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Is Imprecise Knowledge Better than Conflicting Expertise? Evidence from Insurers' Decisions in the United States

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Is Imprecise Knowledge Better than Conflicting Expertise? Evidence from Insurers' Decisions in the United States[2]

Abstract: This paper reports the results of the first experiment in the United States designed to distinguish two sources of ambiguity: *imprecise ambiguity* (expert groups agree on a range of probability, but not on any point estimate) versus *conflict ambiguity* (each expert group provides precise probability estimates which differ from one group to another). The specific context is whether risk professionals (here, insurers) behave differently under risk and different types of ambiguity when pricing catastrophic risks (floods and hurricanes) and non-catastrophic risks (home fires). The data show that insurers charge higher premiums when faced with ambiguity than when the probability of a loss is well specified (risk). Furthermore, they tend to charge more for *conflict ambiguity* than *imprecise ambiguity* for flood and hurricane hazards, but less in the case of fire. The source of ambiguity also impacts causal inferences insurers make to reduce their uncertainty.

Key words: Ambiguity**,** Source of Uncertainty, Insurance Pricing, Decision-Making

JEL Classification: C93, D81, D83

Is Imprecise Knowledge Better than Conflicting Expertise?
Evidence from Insurers' Decisions in the United States

Introduction

Since Ellsberg (1961), there have been important research developments in the economic and decision sciences literature on the impact that ambiguity — that is, uncertainty about probability – can have on how individuals make their decisions (Camerer and Weber 1992). Recent papers demonstrate a growing interest in better understanding how ambiguity affects choices in the experimental literature on decision-making (Viscusi and Magat 1992; Du and Budescu 2005; Hey et al. 2010; Rubaltelli et al. 2010), the formal decision science literature (Abdellaoui et al. 2010; Gajdos et al. 2008; Ghirardato and Marinacci 2002; Klibanoff et al. 2005; Machina 2009; Mukerji, 2003; Neilson 2010; Seo 2009; Snow 2010), and neuro-economics (Chew et al. 2008; Levy et al. 2010).

This research reveals that attitudes to ambiguity are more complex than originally conjectured by Ellsberg (1961) and that the domain of outcomes (loss or gain) and the level of probability influence individuals' choices under ambiguity (Camerer and Weber 1992; Hogarth and Einhorn 1990; Viscusi and Chesson 1999). In the domain of insurance on which this paper focuses, previous surveys of underwriters and actuaries indicate that insurers are ambiguity-averse for low-probability, high-consequence negative events. In other words, they will want to charge higher premiums when there is ambiguity than when the probabilities and losses are well-specified (Kunreuther et al. 1995; Cabantous 2007).

What is less known, however, is whether the nature of the ambiguity also matters. Research on decision-making under uncertainty has recently opened this "black box" to study the impact of various sources of uncertainty on choices. For instance, several empirical papers have focused on the impact of a specific type of ambiguity, namely disagreement or conflict among experts (Baillon et al. 2010; Budescu et al. 2003; Cabantous 2007; Cameron

2005; Dean and Shepherd 2007; Smithson 1999; Viscusi 1997; Viscusi and Chesson 1999). This research reveals that when seeking advice from multiple advisors, individuals are sensitive to whether these experts agree or disagree with each other with respect to a specific forecast and/or in their recommendations for actions.[3]

This paper builds on this emerging literature to investigate the effect of the two different contexts of ambiguity on insurance pricing decisions by sophisticated agents (insurers): *imprecise (but consensual) ambiguity* and *conflict ambiguity*. To illustrate these two conditions, assume that two advisors, A_1 and A_2, are asked to provide estimates about the probability of a given scenario, for instance a Category 3 hurricane hitting the city of New Orleans again in the next 50 years. Under a *risk* situation, they both agree that the probability is, say, 1/2 so there is consensus on a precise probability. Formally, negative risky prospects with two outcomes yield outcome x with probability p and outcome y (with $0 \geq y \geq x$) with probability $(1-p)$.

Now let us discuss the following two contexts of ambiguity. The first one occurs when the two advisors A_1 and A_2 end up with a probability interval rather than a precise estimate. Furthermore, their two intervals are identical. For instance, they both think the probability interval is [1/4; 3/4]. This is a case of consensus but where there is an *imprecise* estimate. We call such a situation *imprecise ambiguity*. Formally, imprecise ambiguity prospects give x with a probability that belongs to the interval $[p-r, p+r]$ with $r \leq p \leq 1-r$. and y (with $0 \geq y \geq x$) otherwise. *Conflict ambiguity* occurs when both advisors A_1 and A_2 provide a precise point estimate but the two probabilities differ from each other (this could also be two different ranges of probabilities, but we will not discuss this case in this paper). For instance, A_1 strongly believes that the hurricane will occur with probability 1/4 and A_2

[3] Formal models of aggregation of beliefs with conflicting probability estimates are proposed in Cres et al. (2010); Gajdos and Vergnaud (2009); Gollier (2007).

strongly believes it will happen with a probability 3/4.[4] Formally, conflict ambiguity prospects give x with a probability of either (p−r) or (p+r) and y (with 0≥y≥x) otherwise (r is fixed and strictly positive).

Table 1 summarizes these three cases for the above example.

INSERT TABLE 1 ABOUT HERE

In this paper, we compare insurance pricing in these three contexts in which information structure differs. Our focus is on professional insurers confronted with events that have low probabilities but which can generate catastrophic losses if they occur. We study decision contexts where actuaries and underwriters in insurance companies seek advice and request probability forecasts from different groups of experts. Are insurance prices that insurers would like to charge different under these three contexts? Is imprecise knowledge better than conflicting expertise in that insurers will ask a lower price for the former than they would for the latter?

We are also interested in the effect of these two sources of ambiguity on cognition. To understand how cognition impacts attitudes towards ambiguous risks and actual choices we use insights from attribution theory (Hilton and Slugoski 1986; Hilton et al. 1995). Although several authors have highlighted the role of attributional explanations in attitudes toward ambiguity (Einhorn and Hogarth 1985; Heath and Tversky 1991; Taylor 1995), to our knowledge no study has explored how causal attribution for analysts' expressions of uncertainty (consensual or conflicting) is utilized by expert insurers to make decisions.

[4] See Cabantous (2007), Gajdos and Vergnaud (2009), Smithson (1999) for further discussion on these three contexts. Our example is such that the risk situation (probability1/2) is the mean of the interval boundaries (1/4 and 3/4) but this does not have to be.

Our experiment shows that risk professionals (here, insurers) behave differently when the probability of the loss is well specified (risk), versus under different types of ambiguity. Specifically, we find that insurers charge higher premiums when faced with ambiguity than when faced with risk. Across three hazards (floods, hurricanes, house fires), we find that on average, insurers report that for *ambiguous* damages, they would charge premiums for a one-year contract that are between 25 percent and 30 percent higher than the premiums they would charge for *risky* damages. Furthermore, they would likely charge more for *conflict ambiguity* than *imprecise ambiguity* for flood and hurricane hazards (8.5 percent and 13.9 percent more for a one-year contract, respectively), but less so in the case of fire (8.3 percent less for a one-year contract), probably because they see much less ambiguity in probabilities concerning typical house fires. Normally, they have considerable data on this risk so the probability is well-specified. We also find that the type of ambiguity impacts on the nature of the causal inferences insurers make to reduce their uncertainty.

1. Predictions and literature review

In this section we specify a set of hypotheses (H) and provide support for each of them by reviewing the relevant literature.

1.1. Insurers are ambiguity-averse for low-probability, high-consequence events (H1)

If insurers are averse to ambiguity with respect to low-probability, high-consequence events whose occurrence is external to the insurers' actions, they will want to charge higher premiums when there is uncertainty about the probability of a loss than when the probability is well-specified. This prediction is consistent with past studies on ambiguity avoidance (Camerer and Weber 1992; Hogarth and Einhorn 1990; Viscusi and Chesson 1999), including studies of how insurance underwriters and actuaries make decisions about the price they will charge for providing insurance coverage. Kunreuther et al. (1995) show that underwriters report they would charge higher premiums to insure against damages with ambiguous probabilities than for damages with precisely-known probabilities (see also Hogarth and Kunreuther 1989; Cabantous 2007).

An explanation for this ambiguity aversion is that individuals avoid situations where they do not have information they think others might have (Frisch and Baron 1988). In a similar vein, Heath and Tversky (1991) show that ambiguity avoidance comes from a "feeling of incompetence" when decision makers perceived that they have insufficient knowledge about a specific event. Below, we use models of attribution to explore the kinds of inferences insurers make by proposing an extension and test of Smithson's (1999) cognitive explanation of conflict aversion. Attribution theory has been applied to understanding how people cope with uncertainty (e.g., McClure et al. 2001) but few studies have used it to understand people's attitudes to ambiguity. Heath and Tversky (1991) and Taylor (1995), for example, link ambiguity aversion to attributions of credit and blame, but they do not study the causal attributions individuals make when they face uncertain events.

1.2.Insurers prefer imprecise ambiguity over conflict ambiguity (H2)

Our second hypothesis is that insurers will want to charge a higher premium under *conflict ambiguity* than under *imprecise ambiguity.* Smithson (1999) shows that the preference for *imprecise ambiguity* over *conflict ambiguity* comes from a cognitive heuristic that leads decision makers to think that conflicting advisors are less credible and trustworthy than consensual (yet imprecise) advisors. This prediction is also consistent with Cabantous (2007) that studies conflict aversion of French actuaries. One of the reasons that insurers would prefer *imprecise ambiguity* over situations of *conflict ambiguity* is that conflict is likely to be seen as an indicator of lack of competence on the part of at least one of the advisors. This leads us to want to test two other hypotheses, H3 and H4.

1.3. Insurers normally expect convergent and precise estimates from their advisors (H3)

Attribution theory has shown that people often make causal inferences by contrasting the current situation to their "world knowledge about the normal state of affairs holding in the world" (Hilton and Slugoski 1986). This means that individuals are more likely to engage in attributional thinking when a situation departs from what they expected to face (Weiner 1985). We expect that professional insurers are used to the standard case where relevant actuarial data exists on the event they cover and that two expert advisors would most likely agree on a point prediction. This is known as the "experts-should-converge" hypothesis (Shanteau 2001). Consequently, they will find both kinds of ambiguity in predictions less normal than the standard *risk* case of perfect convergence of precise estimates.

1.4. Insurers will attribute conflicting estimates to less credible and trustworthy advisors (internal factors) but consensual imprecision to task difficulty (external factors) (H4).

In the framework of classic attribution theory, an event is said to be "explained" when individuals have identified a characteristic of some involved person (internal factor), situation or occasion (external factors) which has produced it (Kelley 1973). Attributing an event to some person, situation or occasion factors depends on the configuration of consensus, distinctiveness and consistency information available (see Hilton 2007 for a review).

Applying standard attributional logic to the case of insurance professionals results in the following predictions. First, in the case of conflicting advice from experts, the low consensus between experts will prompt the attributional inference that at least one of the advisors is wrong and is thus perceived as being "incompetent" (Hilton et al. 1995). This is precisely the basis for testing the first prediction of hypothesis H4, which states that under the *conflict ambiguity* case, the responders will attribute the conflicting forecasts to the incompetence of (at least one of) their advisors as compared to the standard *risk* case where the experts' point predictions converge. The second prediction of H4 is that in the case of *imprecise ambiguity,* compared to the standard *risk* case, insurers are more likely to attribute the ambiguity not to incompetence, but to an external effect such as the difficulty of the judgmental task. This is because the high consensus between expert advisors implies that insurers, who receive imprecise but consensual forecasts, are more likely to identify something unusual about the task in question, such as the inherent difficulty of modeling catastrophe risks for which reliable large-scale actuarial data might not exist.

2. An experiment studying U.S. underwriters and actuaries' behavior under risk, imprecise ambiguity, and conflict ambiguity

We tested these predictions in an experiment using a non-standard participant pool (insurers who are experts in decision-making under uncertainty) with a field context (insurance pricing task) involving three hazards (flood, hurricane, fire). Specifically, we created a web-based questionnaire asking insurers what premiums they would charge a representative client under different situations of uncertainty (namely *risk*, *imprecise ambiguity* and *conflict ambiguity*) and their causal understanding of the situation (i.e., reasons why the probability is not well specified by the experts they have turned to for advice).

2.1. Stimulus

The three different kinds of hazards were crossed with three sources of uncertainty: *risk*, *imprecise ambiguity* and *conflict ambiguity*, leading to nine possible scenarios. The responders were given probability estimates from two different risk modeling companies ("advisors" hereafter) to estimate the probability of each one of these three hazards.

As discussed in the introduction, in the case of *risk*, both advisors agreed on the same probability. In the *imprecise ambiguity* case, neither of the advisors provided a precise probability estimate but both converged on the exact same range of probabilities. In the *conflict ambiguity* case, each advisor provided a point estimate of the probability of the pre-defined damage and amount of insurance claims, but the two likelihood estimates were different. Table 2 depicts the scenarios utilized in the experiment.

INSERT TABLE 2 ABOUT HERE

These scenarios are similar to the ones used in previous studies on insurers' attitudes to ambiguity (Cabantous 2007; De Marcellis 2000; Kunreuther et al. 1995). All the insurers who participated in the experiment were asked to imagine that they were employed by an insurance company that "*provides coverage to 1,000 homeowners in an area that has the possibility of [flood/hurricane/fire] damage.*" They were also told that "*The value of each home in this area is $200,000. If a [flood/hurricane/fire] occurs and severely damages a home it will cause $100,000 in insurance claims (above the deductible).*" (It is therefore known that the amount of the payment the insurance company will have to make if the event occurs is $100,000 per house). In the case of flood damage, which is provided in the United States mainly by the government-run National Flood Insurance Program, we also told the insurers to "*Imagine that the current federal National Flood Insurance Program (NFIP) no longer exists and that flood insurance is offered to homeowners in the private market.*"[5] In this context, their company would also be paying for losses associated with the flood scenario.

Insurers who participated in the survey were asked to base their estimates of the probability of damage on the figures provided by their advisors, the two modeling firms with

[5] See Michel-Kerjan (2010) for an analysis of the operation of this program.

whom they usually work.[6] The probability of damage was set at 1 percent in the *risky* case, and the range between 0.5 percent and 2 percent in the *imprecise ambiguity* case. The probability estimate in the risky context was thus the geometrical mean of the two bounds of the probability range. In the *conflict ambiguity* case, one risk-modeling firm estimated that the probability of the damage was 0.5 percent whereas the other estimated it was 2 percent.[7] Figure 1 provides a graphical representation of the three cases.

INSERT FIGURE 1 ABOUT HERE

2.2. Experiment questions

As we were interested in pricing behavior (see **H1** and **H2**), we asked participants to provide the "pure premiums" they would charge. These pure premiums exclude the other costs the insurance company would incur and want to pass on to its policyholders, such as administrative and marketing costs, loss assessment costs and the opportunity cost associated with capital that insurers need to hold to satisfy rating agencies' and regulatory solvency requirements. Insurers were asked to indicate the minimum pure premium they would charge to provide a 1-year full insurance coverage contract against the specific untoward event, and the annual premium for a 20-year full insurance coverage contract.

[6] We could have used two qualitatively different advisors, like a risk modeling firm and the internal technical team of the insurance company. However, because the study focuses on situations where no *a priori* information about the reliability of the advisors is available, we used two similar advisors. If we had introduced a risk modeling firm and an internal team of experts, the participants would have been less likely to consider that the two sources of information were *a priori* equally reliable.

[7] The geometric mean in this case is $(0.5x2)^{½} = 1\%$. In section 3 we compare the premiums that insurers would charge with actuarially-priced insurance under arithmetic mean of the probability interval (1.25%); where equal weight is given to the two estimates (conflict) and the interval frontiers (imprecise).

We were interested in how these insurers would react to a multi-year contract because there have been recent proposals to modify insurance contracts in that direction so as to provide more stability to the policyholders over time and reduce administrative cost for the insurer.[8] Here, multi-year insurance keeps the annual insurance premium the same over a fixed time horizon. To test hypothesis **H3** we included a question about insurers' perceptions of the degree of "unusualness" of the probability estimates that they were given (see question 2 in appendix 1).

To test hypothesis **H4**, two causal attributions were linked to the advisors (person causal attribution) and one to the task performed by the advisors (situation causal attribution). One question on causal attribution was positive ("*Both modeling firms did their work very well*."; see question 3 in appendix 1) and another was negative, implying incompetence ("*At least one of the modeling firms did not do its work very well*."; see question 4 in appendix 1). Another question also concerned the perception of the competence of the advisors (question 6: "*To what extent do you have the impression that the two modeling firms are both competent in estimating the probability of the [flood/hurricane/fire] damage in this case?*). Question 5 concerned the difficulty of the task: "How strongly do you agree with the following statement?: "*Estimating the probability of the [flood/hurricane/fire] damage in this case is a highly difficult task.*"

After the participants had read the three scenarios and completed the series of questions, we asked several socio-demographic questions (sex, age, training, and experience) and queried about the insurance company they worked for (number of employees, surplus/capital and type of the company). Appendix 1 provides the full list of questions from

[8] For more details on the structure of a multi-year policy see Kunreuther and Michel-Kerjan (2009), Jaffee, Kunreuther and Michel-Kerjan (2011).

the web-based questionnaire, and appendix 2 provides socio-demographics of participants and their company.

2.3. Sampling plan

To reduce the number of scenarios given to each participant, we used a Latin-square design and participants were randomly assigned to three of the nine scenarios. The computer program ensured that each participant was exposed to only one hazard (flood, hurricane or fire) that was associated with only one source of uncertainty (*risk*, *conflict ambiguity* or *imprecise ambiguity*). For example a participant could be exposed to "Fire damage in the *conflict ambiguity* context," "Flood damage in the *imprecise ambiguity* context" and "Hurricane damage in the *risky* context." The order of presentation of the scenarios was randomized.

2.4. Insurers participating in the study

The survey was available online on a dedicated website and required a password. Participants in a pilot study reported that the instrument was user-friendly and that the survey did not take them more than fifteen minutes to complete.[9]

All the responders were from insurance companies operating in the United States. Nearly two-thirds of them were actuaries and the rest either underwriters, risk managers, or at other management positions. The computer treatment of the data assured the anonymity of the answers. We obtained 84 responses, four of which were eliminated because the individuals did not fully complete the questionnaire. The number of responses is consistent

[9] Two insurance trade associations announced the existence of this survey to their members. Because of the way it was made available to all their members without being sent individually to each one of them, it is difficult to determine the response rate.

with other studies.[10] Of the 80 participants, 58 (72.5%) were males and 22 (22.5%) females. The majority of participants were in their 20s and 30s (27.5% and 35% respectively); one-fourth were in their 40s (23.75%) and 13.75% in their 50s. A majority of answers came from publicly-traded insurers (56.25%) and mutual insurance companies (33.75%). More than half of the participants were working for large companies, those with a policyholders' surplus in the $5 billion and $10 billion range and with a number of employees ranging from 5,000 to 20,000 (see appendix 2 for more details).

3. Results and Discussion

Table 3a below reports the geometric means[11] and median values of pure premiums for the main experimental conditions. Mean and median pure premiums are always higher for all three hazards than the expected loss of $1,000 (i.e. 1% annual chance of losing $100,000). This is consistent with findings from previous studies that show that insurers are risk averse.

INSERT TABLE 3a ABOUT HERE
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[10] For example, Ho et al. (2005) report the results of a series of experiments conducted with a total of 92 participants (30 managers in Experiment 1, and 62 participants in Experiment 2). In another paper published in 2002, the same authors ran an experiment with a total of 79 MBA students (39 MBA students in Experiment 1, and 40 MBA students in Experiment 2).

[11] Descriptive statistics revealed that the premium distributions violated the normality assumption (skewness coefficient = 2.98 and 6.82 for the 1-year contract and the 20-year contract respectively). We therefore performed a log transformation (skewness coefficient = 0.53 and 0.76 for the log(1yP) and log(20yP) respectively). Such a procedure allows counteracting the effect of outliers and is useful when the distribution of the dependent variable is highly skewed (see Kunreuther et al. 1995 for a similar analysis). In the subsequent analysis, we use the log (Premium/EL) as our main dependent variable.

3.1. Ambiguity aversion hypothesis (H1)

To test **H1**, we compared the premiums under *risk* with those under both types of *ambiguity.* Table 3a shows that, on average across natural hazards, the mean premiums for one year contracts for *imprecise ambiguouity* are 25 percent higher than the mean premiums for *risky* damages; they are 30 percent higher for *conflict ambiguity* than for *risky* damages.[12] (Median premiums for *ambiguous* damages under one year contracts ranged from 50 percent to 92.5 percent higher than for *risky* damages). This suggests that insurers are averse to both types of ambiguity.

To formally test this ambiguity aversion we undertook a Multivariate Analysis of Variance (MANOVA) on the log premiums charged for the 1-year and the 20-year contracts, and determined the main effects of each of three fixed factors: Source of Uncertainty, Natural Hazard and Participant ID.[13] We found that the premiums under *imprecise ambiguity* are significantly higher than premiums under *risk* (F=14.62, p=0.000 and F=10.74, p=0.002 for 1-year contracts and 20-year contracts respectively). In other words, *imprecise ambiguity* significantly increases the premiums insurers indicated they would charge to insure against the damage. We also found that premiums under *conflict ambiguity* are significantly higher than premiums under *risk* (F=22.45, p=0.000 and F=16.29, p=0.000 for the 1-year and the 20-year contracts respectively). These results indicate that **H1** holds, i.e., insurers are indeed averse to both types of ambiguity.

Although we computed our results using the geometric mean, we are also aware that some insurers might have considered using the arithmetic mean of the two expert estimates

[12] Specifically, 41 (51.25%) participants charged simultaneously a smaller premium under *risk* than under *imprecise ambiguit*y, **and** a smaller premium under *risk* than under *conflict ambiguity*. Sixteen (20%) participants charged a higher premium under one source of ambiguity than under *risk*.

[13] In the text, we report the main effect of the Natural Hazard factor only when it was significant.

rather than the geometric mean. We thus also computed the risk premium for each response under *risk*, *imprecise ambiguity* and *conflict ambiguity* (Table 3b). In the case of *risk,* the risk premium (RP) is the difference between the pure premium and the expected loss (i.e., \$1,000). For the two types of *ambiguity*, we calculated the risk premium (RP) as the difference between the pure premium and the arithmetic mean of the expected losses; that is \$1,125 (\$1,000*0.5*(0.02+0.005)).

INSERT TABLE 3b ABOUT HERE

Table 3b presents the means and medians of the risk premium (RP) distributions, by hazard and by source of uncertainty. We can see that mean risk premiums under *imprecise ambiguity* and *conflict ambiguity* are higher than risk premiums under *risk* when insurers sell the standard one-year contracts. We ran similar statistical analysis on the risk premiums distributions (mean) as we did on the mean log premiums in Table 3a. These tests shows that insurers charge significantly higher RP under *imprecise ambiguity* than under *risk* ($F=11.388$, $p=0.001$ for one-year contracts; $F=4.354$, $p=0.040$ for 20-year contracts); and under *conflict ambiguity* than under *risk* ($F=12.504$, $p=0.001$ for one-year contracts; $F=2.848$, $p=0.048$ – one sided test – for 20-year contracts). These results confirm that insurers are ambiguity averse, and that **H1** is supported.

3.2. Conflict aversion hypothesis (H2)

To test **H2** we restricted our analysis to the *imprecise ambiguity* and *conflict ambiguity* contexts and performed a MANOVA on the log premiums with Source of Uncertainty, Natural Hazard and Participant ID as fixed factors. Looking at all three hazards combined, participants said they would charge premiums between 2.7 percent and 4.5 percent higher under *conflict ambiguity* than under *imprecise ambiguity* (for the 20-year and 1-year contracts, respectively; Table 3a). This suggests a tendency for conflict aversion, but this difference was not large enough to be statistically significant (F=0.58, p=0.45 and F=0.19, p=0.66 for 1-year and 20-year contracts respectively) so that **H2** was not supported.[14]

We also examined whether insurers assessed the three types of hazard differently. To do so, we ran three MANOVAs (one for each hazard), with Source of Uncertainty as a fixed factor, and asked for simple contrasts in order to compare the premiums charged under *imprecise ambiguity* with those charged under *conflict ambiguity*. When the data were disaggregated, we found that, contrary to what we predicted, for the fire hazard insurers charged smaller premiums under *conflict ambiguity* than under *imprecise ambiguity* (8.3 percent and 29.4 percent smaller for the 1-year and 20-year contracts, respectively; Table 3a). These contrasts are significant for both the 1-year premiums (p=0.049) and the 20-year premiums (p=0.013). For the two other hazards however, we observed the predicted trend. Insurers charged on average more under *conflict ambiguity* than under *imprecise ambiguity* for flood (8.5 percent and 30.4 percent higher for the 1-year and 20-year contracts, respectively), and for hurricane (13.9 percent and 16.3 percent higher for the 1-year and 20-year contracts, respectively) but none of these contrasts are statistically significant (Table 3a).

[14] It is worth noting that the same pattern was obtained when the responders were asked about the level of confidence they had in their estimates of the premium (see question 8 in appendix 1). A MANOVA on confidence scores across all respondents revealed that insurers were much more confident in their decisions under *risk* (3.55 and 3.15) than under *imprecise ambiguity* (3.11and 2.89) (F=11.22, p=0.001 and F=16.34, p = 0.000 for 1-year and 20-year premiums, respectively); and under *risk* than under *conflict ambiguity* (3.16 and 2.79) (F=6.55, p = 0.012; and F=9.37, p = 0.003 for 1-year and 20-year premiums, respectively). In addition, we did not find any statistically significant difference between the confidence scores under *imprecise ambiguity* and *conflict ambiguity* (F=0.24, p = 0.63 and F=0.07, p = 0.79 for the 1-year and 20-year premiums, respectively).

These results suggest that the nature of the hazard matters, even though the expected loss is the same for each one of these three hazard scenarios.

There might be several reasons for this behavior. It might be due to the potential for truly catastrophic losses from hurricanes and floods. Of the twenty-five most costly insured disasters that occurred in the world between 1970 and 2010, twenty-two of them were hurricanes and floods. Moreover, when we ran this experiment in 2008, seven major hurricanes had made landfall in the U.S. in 2004 and 2005, including Hurricane Katrina which inflicted over $150 billion in economic losses, $48 billion of which was borne by private insurers (2008 prices) (Kunreuther and Michel-Kerjan 2009). In contrast, with the exception of large-scale wild fires such as those in Russia during the summer of 2010, events resulting in insurance losses for house fires tend to be relatively small in size.

Another explanation relates to the available data for estimating the likelihood of these three different hazards. After the seven major hurricanes of 2004 and 2005, some risk modeling firms and insurers revised their catastrophe models to reflect a potential increase in climate-related risk. In contrast, insurers typically have large historical database for house fires from their own claims and from engineering studies to improve building safety.

3.3. Insurers normally expect convergent and precise estimates from their advisors (H3)

We now turn to testing **H3** which predicts that insurers expect *a priori* the two risk-modeling firms to provide the same precise probability (normal condition). To test this prediction, we asked the surveyed insurers "*To what extent do you have the impression that there is there something unusual about the estimates of the probability of the damage you have been given?*" (question 2 in appendix 1). Answers were given on a 7-point scale ranging from -3 "nothing unusual" to +3 "extremely unusual." This scale captures the degree of "unusualness" of the decision context. We transformed this scale into a 3-point scale ranging from 1 “nothing unusual” (old scores -3, -2, -1), to 2 “neutral” (old score 0), and 3 “something unusual” (old scores +1, +2, +3). Table 4 gives the frequencies of answers (and percentage) to the unusualness question by type of hazards.

INSERT TABLE 4 ABOUT HERE

We can also look at the results by type of hazards. For each hazard, we ran a series of two-way Chi-square tests to determine whether the distribution of answers to the “unusualness” question under *risk* was different from the distributions of answers under *imprecise ambiguity,* and under *conflict ambiguity*. For fire, we found that these differences were highly significant both for the comparison between *risk* and *imprecise ambiguity* (Cramer’s V=0.428, p = 0.007) and for the comparison between *risk* and *conflict ambiguity* (Cramer’s V = 0.576, p = 0.000). Specifically, Table 4 shows that under *risk,* a large majority of insurers (70 percent) said that there was “nothing unusual” about the estimates of the probability of the damage they were given, whereas only a minority of insurers exposed to the *imprecise ambiguity* context (28 percent) and to the *conflict ambiguity* context (20 percent) considered this to be the case. In other words, insurers exposed to the fire scenario said that they were expecting the two-risk modeling firms to come up with the same precise probability, as H3 predicts.

For flood, we did not find any significant difference between the distributions of answers to the unusualness question under *risk* and *imprecision ambiguity* (Cramer’s V = 0.042, p = 1), and under *risk* and *conflict ambiguity* (Cramer’s V = 0.177, p = 0.426). This means that H3 is not supported. Yet, Table 4 shows that the distribution of the perception of unusualness under *risk* and *imprecise ambiguity* are highly similar (52 percent, 16 percent and 32 percent; and 50 percent, 19 percent and 31 percent, respectively). Although perceptions of unusualness under *risk* and *conflict ambiguity* are not significantly different,

Table 4 thus shows that we observed the expected trend. The proportion of "neutral" answers is similar under *risk* and *conflict ambiguity* (16 percent and 21 percent, respectively) but, under *risk*, a large proportion of insurers (52 percent) considered that there was "nothing unusual" about the probability estimates they were given; whereas under *conflict ambiguity*, a large proportion of insurers (45 percent) said that there was "something unusual" about the probability estimates. Taken all together, these results suggest that insurers exposed to the flood scenario tended to expect the two modeling firms to come up with the same precise probability estimate (or the same imprecise probability) and did not expect them to disagree on the probability of the damage.

For hurricane, we also found that H3 was not supported by the data. The series of 2-way Chi-square tests showed that the distributions of answers to the unusualness question under *risk* did not differ from the distributions of answers under *imprecise ambiguity* (Cramer's V = 0.199, p = 0.36), and under *conflict ambiguity* (Cramer's V = 0.120, p = 0.72).

3.4. Conflict imprecision leads to person attribution whereas imprecise ambiguity leads to task attribution (H4)

Finally, we test the **H4** predictions. The abnormal conditions focus model of causal attribution (Hilton and Slugoski 1986) contends that due to low consensus (disagreement between advisors), insurers will attribute *conflict ambiguity* to the incompetence of their advisors and perceive their advisors to be less credible and trustworthy than in cases of high consensus where the advisors agree. On the other hand, the same causal attribution model contends that when expert advisors provide similar but imprecise estimates of the probability of an event, insurers will attribute the *imprecise ambiguity* to the difficulty of the task.

Based on this causal attribution model, we made the following two predictions (H4). First, we predicted that under the *conflict ambiguity* case, the insurers will attribute the uncertainty they face to the incompetence of (at least one of) their advisors compared to the standard *risk* case. Second, we predicted that in the case of *imprecise ambiguity*, compared to the standard *risk* case, insurers will be more likely to attribute the uncertainty they face to the difficulty of the task.

First, to test whether *conflict ambiguity* generates doubt about the advisors' competence compared to *risk*, we focused on the comparison between the two. For each hazard, we run a series of two-way Chi-square tests, one for each of the two person attribution questions (questions 3 and 4 in appendix 1) and one for the competence question (question 6 in appendix 1). Table 5 shows that for all three hazards, as hypothesized, the proportion of insurers considering their advisors to be "competent" was consistently higher in the *risk* context than in the *conflict ambiguity* context, as evidenced by the percentages that are systematically higher under *risk* – 100 percent, 88 percent and 66 percent – than under *conflict ambiguity* –76 percent, 69 percent, 60 percent (scores are given for flood, hurricane and fire, respectively). A statistical test showed that the distribution of answers to the competence question under *risk* was significantly different from the distribution of answers under *conflict ambiguity* across the three hazards (Cramer's V = 0.190, p =0.025; one-sided test) This effect, however, was mainly due to results from the fire scenario where the difference is significant (Cramer's V = 0.504, p = 0.000) whereas the effect is not significant for flood (Cramer's V = 0.178, p = 0.58) and hurricane (Cramer's V = 0.051, p = 1) scenarios.

INSERT TABLE 5 ABOUT HERE

We then looked at the Positive Source attribution question. As predicted, across hazards, insurers were more likely to agree with the statement that their advisors "did their work very well" (Positive Source) under *risk* than under *conflict ambiguity* (Cramer's V =

0.222, p = 0.022). This global effect was significant mainly because of the fire scenario, where we found that the distribution of answers to the positive source question under *risk* was significantly different from the distribution of answers under *conflict ambiguity* (Cramer's V = 0.511, p = 0.001). Thus, in the fire scenario, Table 5 shows for instance that more insurers agreed with the positive source statement under *risk* (57.7 percent) than under *conflict ambiguity* (20 percent). Conversely, more insurers disagree with the statement under *conflict ambiguity* (52 percent) than under *risk* (7.7 percent). In the flood and hurricane scenarios, however, even though a larger number of insurers disagreed with the positive statement under *conflict ambiguity* than under *risk* (17.2 percent versus 8 percent for flood; 31 percent versus 24 percent for hurricane), a large proportion of insurers opted for the "neutral" answer under both *conflict ambiguity* and *risk*. Statistical tests confirmed that the distributions of answers to the positive source question under *risk* and under *conflict ambiguity* were not statistically different (Cramer's V = 0.175, p = 0.437; Cramer's V = 0.102, p = 0.786 for flood and hurricane respectively).

When looking at the Negative Source question, across hazards, we found no significant difference between the distributions of answers under *risk* and *conflict ambiguity* (Cramer's V = 0.166, p = 0.115). This aggregated result, however, hides the fact that in the fire scenario, the difference was significant, and was in the predicted direction (Cramer's V = 0.434, p = 0.007). For instance, Table 5 shows that in the fire scenario, more insurers agreed with the statement that "at least one firm did not do its work well" under *conflict ambiguity* (44 percent) than under *risk* (15 percent). In the flood scenario, although Table 5 shows that the distributions of answers exhibit the predicted pattern – more agreement under *conflict ambiguity* (17 percent) than under *risk* (4 percent), and more disagreement under *risk* (48 percent) than under *conflict ambiguity* (31 percent) – the effect was not significant (Cramer's V = 0.242, p = 0.244). This might be due to the fact that in this case, a large proportion of insurers were actually "neutral" under both *conflict ambiguity* (52 percent) and *risk* (48 percent). In the hurricane scenario, we found no significant difference between the distributions of answers to the negative source attribution question under *conflict ambiguity* and *risk* (Cramer's V = 0.243, p = 0.205).

We then tested for the second part of H4, which predicts that insurers will be more likely to attribute the uncertainty they face to the difficulty of the task under *imprecise ambiguity* than under *risk*. To do so, we compared the distributions of answers to the task attribution question under *imprecise ambiguity* and *risk*. As predicted, across hazards, we found that the two distributions of answers were different (Cramer's V = 0.417, p = 0.000). Table 5 shows indeed that more insurers agreed with the statement "estimating the probability is a highly difficult task" under *imprecise ambiguity* (69 percent, 85 percent, 92 percent for fire, flood and hurricane, respectively) than under *risk* (38 percent, 8 percent, 83 percent for fire, flood and hurricane, respectively). The difference between the two distributions was significant for fire (Cramer's V = 0.346, p = 0.041) and for flood (Cramer's V = 0.836, p = 0.000), but not for hurricane (Cramer's V = 0.140, p = 0.707).

In sum, both predictions of H4 were supported for the fire scenario, but not for the flood and hurricane scenarios. This raises questions about expert insurers' differing expectations concerning these scenarios, which we discuss below.

4. Summary and Conclusion

Our results provide additional evidence that sophisticated subjects – insurers are experts in decision-making under uncertainty – behave as if they are ambiguity-averse in the loss domain when faced with the task of pricing risks having a low probability of occurrence but potentially catastrophic effects (**H1**).

Furthermore, our results show that the source of ambiguity can have an important impact on choices. When all hazards are combined, our prediction that insurance professionals would be more concerned with *conflict ambiguity* than *imprecise ambiguity* was not confirmed (**H2**). But when the data were disaggregated, we found that on average, insurers tended to charge higher premiums under *conflict ambiguity* than under *imprecise ambiguity* for hazards perceived as potentially catastrophic such as floods and hurricanes, but lower premiums for non-catastrophic hazards such as house fires.

We then asked whether this tendency for aversion to conflict came from a cognitive heuristic that leads individuals to attribute the cause of conflicting uncertainty to the incompetence of their advisors. If they doubted the quality of their advisors' estimates, they might want to increase the price of coverage by assigning a larger weight to the highest probability estimate from the two advisors. To answer this question, we used attribution theory (Hilton and Slugoski 1986; Hilton et al. 1995). We reasoned that insurers would normally expect risk-modeling firms to be in agreement and to communicate a precise probability (**H3**).

We found that the *risky* context was perceived as the most usual context for fire, whereas *conflict ambiguity* was rated as the most unusual context. For hurricane, *imprecise ambiguity* was rated the most usual context, and *risk* the most unusual. We believe this is due to the nature of hurricane assessment which requires one to use climate models to project losses in the future. The choice of different climate models and slightly different assumptions or other elements of the selected model will generate different outcomes. We assumed that insurers will expect consensual and precise probability forecasts from their advisors. We thus predicted that disagreeing advisors will be considered as less credible and competent than advisors converging on the same precise estimate. We also predicted that imprecise but consensual advisors will not be considered as less credible and competent than advisors converging on the same precise estimate, and that imprecise ambiguity will be attributed to the difficulty of the judgmental (**H4**). In the fire scenario in particular, we found that insurers indeed perceived the risk modeling firms that provided the estimates as being less competent under *conflicting uncertainty* than under *risk;* and that they were more likely to attribute the uncertainty they face to the difficulty of the task under *imprecise ambiguity* than under *risk*.

Our data also suggest that expert insurers have strong *a priori* expectations associated with different kinds of hazards which influence their judgments. Indeed, their responses differ between a hazard where there is a potential catastrophe (flood and hurricane) and the more standard case where the losses are non-catastrophic (fire) where the expected loss is the same for each hazard. These systematic differences suggest that future research should address the correspondence between risk and ambiguity domains, availability of actuarial estimates, and insurers' expectations about risk modelers' predictions. For example, the expectation that experts should converge to precise point estimates may hold only in cases where there is enough relevant actuarial data. If we assume that the experienced insurers in our sample know that such actuarial data exists for fire but not for flood and hurricane, this could explain why consensus over precise estimates would be seen as a cue to competence only for the fire hazard.

In future research it would also be useful to test whether individuals consider that they are less informed when their advisors exhibit *conflict ambiguity* than *imprecise ambiguity*. In other words, one could test whether individuals would treat *conflict ambiguity* as a form of "epistemic uncertainty" due to lack of knowledge that could be reduced and *imprecise ambiguity* as "aleatory uncertainty" due to randomness. In the former case, individuals would be better informed if they rely on more competent advisors, whereas in the latter case they could not reduce the uncertainty by simply requesting the estimates of more advisors.

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TABLES

Table 1. Differences between Risk, Imprecise Ambiguity and Conflict Ambiguity

	Risk	Imprecise Ambiguity	Conflict Ambiguity
Advisor A_1	½	[1/4;3/4]	¼
Advisor A_2	½	[1/4;3/4]	¾

Table 2. Scenarios: The Three Sources of Uncertainty

Source of Uncertainty	Implementation
Risk The probability of the risk is well established. There is a consensus on a precise probability.	You have asked two modeling firms with whom you usually work to evaluate the annual probability of a flood severely damaging a home in the area. Both modeling firms estimate that there is **1 in 100 chance** that a flood will severely damage homes in this area this year (i.e., the annual probability is 1%). They both are confident in their estimate.
Imprecise ambiguity There is uncertainty about the probability of the risk but there is no controversy.	You have asked two modeling firms with whom you usually work to evaluate the annual probability of a hurricane severely damaging a home in the area. Both modeling firms recognize it is difficult to provide you with a precise probability estimate. The two modeling firms however agree that the probability that a hurricane will severely damage homes in this area this year ranges somewhere between **1 in 200 chance and 1 in 50 chance** (i.e., they have converged to the same 0.5% to 2% probability range).
Conflict ambiguity There is controversy about the probability of the risk.	You have asked two modeling firms with whom you usually work to evaluate the annual probability of a fire severely damaging a home in the area. There is a strong disagreement between the two modeling firms. One modeling firm confidently estimates that there is **1 in 200 chance** that a fire will severely damage homes in this area this year (i.e., the annual probability is 0.5%). The other modeling firm confidently estimates that the chance that a fire will severely damage homes in this area this year is much higher: **1 in 50 chance** (i.e., the annual probability is 2%).

Table 3a. Geometric Mean and Median Pure Premiums in $/Year

	1-year contract			20-year contract		
	Risk	Imprecise Ambiguity	Conflict Ambiguity	Risk	Imprecise Ambiguity	Conflict Ambiguity
Fire						
Geometric Mean	1,137	1,614	1,479	1,076	1,780	1,256
Median	*1,000*	*1,500*	*1,500*	*1,000*	*1,500*	*1,250*
Flood						
Geometric Mean	1,342	1,620	1,758	1,282	1,450	1,891
Median	*1,100*	*1,500*	*2,000*	*1,000*	*1,600*	*1,600*
Hurricane						
Geometric Mean	1,369	1,549	1,765	1,583	1,510	1,756
Median	*1,100*	*1,250*	*1,925*	*1,025*	*1,500*	*2,000*
Total (n=80)						
Geometric Mean	1,281	1,596	1,668	1,307	1,582	1,624
Median	*1,000*	*1,500*	*1,925*	*1,000*	*1,500*	*1,650*

Table 3b. Mean and Median Risk Premiums in $/Year

	1-year contract			20-year contract		
	Risk	Imprecise Ambiguity	Conflict Ambiguity	Risk	Imprecise Ambiguity	Conflict Ambiguity
Fire						
Mean	672	816	652	320	1988	464
Median	0	375	375	0	375	125
Flood						
Mean	654	1143	959	895	860	2069
Median	100	375	875	0	475	475
Hurricane						
Mean	578	1007	1219	1277	1089	1082
Median	100	125	800	25	375	875
Total (n=80)						
Mean	632	982	948	847	1341	1247
Median	0	375	800	0	375	525

Table 4. Distribution of Answers (%) to the Unusualness Question

	Risk	Imprecision	Conflict
Fire			
Nothing unusual	18 (70)	8 (28)	5 (20)
Neutral	4 (15)	7 (24)	2 (08)
Something unusual	4 (15)	14 (48)	18 (72)
Flood			
Nothing unusual	13 (52)	13 (50)	10 (34)
Neutral	4 (16)	5 (19)	6 (21)
Something unusual	8 (32)	8 (31)	13 (45)
Hurricane			
Nothing unusual	10 (34)	12 (48)	8 (31)
Neutral	4 (14)	5 (20)	6 (23)
Something unusual	15 (52)	8 (32)	12 (46)

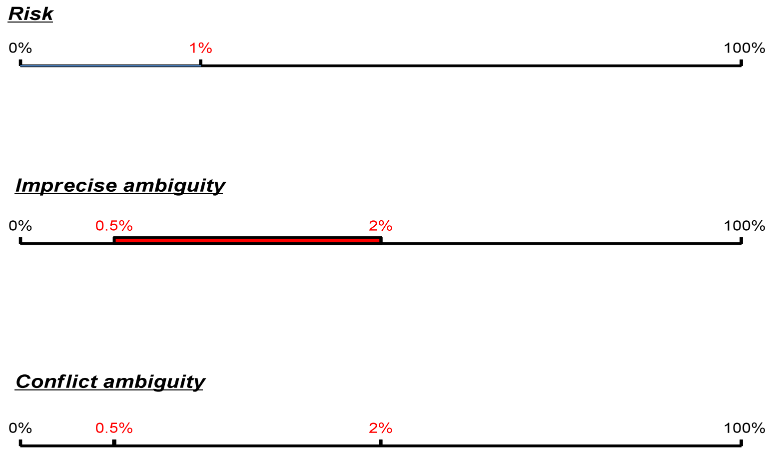
Table 5. Distribution of Answers (%) to the Competence Question and Attribution Questions[(a)]

	Fire			**Flood**			**Hurricane**		
	Risk	**Imprecis.**	**Conflict**	**Risk**	**Imprecis.**	**Conflict**	**Risk**	**Imprecis.**	**Conflict**
Competence: *Impression that the two modeling firms are competent in…*									
Not competent	0 (0)	2 (7)	1 (04)	2 (08)	0 (0)	3 (10)	3 (10)	2 (8)	2 (8)
Neutral	0 (0)	4 (14)	9 (36)	1 (04)	4 (15)	4 (14)	7 (24)	3 (12)	6 (23)
Competent	26 (100)	23 (79)	15 (60)	22 (88)	22 (85)	22 (76)	19 (66)	20 (80)	18 (69)
Positive Source : *Both modeling firms did their work very well*									
Do not agree	2 (7.7)	4 (14)	13 (52)	2 (08)	5 (19)	5 (17.2)	7 (24)	5 (20)	8 (31)
Neutral	9 (34.6)	14 (48)	7 (28)	16 (64)	6 (23)	14 (48.3)	14 (48)	9 (36)	10 (38)
Agree	15 (57.7)	11 (38)	5 (20)	7 (28)	15 (58)	10 (34.5)	8 (28)	11 (44)	8 (31)
Negative Source: *At least one modeling firm did not do its work very well*									
Do not agree	16 (62)	10 (34)	5 (20)	12 (48)	13 (50)	9 (31)	8 (27.6)	12 (48)	13 (50)
Neutral	6 (23)	14 (48)	9 (36)	12 (48)	7 (27)	15 (52)	15 (51.7)	7 (28)	8 (31)
Agree	4 (15)	5 (17)	11 (44)	1 (04)	6 (23)	5 (17)	6 (20.7)	6 (24)	5 (19)
Task: *Estimating the probability of (…) is a highly difficult task*									
Do not agree	14 (54)	6 (21)	6 (24)	19 (76)	0 (0)	0	3 (10)	1 (4)	3 (11.5)
Neutral	2 (08)	3 (10)	2 (08)	4 (16)	4 (15)	0	2 (07)	1 (4)	2 (7.7)
Agree	10 (38)	20 (69)	17 (68)	2 (08)	22 (85)	29 (100)	24 (83)	23 (92)	21 80.8)

(a) As for the unusualness question, answers which were given on a 7-point scale ranging from -3 (strongly disagree) to +3 (strongly agree). We then transformed into 3-point scale ranging from 1 "do not agree" (old scores -3, -2, -1), to 2 "neutral" (old score 0), and 3 "agree" (old scores +1, +2, +3).

FIGURE

Figure 1. Graphical Representation of Experts' Judgments in the Experiment



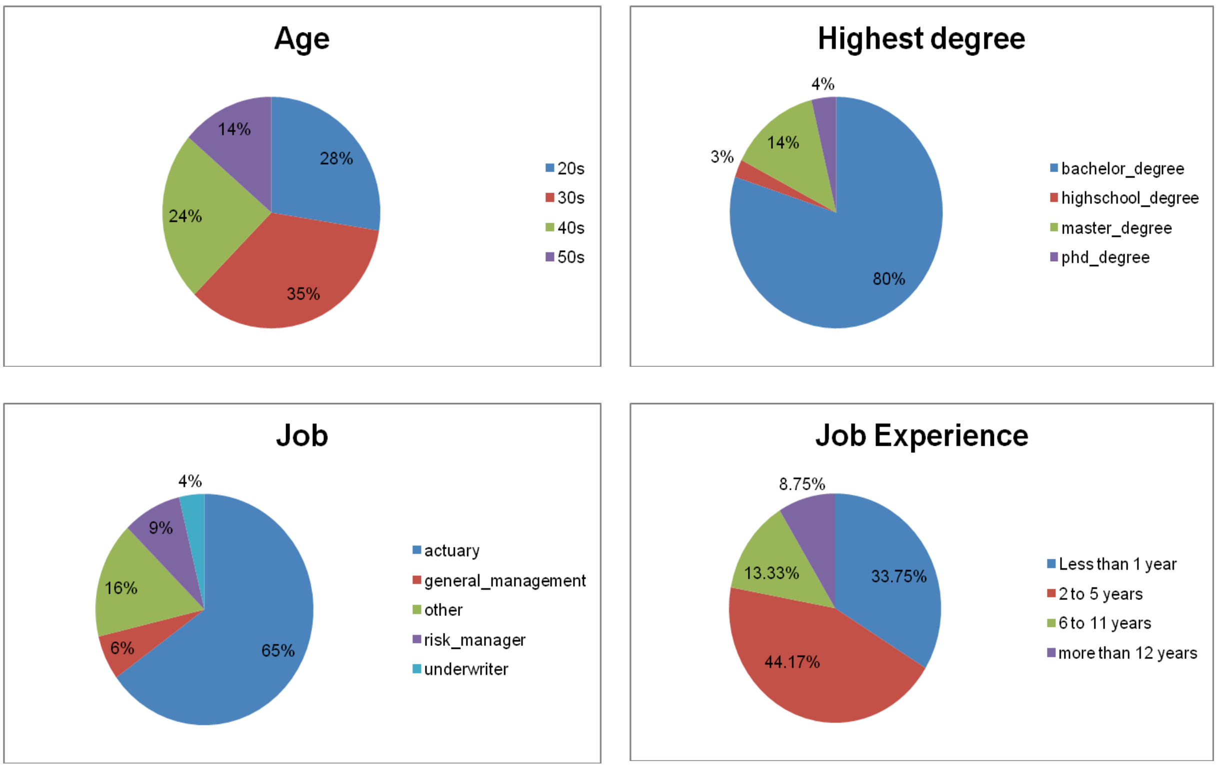
APPENDIX 1: EXPERIMENT QUESTIONS

For each scenario, the participants were asked to answer 10 questions, presented in the following order:

1. Perception of disagreement. We asked participants to answer the question "*To what extent do you have the impression that the two modeling firms are in agreement on the estimate of the probability of the damage?*" on a 7-point scale, ranging from -3 = "Not in agreement at all" to +3 = "In complete agreement."
2. Degree of "unusualness". We asked participants to rate on a 7-point scale, ranging from -3 = "Nothing unusual at all" to +3 = "Extremely unusual" the degree of "unusualness" of the scenario. The question was: "*To what extent do you have the impression that there is there something unusual about the estimates of the probability of the damage you have been given?*"
3. Positive person attribution. We asked participants: "How strongly do you agree with the following statement? "*Both modeling firms did their work, i.e., estimating the probability of the [flood/fire/hurricane] damage in this case, very well.*" Participants could answer this question on a 7-point scale ranging from -3 = "Strongly disagree" to +3 = "Strongly agree."
4. Negative person attribution. We asked participants: "How strongly do you agree with the following statement? "*At least one of the two modeling firms did not do its work, i.e., estimating the probability of the [flood/fire/hurricane] damage in this case, very well.*" We used the same scale as for question 3.
5. External (Task) attribution. We asked participants: "How strongly do you agree with the following statement?: "*Estimating the probability of the [flood/fire/hurricane] damage in this case is a highly difficult task.*" We used the same scale as for question 3.
6. Perception of the competence of the advisors. The participants were asked to answer the question "*To what extent do you have the impression that the two modeling firms are both competent in estimating the probability of the [flood/fire/hurricane] damage in this case?*" on a 7-point scale, ranging from -3 = "Both firms are not competent at all"; 0 = "At least one firm is not competent"; +3 = "Both firms are extremely competent."
7. Pricing (1-year contract). Participants were told that they had the possibility of offering a typical one-year contract. We asked them to report the "*minimum annual premium (excluding administrative costs) that they would charge against the risk.*"
8. Confidence (1-year contract). Participants were asked to rate on a 7-point scale ranging from 1 = "Not at all confident" to 7 = "Extremely confident" they degree of confidence in their estimate of the premium.
9. Pricing (20-year contract). Participants were asked to give "*the minimum annual premium (excluding administrative costs)*" that they would like to charge against the risk in a case where they could offer a "*20-year insurance contract against the damage to the property that would be tied to the homeowner mortgage*."
10. Confidence (20-year contract). Participants were asked to give "*the minimum annual premium (excluding administrative costs)*" that they would like to charge against the risk in the 20-year contract case.

APPENDIX 2: INFORMATION ABOUT THE PARTICIPANTS AND THEIR COMPANY

This appendix provides descriptive statistics on our random sample of 80 U.S. insurers. We had 52 answers from actuaries (65%), 3 answers from underwriters (3.75%), 7 answers from risk managers (8.75%), 5 answers from general managers (15%), and 13 answers (16.25%) from other jobs (product management, pricing management, analysts…). With regard to past experience, 33.75% of our sample had less than 2 years of experience in their job, 44% had between 2 and 5 years of experience in their job, 13% had between 6 and 11 years of experience in their job, and 8.75% had more than 12 years of experience in their job. Three (3) participants had a PhD (3.75%), and 2 participants (2.5%) had a high school degree as their highest degree. 80% of the participants (n=64) had a Bachelor's degree as their highest degree, and 13.75% had a Master's degree (n=11).



Graph 1: Descriptive statistics – Random Sample of 80 U.S. insurers

On average, a majority of participants (56.25%) were working for a publicly-traded company and only 5 participants were working in a private company (see Graph 2). Among the remaining participants, 33.75% of the participants were working for a mutual, and 5% (n=4) did not know the type of company they were working for. We had a majority of answers (51.25%) from large companies with a surplus between $5 and $10B; 25% of participants worked for a company having a surplus larger than $10B. Two percent of the participants worked for a company having a surplus between $1 and $5B. Five percent of the participants did not answer the question. In terms of number of employees, 68.5% of the participants reported working for a company having between 5,000 and 20,000 employees, 5% were in companies with more than 20,000 employees, and 12.5% were in companies having between 1,000 and 5,000 employees (11.25% did not provide the number of employees of their company).

Graph 2: Characteristics of the companies