially represent the relevant range of risks in most insurance markets. The level effect thus implies that aggregate demand will be higher in a market without simple information ($I \neq p$) than in a market where all agents receive simple information ($I = p$). Second, since information and risk premia are negatively correlated, those who end up buying insurance are no longer only the most risk averse but also those with high information premia who are not necessarily very risk averse.

We next illustrate the extent of these effects using the UAS dataset to simulate a competitive insurance market. To do so we construct a demand curve for insurance by applying our WTP data to the empirical distribution of risk probabilities in existing insurance markets. Specifically, we use the estimates of the claim rates for auto-collision insurance estimated by Barseghyan et al. (2011) to generate a distribution of risk probabilities. We then discretize this distribution using as a support the eleven risk

		Baseline					Treatment				
		p1	p2	p3	p4	p5	p1	p2	p3	p4	p5
Baseline	p1	1									
	p2	0.90	1				0.77				
	p3	0.81	0.91	1			0.73	0.79			
	p4	0.62	0.74	0.83	1		0.60	0.70	0.78		
	p5	0.37	0.49	0.61	0.78	1	0.39	0.51	0.63	0.76	
Treatment	p1	0.78					1				
	p2	0.75	0.79				0.89	1			
	p3	0.69	0.76	0.80			0.79	0.90	1		
	p4	0.55	0.65	0.73	0.81		0.62	0.75	0.84	1	
	p5	0.35	0.46	0.57	0.72	0.85	0.38	0.51	0.65	0.80	1

Figure 7: Correlation of interpersonal rankings - UAS Sample.

probabilities (from 0.02 to 0.90) covered by the UAS dataset. We can then calculate the demand for insurance, given by the share of agents with WTP above the price, by weighting each observation according to how likely its associated risk probability is given the estimated discrete distribution of risk probabilities.

Equipped with this demand curve, we consider a market where insurers do not observe the information held by each agent or their underlying risk probabilities and thus charge a single price for full insurance. Accordingly, insurers are exposed to adverse selection. We then look at the market allocation of insurance for prices that range from perfect competition to monopoly. By doing so, we do not need to impose further assumptions on the nature of competition among insurers.

Constructing the demand for insurance We assume that the need of agent i to fill an insurance claim follows a Poisson process with arrival rate λ_i. Given this, agent i's probability of suffering a loss, i.e., of filling at least a claim, is given by $p_i = 1 - e^{-\lambda_i}$. To construct the distribution of p_i we assume that λ_i follows a gamma distribution with mean $\bar{\lambda} = 0.116$ and standard deviation 0.272, which correspond to the (annualized) mean and std. deviation of claim rates in auto-collision insurance estimated by Barseghyan et al. (2011).[20]

Accordingly, the cdf of risk probabilities is given by $F(p) = G(-\log(1 - p); 0.182, 0.638)$, where $G(\cdot; \alpha, \beta)$ is the cdf of a gamma distribution with shape parameter α and scale parameter β. Next, we discretize this distribution to generate a

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

cdf $\hat{F}$ whose support points coincide with the eleven different risk probabilities covered in the UAS data.[21]

Finally, we use this distribution to weigh each observation (WTP, p) in both the baseline and the compound treatments in the UAS panel dataset by how likely p is according to $\hat{F}$, the discrete version of F.[22]

To determine the market allocation for insurance, we consider the set of prices, up to the monopoly price, that yield non-negative profits to insurers taking into account the presence of adverse selection.[23] Let ρ denote the price for insurance and $s(\rho) = 1-\hat{F}(\rho)$ the fraction of agents in the population with $WTP > \rho$, i.e., the share of agents that buy insurance when the price is ρ. Profits are given by

$$\pi(\rho) = (\rho - E(p|W(I) \geq \rho))s(\rho).$$

The left graph in Figure 8 depicts the demand for insurance ($s(\rho)$) and the range of possible prices for both the baseline and the treatment. It turns out that in both cases the set of prices associated with non-negative profits is the interval $[13, 50]$, where $\rho = 13$ is the price under perfect competition and $\rho = 50$ is the monopoly price. The informational effects on aggregate demand are substantial: for $\rho \in [13, 50]$, the absence of simple information leads to a $10-14\%$ higher demand than when agents receive $I = p$.

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

Table 3 provides a comparative of the main features, such as average risk premia and risk probabilities, of the simple risk and compound/ambiguous risk markets for the case of perfect competition ($\rho = 13$) and monopoly ($\rho = 50$). In both markets, the presence of adverse selection implies that the risk probability of the pool of insured agents is between 25-33% higher than in the population when the market is competitive

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

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

[23]Since our experiment only asks for WTP for full insurance we do not consider the possibility of insurers offering a menu of contracts with different premium-deductible combinations.

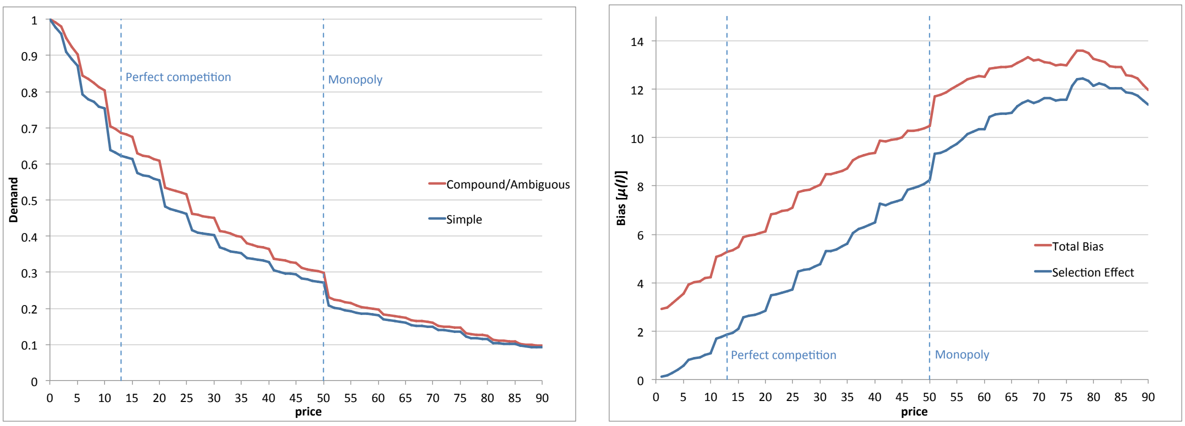

Figure 8: Demand for Insurance (left) and Bias in Risk Premium Estimates (right).

(under monopoly risk probabilities are more than 50% higher).

Table 3: Demand for Insurance - Aggregate Outcomes

	Whole Population	Perfect Competition		Monopoly	
		Simple	Compound	Simple	Compound
Demand	100%	62.3%	68.6%	27.2%	29.8%
Risk Probability	9.6%	12.8%	12.1%	15.6%	15.0%
Risk Premium	22.1	34.5	29.9	58.5	48.3
Info Premium	2.8		5.3		10.5
Estimation Bias			17.7%		21.7%
Selection Effect[a]			35.2%		78.6%
Welfare		21.3	19.9	6.6	4.0
Welfare Loss[b]			6.7%		39.4%
Selection Effect[c]			88.4%		95.1%
Corr(risk, coverage)		0.263	0.238	0.238	0.228
risk prefs $\perp$ *risk*[d]		0.347	0.320	0.423	0.417

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

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

The presence of such effects leads to large biases in the estimation of risk attitudes using data (WTP, p) from the pool of insured agents. The right graph in Figure 8 and Table 3 show the size of the bias in the treatment, given by the average information premium, i.e., the average difference between WTP and risk premium. On average, risk premium estimates are 18-22% higher than the actual level of risk premium in the pool of insured agents. To quantify the relative contribution of the selection effect to the overall bias we proceed as follows. First, we keep aggregate demand constant under compound risk but reallocate insurance to those with the highest risk premium. Second, we compute the selection effect as the change in the average risk premium in the pool of insured agents caused by the reallocation. Figure 8 shows that the selection effect increases with the price of insurance, accounting for a sizable 35% of the bias under perfect competition to a whooping 79% under monopoly.

Regarding the efficiency of the allocation of insurance, the absence of simple information can lead to large welfare losses. To assess these losses, we measure the welfare from being insured as the difference between the WTP for insurance under simple information $(\mu(p) + p)$ and the price (ρ) of those who buy insurance. That is, we do not include the information premium since the underlying risks covered by the policy are not altered by the information provided to agents. Accordingly, the average welfare in the market is given by

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

where $1_{\{.\}}$ is the indicator function. The bottom panel in Table 3 shows the welfare estimates. The lack of simple information leads to welfare losses ranging from 7% to about 40%, depending on how competitive the market is. They are primarily driven by the selection effect, with roughly 90% of overall welfare losses caused by the negative correlation between risk and information premia.

The magnitude of the welfare losses suggests the potential benefits of regulations aimed at providing simple information about underlying risks in insurance markets, regardless of other aspects such as the degree of competition among insurers.

Finally, the negative relationship of both risk and information premia with underlying risk depicted in Figures 1 and 2 has important implications for measuring the extent of asymmetric information in insurance markets. Existing research emphasizes the positive correlation between risk (p) and coverage $(W(I) \geq \rho)$ as evidence of asymmetric information. However, when risk premium is negatively correlated with risk then this correlation will be lower than under independence of risk premium and underlying risk (the correlation between the insurance premium $W(I) - p$ and risk probability p is roughly -0.4 in our data). To show these potential differences we compute a conterfactual correlation between risk and coverage under independence by randomly drawing p and $W(I) - p$ from their marginal distribution in each market to construct individual WTP for insurance. Table 3 shows that the correlation between risk and coverage is substantially higher under independence: with perfect competition the correlation under independence is 0.32-0.35 versus the actual 0.24-0.26. These differences are bigger as market power goes up, with the correlation under independence being twice as high in the monopoly case (0.42 versus 0.23-0.24).

Overall, the demand simulation exercise highlights the need to account for the information structure underlying insurance markets and, crucially, for the relationship between risk and information attitudes, since the latter can have a significant impact in the composition of the insured pool. In particular, the instability of interpersonal rankings can have large selection effects, even if interpersonal rankings exhibit a high correlation. This is especially relevant given the fact not much attention has been paid to the relationship between risk preferences and attitudes toward compound and ambiguous lotteries, which, as we show in the next section, it does not seem to be driven by sociodemographic characteristics, financial literacy or the ability to reduce compound lotteries.

6 Covariates of Information Premium

A preference for simple information reflects aversion to the dispersion or perceived randomness of risk probabilities, and can have multiple causes. It could be due to ambiguity aversion if the information about how the risk probability is selected from the range of possible probabilities. Or it could be the result of being unable to reduce compound risks (probability misperception). It could also reflect aversion to the perceived complexity of information about risks. Our experimental design allows to gauge the relative contribution of these sources, as well as look at how information attitudes depend on risk attitudes and on sociodemographic characteristics. Specifically, to gauge the relative contribution of ambiguity aversion, half of the sample in both the lab and the UAS were given ambiguous ranges while the other half have were given completely specified compound risks. We can also measure the effect of the ability to reduce compound risks by looking at whether the subject answered correctly the incentivized questions about reducing reduced compound risks. Finally, measures of cognitive ability and financial literacy can serve as proxies for aversion to complexity.

We focus our analysis on the UAS data, given our rich set of demographics as well as the fact that it includes measures of cognitive ability and financial literacy. Nonetheless, we conduct a similar analysis with the lab data and find that results are qualitatively similar in the lab (see Appendix C). Table 4 shows the results of regressing information premia $\mu(I)$ on range size, whether the information about the range is ambiguous, the error in the quiz regarding reducing compound risk (normalized by the size of the range), measures of financial literacy and cognitive ability, as well as sociodemographic variables. All the regressions control for the underlying risk p and for whether the baseline questions were asked before the range ones or the reverse order (p-values are adjusted to control for multiple hypothesis testing). The first column shows the regression estimates without controlling for risk attitudes ($\mu(p)$), while the second column does control for risk premia.

Several conclusions emerge from these estimates. First, risk attitudes are by far the most important covariate of information premia: Risk premium accounts for about 10% of the overall variation of the information premium, while the rest of variables combined only account for a R^2 of 1%. Second, the table reflects the relationship between risk probabilities and range sizes depicted in Figure 2, namely, the wider the dispersion in risk probabilities and the lower the risk probability the higher the information premium. Once we control for range size, ambiguous information or the inability to reduce compound lotteries do not significantly increase the information premium. Third, cognitive and socio-demographic variables do not seem to significantly drive preferences for information. In contrast, gender, income, as well as cognitive ability and financial literacy are significantly associated with risk attitudes. The third column in Table 4 shows that individuals with higher financial literacy and cognitive ability are less risk averse. Similarly, being male and earning an income above $100k are associated with lower risk aversion. These relationships are consistent with previous studies about risk attitudes (Outreville, 2014).

Finally, it is interesting to note that there are significant order effects in the field experiment, with higher information premia associated with the reverse order, i.e., when agents were asked about WTP for range risks first. This may suggest that being exposed to simple risk may have an anchoring effect on WTP for insurance against range risks with the same underlying risk probability. In contrast, no such order effects seem to be present in the lab (see Table 13 in Appendix C).

Table 4: Covariates of Information Premium and Risk Premium - UAS

	$\mu(I)$	$\mu(I)$	$\mu(p)$
Risk Probability	-0.06***	-0.14***	-0.41***
	(0.01)	(0.01)	(0.01)
Probability Range	0.11***	0.11***	
	(0.01)	(0.01)	
Ambiguity	0.54	0.50	
	(0.33)	(0.32)	
Financial literacy	-0.15	-0.45	-1.71*
	(0.23)	(0.23)	(0.50)
Average Cognitive Score	0.49	0.30	-1.34*
	(0.24)	(0.23)	(0.48)
Quiz Error	-0.06	0.22	
	(0.09)	(0.09)	
$\mu(p)$		-0.19***	
		(0.01)	
Age	-0.05	-0.04	0.08
	(0.07)	(0.06)	(0.14)
$\text{Age}^2/100$	0.04	-0.01	-0.24
	(0.07)	(0.06)	(0.13)
Female	-0.64	0.11	3.90***
	(0.35)	(0.35)	(0.76)
Married	-0.60	-0.73	-0.59
	(0.37)	(0.36)	(0.83)
Some College	0.29	0.01	-1.22
	(0.48)	(0.47)	(1.02)
Bachelor's Degree or Higher	0.28	-0.15	-2.19
	(0.54)	(0.54)	(1.16)
Hh Income: 25k-50k	0.45	0.53	0.21
	(0.54)	(0.53)	(1.16)
Hh Income: 50k-75k	0.38	-0.11	-2.82
	(0.60)	(0.58)	(1.26)
Hh Income: 75k-100k	0.75	0.59	-0.97
	(0.62)	(0.62)	(1.41)
Hh Income: Above 100k	0.29	-0.85	-6.38***
	(0.62)	(0.62)	(1.33)
Non-Hispanic Black	-1.70	-1.21	2.58
	(0.75)	(0.71)	(1.53)
Other Race/Ethnicity	-0.12	0.10	1.23
	(0.66)	(0.63)	(1.24)
Spanish/Hispanic/Latino	0.31	0.30	0.04
	(0.70)	(0.70)	(1.37)
Reverse Order	4.64***	4.13***	-2.51***
	(0.33)	(0.32)	(0.71)
R^2	0.03	0.13	0.20
N	19050	19050	19432

Note: OLS with clustered standard errors. Regressions include a constant.
Bonferroni-adjusted p-values: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

7 Discussion and Conclusion

There are several takeaways from our experimental analysis, which point to policy interventions, methodological changes and potential avenues for future research. Such implications of our analysis acquire particular relevance given that fact that informational effects, and the relationship between risk and information attitudes, are strikingly similar in the lab and in the field despite their stark differences in the level of risk aversion.

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

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

Finally, the sources of agents reaction to compound risks remain elusive. Existing theories such as ambiguity aversion, inability to reduce compound lotteries or aversion to complexity account for a small share of the variation of information premia. In addition, while preferences for simple information and risk attitudes are strongly related, most of the sociodemographic variables traditionally associated with risk attitudes, such as income or education, lack explanatory power when it comes to preferences for simple information. In addition, our results raise the question of which models of decision making under risk and ambiguity can account for the patterns exhibited by the data, in particular, the the negative correlation of risk and information premia.

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Appendix A Statistical Analysis of WTP

In this section we present the average WTP for the baseline and each of the treatments for both the lab and the UAS samples. We report WTP for the whole samples, and also distinguishing by whether the decisions involved ambiguous ranges. Finally, we use our incentivized quiz about reducing compound risks, to contrast average WTP by subjects' ability to reduce compound lotteries.

A.1 Laboratory

In this section we Table 5 presents the average WTP for each treatment. The table also reports both whether baseline WTP are different from risk probabilities and whether WTP in each treatment are significantly different than those of the baseline according to one-sided paired t-tests.

Table 5: WTP for Insurance

p	Baseline	Range Small	(size)	Range Big	(size)	Multiplicative Risk
2	3.98**	3.84	(2)	5.26	(4)	10.72***
5	5.51	8.06**	(4)	10.88***	(8)	16.39***
10	13.38**	16.08***	(14)	18.58***	(18)	24.66***
20	23.27**	24.21	(8)	26.54***	(24)	35.50***
30	31.38	30.87	(2)	33.49*	(18)	40.79***
40	38.94	40.72**	(4)	44.35***	(24)	52.82***
50	50.29	49.85	(8)	51.82	(24)	59.76***
60	58.11	58.94	(4)	59.03	(24)	67.21***
70	65.80**	67.47**	(2)	65.72	(18)	73.66***
80	75.58**	73.92*	(8)	74.06	(24)	79.18**
90	82.92***	81.57*	(14)	81.72	(18)	84.97
95	86.61***	85.31	(4)	87.18	(8)	87.86
98	89.04***	88.62	(2)	88.24	(4)	90.33

Ambiguity. Table 6 shows the effect of presenting agents with non-ambiguous versus ambiguous ranges. As expected ambiguity seems to elicit a stronger response from agents. Nonetheless, the effect of non-ambiguous ranges is quite large and significant at low to moderate probabilities, especially at big ranges.

Table 6: WTP by Ambiguity

	Non-Ambiguous					Ambiguous				
p	Baseline	Range Small	(size)	Range Big	(size)	Baseline	Range Small	(size)	Range Big	(size)
2	3.48*	3.03	(2)	3.43	(4)	4.46*	4.61	(2)	7.01*	(4)
5	4.77	7.19	(4)	8.33**	(8)	6.21	8.89*	(4)	13.31***	(8)
10	12.40	15.60**	(14)	16.79***	(18)	14.31**	16.52**	(14)	20.28***	(18)
20	22.21	24.00*	(8)	24.79*	(24)	24.28**	24.41	(8)	28.20**	(24)
30	31.05	30.84	(2)	32.33	(18)	31.69	30.89	(2)	34.59*	(18)
40	38.05	40.60**	(4)	43.95***	(24)	39.79	40.84	(4)	44.74***	(24)
50	50.28	49.31	(8)	50.52	(24)	50.31	50.36	(8)	53.07	(24)
60	56.84	57.47*	(4)	58.31	(24)	59.31	60.34	(4)	59.72	(24)
70	63.97**	65.93*	(2)	64.27	(18)	67.54	68.95	(2)	67.10	(18)
80	72.72***	72.60	(8)	72.03	(24)	78.30	75.16***	(8)	75.98	(24)
90	80.14***	78.95	(14)	79.66	(18)	85.56**	84.07	(14)	83.69	(18)
95	83.26***	83.83	(4)	85.28	(8)	89.79**	86.72**	(4)	88.98	(8)
98	86.74***	86.41	(2)	86.79	(4)	91.23***	90.72	(2)	89.62	(4)

Ability to reduce compound lotteries. Finally, we check whether the results might be solely driven by subjects' lack of understanding of how to reduce compound lotteries. The next table shows the WTP 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 7 presents the results.

Table 7: WTP by Ability to Reduce Compound Lotteries - Lab

		Correct			Incorrect		
Decision	p	Baseline	Treatment	n	Baseline	Treatment	n
Range							
0-4	2	3.18**	3.49	105	10.00	18.64	14
3-17	10	13.02*	15.15**	88	14.39*	18.71**	31
61-79	70	64.56***	64.88	89	69.47	68.23	30
Compound Risks							
10; 50	5	4.69	14.19***	84	7.49	21.69***	35
50; 80	40	37.61	49.08***	77	41.38	59.69***	42
95; 84	80	73.88**	77.98**	50	76.81*	80.04*	69

A.2 UAS

Table 8 presents the average WTP for the baseline and instead of reporting the WTP in the treatment, we show the difference in WTP between the range and the baseline, i.e., the average information premium. We do so to facilitate comparisons by range sizes given that the whole sample is divided in four groups, each exhibiting a different WTP in the baseline. The table also reports both whether baseline WTP are different from risk probabilities and whether WTP in each treatment are significantly different than those of the baseline treatment according to one-sided paired t-tests.

Table 8: WTP for Insurance - UAS

	Group 1		Group 2		Group 3		Group 4	
p	Baseline	ΔWTP (size)	Baseline	ΔWTP (size)	Baseline	ΔWTP (size)	Baseline	ΔWTP (size)
2					28.2***	2.5*** (2)	28.3***	3.0*** (4)
5	25.8***	2.8*** (4)	28.9***	4.4*** (8)				
10	28.5***	3.6*** (18)	31.4***	3.5*** (14)	31.4***	2.2*** (8)	30.9***	2.3*** (4)
20	34.1***	3.5*** (14)	36.8***	2.5*** (4)	36.6***	4.6*** (24)	37.1***	2.0*** (8)
30							42.4***	3.0*** (18)
40			48.1***	3.5*** (24)	49.1***	1.7*** (4)		
50	54.7***	-0.6* (8)						
60							60.3	2.2*** (24)
70			66.5***	-0.6 (18)				
80	69.8***	-0.1 (4)						
90					77.9***	-1.1** (14)		

Ambiguity Tables 9 and 10 show the effect of presenting agents with non-ambiguous versus ambiguous ranges. There is no clear effect of ambiguity on the information premium. For some probabilities it is bigger under non-ambiguity and for other ambiguity is associated with a higher information premium. Overall, effects seem to be quantitatively of the same order of magnitude.

Table 9: WTP for Insurance: Non-Ambiguous Range - UAS

	Group 1		Group 2		Group 3		Group 4	
p	Baseline	ΔWTP (size)	Baseline	ΔWTP (size)	Baseline	ΔWTP (size)	Baseline	ΔWTP (size)
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)		

Ability to reduce compound lotteries. Table 11 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 WTP between those who answered correctly and those who did not correctly reduce the range, except for the last 2 ranges, in which those who reduced the range properly actually exhibit a higher WTP.

Table 10: WTP for Insurance: Ambiguous Range - UAS

	Group 1		Group 2		Group 3		Group 4	
p	Baseline	ΔWTP (size)	Baseline	ΔWTP (size)	Baseline	ΔWTP (size)	Baseline	ΔWTP (size)
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)		

Table 11: WTP by Ability to Reduce Compound Lotteries - UAS

		Correct			Incorrect		
Decision	p	Baseline	Treatment	n	Baseline	Treatment	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

Appendix B Descriptive Statistics: UAS

Table 12 presents the summary statistics of the main sociodemographic variables in our field data. Among other things, they contain measures of financial literacy, cognitive ability, education and income.

Table 12: Descriptive Statistics - UAS

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

Appendix C Covariates of Information Premium in the Laboratory

Table 13 presents the regression estimates for the laboratory. We run separate regressions for the range and multiplicative risk treatments. In the latter regressions we include the first stage risk probability since it is associated with negative skeweness: controlling for the overall risk probability, the lower the first stage probability the more negatively skewed is the lottery associated with multiplicative risks (see Appendix E). We also include as proxies for financial literacy whether the subject's major is quantitative (life sciences, natural sciences, economics and business, and engineering majors) and whether she took an economic course. GPA and the number of correct answers in the cognitive reflection test (CRT) (Frederick, 2005) are proxies for cognitive ability.

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

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

Table 13: Covariates of Information Premium and Risk Premium - Lab

	$\mu(I)$				$\mu(p)$
	Range		Multi-Risk		
Risk Probability	-0.04*	-0.07***	-0.07	-0.12***	-0.12***
	(0.01)	(0.01)	(0.04)	(0.03)	(0.03)
Probability Range	0.25**	0.26***			
	(0.08)	(0.07)			
(Probability Range)^2	-0.01	-0.01			
	(0.00)	(0.00)			
1st Stage Probability			-0.04	-0.02	
			(0.03)	(0.03)	
Ambiguity	-0.28	0.54			
	(1.21)	(1.19)			
Quiz Score	-0.12	-0.29	0.39	0.18	
	(0.47)	(0.46)	(0.48)	(0.46)	
Quantitative Major	1.35	0.72	-2.11	-3.24	-2.84
	(1.41)	(1.34)	(2.17)	(2.23)	(3.02)
Statistics Course	1.88	1.07	-2.73	-3.63	-3.22
	(1.97)	(1.68)	(2.74)	(2.79)	(4.04)
Cumulative GPA	0.88	1.19	-0.12	0.28	1.20
	(0.96)	(0.90)	(1.53)	(1.37)	(1.59)
CRT Score	-0.46	-0.29	-3.09***	-3.03***	0.15
	(0.56)	(0.55)	(0.86)	(0.85)	(1.13)
$\mu(p)$		-0.24***		-0.38***	
		(0.04)		(0.06)	
Age	-0.20	-0.15	1.48***	1.58***	0.15
	(0.09)	(0.10)	(0.18)	(0.14)	(0.22)
Female	0.27	-0.91	3.63	1.36	-4.56
	(1.43)	(1.53)	(1.87)	(1.88)	(2.63)
Years in College	-0.18	0.07	-0.36	-0.07	0.96
	(0.76)	(0.75)	(1.16)	(1.21)	(1.69)
Black/African American	-2.51	-2.92	-2.92	-3.74	-0.19
	(3.88)	(4.15)	(8.40)	(9.88)	(3.86)
Asian	-1.97	-1.82	-1.61	-0.98	0.94
	(1.53)	(1.36)	(2.14)	(2.20)	(3.45)
Hispanic	3.14	5.67	0.71	4.98	10.30
	(1.66)	(2.43)	(3.18)	(3.73)	(6.07)
Reverse Order	-2.21	-1.20	-1.67	-0.72	4.08
	(1.21)	(1.19)	(1.64)	(1.55)	(2.42)
R^2	0.04	0.15	0.14	0.28	0.09
N	3094	3094	1547	1547	1547

Note: OLS with clustered standard errors. Regressions include a constant.
Bonferroni-adjusted p-values: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Appendix D Instructions

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

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

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

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

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

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

Each Decision Period

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

Paying for Insurance

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

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

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

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

Failure of the A unit

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

Known Failure Rate

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

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

Uncertain Failure Rate

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

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

Failure Rate Depends on Environmental Conditions

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

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

In summary:

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

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

Your decisions

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

D.2 Laboratory Experiment: Order 1, Ambiguity in Ranges

Note that the ambiguity instructions are exactly the same as the instructions without ambiguity, except that for the 'uncertain failure rate' scenarios, rather than informing subjects that any probability in the range is equally likely, we say that the probability is unknown. In the below, we provide just the instructions that are different from D.1.

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.

D.3 Field Experiment

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.

Appendix E Omitted Proofs

The proofs of Propositions 1 and 2 are trivial and therefore omitted.

Proof of Proposition 3. Note that $W^i(I) = \mu^i(I)+\mu^i(F)+l_F$, where l_F does not depend on i. Let individuals i, j satisfy $\mu^i(I) \geq \mu^j(I)$. Then, the condition in the proposition implies that $W^i(I)-W^j(I) = (\mu^i(I)-\mu^j(I))+(\mu^i(F)-\mu^j(F)) \geq 0$, i.e., $\theta^i(I) \geq \theta^j(I)$. Since preferences over $\mathcal{I}$ are complete, we can always rank i, j in terms of their $\mu(I)$. Hence, if pairwise rankings i, j are the same across I so are global rankings across I and I': i.e., $\theta^i(I) = \theta^i(I')$ for all I, I'. □

The following definition, proposed by Dillenberger and Segal (2017) and adapted to our binary risk framework, roughly states that the first-stage probability distribution over compound risks is negatively skewed if the right tail area below the cdf is always bigger than the left tail area.

Definition 4 (Skewness)**.** Let $I \in \mathcal{I}^{CR}(p)$ be a probability distribution over binary risks with mean p and cdf G_I. I is negatively skewed if $\int_0^{p-\tau} G_I(z)dz \leq \int_{p+\tau}^1 (1 - G_I(z))dz$ for all $\tau > 0$.[24]

Positive skewness implies $\int_0^{p-\tau} G_I(z)dz \geq \int_{p+\tau}^1 (1 - G_I(z))dz$ for all $\tau > 0$.

Lemma 1. *$I \in \mathcal{I}^{MR}(p)$ is negatively (positively) skewed if $p_1 \leq\ (\geq)\ \frac{1}{2}$.*

Proof. The cdf of $I = (p_1, p_2; 1 - p_1, 0)$ given that $p_2 = \frac{p}{p_1}$ is

$$G_I(z) = \begin{cases} 1 - p_1 & z \in \left[0, \frac{p}{p_1}\right) \\ 1 & z \in \left[\frac{p}{p_1}, 1\right] \end{cases}.$$

Hence, I is negatively skewed if

$$\int_0^{p-\tau} G_I(z)dz = (1-p_1)\max\{0, (p-\tau)\} \leq \int_{p+\tau}^1 (1-G_I(z))dz = p_1 \max\{0, (\frac{p}{p_1}-(p+\tau))\}.$$

Note that the LHS of the inequality is strictly positive whenever $\tau \leq p$, while the RHS is strictly positive when $\tau \leq p\frac{1-p_1}{p_1}$. Hence, if $p_1 \leq \frac{1}{2}$ the LHS is weakly lower than the RHS for $\tau > p$, while both are positive for $\tau \leq p$, leading to inequality

$$(1 - p_1)p - (1 - p_1)\tau \leq p(1 - p_1) - p_1\tau \quad \Leftrightarrow \quad 1 - p_1 \geq p_1 \quad \Leftrightarrow \quad p_1 \leq \frac{1}{2}.$$

□

[24] Dillenberger and Segal (2017) define negative skewness in terms of two-stage lotteries, whereas here we adapt their definition to two-stage risks. That is, while here $G_I(z)$ is the probability that the second-stage risk involves $Prob(x = 0) \leq z$, in their context the cdf of the first-stage lottery is defined over the probability of *not* suffering a loss, $Prob(x = 1)$.