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

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Keywords

Ambiguity, Source of Uncertainty, Insurance Pricing, Decision-Making

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Abstract: Testing whether risk professionals (here insurers) behave differently under risk and ambiguity when they cover catastrophic risks (floods and earthquakes) and non-catastrophic risks (fires), this paper reports the results of the first field experiment in the United States designed to distinguish two sources of ambiguity: *imprecise ambiguity* (outside experts 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). Insurers charge higher premiums when faced with ambiguity than when the probability of a loss is well specified. Furthermore they charge more for *conflict ambiguity* than *imprecise ambiguity* for flood and hurricane hazards, but less so in the case of fire. The source of ambiguity also impacts causal inferences insurers make to reduce their uncertainty.

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1. 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 decision making (Camerer and Weber 1992). In particular, results of experimental research show that individuals are averse to ambiguity for low probability losses (Hogarth and Einhorn 1990; Viscusi and Chesson 1999). Earlier surveys of underwriters and actuaries indicate that insurers will want to raise their premiums when there is ambiguity compared to what they would charge for situations where the probabilities and losses are well-specified (Kunreuther et al. 1995; Cabantous 2007).

Few studies, however, have looked at whether the nature of the ambiguity mattered for decision-makers' preferences (Cabantous 2007; Smithson 1999). This is surprising because there is evidence that decision makers are likely to react differently depending on the source of uncertainty (Abdellaoui et al. 2010) and the way this information is presented to them. For example, when seeking advice from multiple advisors, individuals are sensitive to whether these experts agree or disagree with each other on the same forecast and/or in their recommendations for actions (Budescu et al. 2003; Cabantous 2007; Dean and Shepherd 2007; Viscusi and Chesson 1999; Viscusi 1997).

Smithson (1999) shows that individuals react differently when they receive conflicting messages (e.g., your advisors are not in agreement about what will happen) compared to how they react when they receive consensual but imprecise information (advisors agree on a range of events that could happen but do not specify one as more likely). Smithson shows that individuals prefer an imprecise situation to one with conflicting messages because disagreement among advisors raises doubt as whether any of them are trustworthy and knowledgeable.

Building on this literature, this paper investigates the effect of the source of ambiguity. The focus here is on professional insurers confronted with events that have low probabilities but catastrophic consequences. We study decision contexts where actuaries and underwriters in insurance companies seek advice and request probability forecasts from different groups of experts. We examine two different ambiguity contexts: *imprecise ambiguity* where different experts agree on a range of probabilities, not on any specific point estimate, and *conflict ambiguity* where each expert strongly supports one probability point estimate but these point estimates differ between experts.

The paper centers on the effect of these two sources of ambiguity on cognition and choices. To understand how cognition impacts attitudes towards ambiguous risks and actual choices we use insights from attribution theory (Hilton and Slugoski 1986; Hilton, Smith and Kim 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 experts' (consensual or conflicting) expressions of uncertainty is utilized by individuals to make decisions.

The paper is structured as follows. Section 2 specifies a set of hypotheses which will be tested using data from an experiment with underwriters and actuaries from large insurance companies. Section 3 describes the experimental design. Section 4 reports the results. Section 5 discusses the results and raises questions for future research.

2. 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.

<u>H1. Insurers are ambiguity-averse for low-probability, high-consequence events</u>

If insurers are averse to ambiguity with respect to low-probability, high-consequence events, they will want to charge higher premiums when there is uncertainty about the probability of a loss compared to a situation where 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" and 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 through 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.

H2. Insurers prefer imprecise ambiguity over conflict ambiguity

Our second hypothesis is that insurers will want to charge a higher premium under *conflict ambiguity* than under *imprecise ambiguity.* Smithson (1999) showed 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) which studies conflict aversion in a population 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.

<u>H3: Insurers normally expect convergent and precise estimates</u>

Attribution theory has shown that people often make causal attributions 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 "normal" case where relevant actuarial data exists and two expert advisors will agree on point predictions. Furthermore, they will find both kinds of ambiguity in predictions less normal than the standard risk case of perfect convergence of precise estimates. This is known as the "experts-should-converge" hypothesis (Shanteau 2001).

<u>H4: Insurers will attribute conflicting imprecision to less credible and trustworthy advisors (internal factors) but consensual imprecision to task difficulty (external factors).</u>

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). Attribution of an event to 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, Smith and Kim 1995). This is precisely the basis for testing assumption H4, which states that under the *conflict ambiguity* case, the responders will attribute the conflicting forecasts to the incompetence of their advisors. Our second prediction is that in the case of *imprecise ambiguity,* insurers are more likely to attribute the ambiguity not to incompetence, but to an external effect. 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 the task of modeling catastrophe risks for which reliable actuarial data does not exist like floods and hurricanes notably, but also fire.

3. A field experiment to study U.S. underwriters and actuaries' behavior under risk, imprecise ambiguity, and conflict ambiguity

In order to test these four hypotheses, we created a web-based questionnaire asking insurers what premiums they would charge a representative client under different situations (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).

3.1. Stimulus

Three different kinds of hazards were considered: flood, hurricane and fire. They 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 natural hazards.

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 to 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 1 depicts the scenarios utilized in the experiment.

TABLE 1. 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%).

These scenarios are similar to the ones used in previous studies on insurers' attitudes to ambiguity (Kunreuther et al. 1995; Cabantous 2007; De Marcellis 2000). All the insurers who participated in the field 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 [hurricane/flood/fire] damage.*" They were also told that "*The value of each home in this area is $200,000. If a [hurricane/flood/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.*" In this context their company would also be paying for losses associated with the flood scenario.

Surveyed insurers were asked to base their estimates of the probability of damage from the figures provided by their advisors, the two modeling firms with whom they usually work.[1] 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.[2] 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 (four times greater).

3.2. Field experiment questions

As we were interested in pricing behavior (see **H1** and **H2**), we asked participants to provide the "pure premiums" they would charge. This premium excludes the other costs the insurance company would have to incur and might want to pass on to its policyholders, such as administrative and marketing costs, loss assessment costs and the cost of 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 risk, and the annual premium for a long-term 20-year full insurance coverage contract.

We were interested in how these insurers would react to a multiyear 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

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[1] 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 decided to structure the experiment using 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 are *a priori* equally reliable.

[2] The geometric mean in this case is $(0.5 \text{ x}2)^{\frac{1}{2}} = 1\%$.

insurer. Here long-term insurance keeps the annual insurance premium the same over a fixed time horizon.[3]

In order to test assumption **H3** (insurance professionals' expectations about the normal state of risk-modeling firms' forecasts), we included a question about their perception of the degree of "unusualness" of the probability estimates that they were given (see Q_2 in appendix 1).

To test assumption **H4**, two causal explanations were linked to the advisors (person causal attribution) and one to the task performed by the advisors (situation causal attribution). The first person causal attribution was positive ("*Both modeling firms did their work very well.*"; see Q_3 in appendix 1) and the second was negative, implying incompetence ("*At least one of the modeling firms did not do its work very well.*"; see Q_4 in appendix 1). A third question inquired about the participants' perception of the competence of the advisors (Q_6: "*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?*).

After the participants had read the three scenarios and completed the series of questions, we also 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 the web-based questionnaire, and appendix 2 provides socio-demographics of participants and their company.

3.3. 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

[3] For more details on the structure of a long-term policy see Jaffee et al. 2008, and Kunreuther and Michel-Kerjan 2009.

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.

3.4. 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.[4]

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. 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. On average, a majority of answers (56.25%) came from publicly-traded insurers 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).

4. Results and Discussion

[4] We would like to thank the American Insurance Association, the Casualty Actuarial Association and the Property and Casualty Insurance Association of America for helping us distribute the surveys to their members.

Table 2 reports the geometric means[5] for premiums for the main experimental conditions (as well as median value for information purposes).

Mean and median premiums for one-year contracts under both types of ambiguity (second and third columns in Table 2) are always significantly higher for all three hazards than the expected loss of $1,000 (i.e. 1% annual chance of losing $100,000). Our first conclusion is that this field experiment confirms findings from previous studies: insurers are ambiguity averse.

TABLE 2. GEOMETRIC MEAN AND MEDIAN 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*

To test **H1**, we compared the premiums under *risk* with those under *imprecise ambiguity* and *conflict ambiguity* by undertaking 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.[6] Across natural hazards, on average, insurers report they would charge premiums for *ambiguous* damages that are between 21% and 30% higher than the

[5] 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(1P) and log(20P) 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. The geometric mean of a variable X is equal to the antilog of log (X).

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

premiums they would charge for *risky* damages.[7] This means that they are averse to ambiguity (**H1**).

More specifically, 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, i*mprecise 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). **H1** holds.

To test **H2** we restricted our analysis to the *imprecise ambiguity* and c*onflict 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 2.6% and 4.5% higher under *conflict ambiguity* than under *imprecise ambiguity* (for the 20-year and 1-year contract respectively). 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.[8]

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

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[7] 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*.

[8] 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).

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, for the fire hazard, insurers charged smaller premiums under *conflict ambiguity* than under *imprecise ambiguity* (9% and 41% smaller for the 1-year and 20-year contracts, respectively). These contrasts are significant for both the 1-year premiums (p=0.049) and the 20-year premiums (p=0.013). For the flood situation, however, insurers charged on average more under *conflict ambiguity* than under *imprecise ambiguity* (9% and 30% higher for the 1-year and 20-year contracts, respectively; these contrasts are not statistically significant). For the hurricane situation, insurers also charged on average more under *conflict ambiguity* than under *imprecise ambiguity* (14% and 16% higher for the 1-year and 20-year contracts, respectively; these contrasts are not statistically significant). These results suggest that the nature of the hazard matters a lot, even though the expected loss is the same for each one of these three hazards.

H3 predicts that insurers expect *a priori* the two risk-modeling firms to come up with the same precise probability (normal condition). To do so, 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?*" (Q_2 in appendix 1).

Answers were given on a 7-point scale ranging from -3 "nothing unusual" to +3 "extremely unusual." This scale hence captures the degree of "unusualness" of the decision context. As predicted, a MANOVA revealed that the Source of Uncertainty had a significant main effect on the perceived degree of usualness (F=8.61, p = 0.000). This means that across natural hazards, respondents found the *risky* context less unusual (-0.41) than the *imprecise ambiguity* (-0.16) and the *conflict ambiguity* (0.51) contexts (see Table 3). In particular, a series of two-by-two *t*-tests with Bonferroni adjustment showed that the unusualness scores were significantly higher under the *conflict ambiguity* context than under the *risky* and the *imprecise ambiguity* cases (p=0.000 and p=0.012 respectively). This means that **H3** is supported.

Here again one can look at the results by type of hazards. To do so, we ran three separate MANOVAs, one for each natural hazard, with Source of Uncertainty as a fixed factor. On the same scale (-3 "nothing unusual" to + 3 "*extremely* unusual"), inspection of Table 3 shows that in the case of fire, expert insurers consider imprecise estimates to be more unusual (0.28) than precise estimates (-1.23) and conflicting estimates even more unusual (1.20). A statistical test on the unusualness variable shows that all these scores are significantly different: thus *risk* is perceived as significantly less unusual than both *imprecise ambiguity* and *conflict ambiguity* (p = 0.000), and *imprecise ambiguity* is seen as significantly less unusual than *conflict ambiguity* (p = 0.000). Interestingly, in the case of both flood and hurricane, while *conflict ambiguity* is still perceived as the most unusual case, unlike fire, *risk* is seen as more unusual than *imprecise ambiguity.* However, in the case of flood and hurricane, none of these contrasts are statistically significant.

A further indication that expert insurers responded differently to the hurricane and flood scenarios as compared to the fire scenario can be gauged by the finding that insurers clearly consider hurricane and flood to be more difficult prediction tasks than fire (as indicated by scores that are systematically higher in Table 3; 1.72, 2.16 and 1.77 for Hurricane, and 1.60. 1.85 and 1.86, for Flood; scores for Fire are: -0.23, 0.93 and 1.12). A statistical test reveals that on average, across Sources of Uncertainty, the perceived difficulty of the Task was significantly lower in the fire case than in the hurricane and flood cases considered jointly (p=0.000).[9]

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[9] Results of a MANOVA on the attribution variables, and the variable Task, with Source of Uncertainty, Natural Hazard and Participant ID as fixed factors. The statistical test concerns the comparison between fire on the one hand, and flood and hurricane on the other hand, across sources of uncertainty.

These results are understandable based on our general framework if we assume hurricane and flood to be ambiguous and hence inherently difficult to estimate with great precision, and fire to be a standard risk case (with reliable information on a very large number of events) and hence easier to estimate.

We now turn to our **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 (the standard risk condition and the imprecise ambiguity condition). On the other hand, 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, compared to the *conflict ambiguity* condition.

To test whether *imprecise ambiguity* suggests that the forecasting task was difficult and *conflict ambiguity* generates doubt about the advisors' competence, we focused on the comparison between the two. We ran a MANOVA on the competence question and the three attribution questions (Questions 3, 4 and 5 in appendix 1) with Source of Uncertainty, Hazard and Participant ID as fixed factors. Table 3 reports these descriptive statistics as well.

As hypothesized, insurers considered their advisors to be less competent under *conflict ambiguity* (0.85) than under *imprecise ambiguity* (1.05) ($F=2.88$, $p=0.047$ one-tailed test). They were also significantly more likely to agree with the statement that their advisors "did their work very well" (Positive Source) under *imprecise ambiguity* (0.36) than under *conflict ambiguity* (-0.14) ($F=12.025$, $p=0.001$). Conversely, they tended to agree more with the statement that their advisors "did **not** do their work very well" (Negative Source) under *conflict ambiguity* (-0.18) than under *imprecise ambiguity* (-0.44) ($F=1.61$, $p = 0.201$), even though these differences are not statistically significant. These results suggest that conflict raises a doubt as to whether the advisors are competent and have done their job well.

TABLE 3. UNUSUALNESS, ATTRIBUTION AND COMPETENCE MEAN SCORES

	Risk	Imprecision	Conflict
Unusualness[a]			
Fire	-1.23	0.28	1.20
Flood	-0.28	-0.54	0.17
Hurricane	0.21	-0.28	0.23
3 natural hazards (n=80)	**-0.41**	**-0.16**	**0.51**
Positive Source[b]			
Fire	0.92	0.34	-0.68
Flood	0.32	0.46	0.28
Hurricane	0.10	0.28	-0.08
3 natural hazards (n=80)	**0.44**	**0.36**	**-0.14**
Negative Source[b]			
Fire	-1.23	-0.24	0.28
Flood	-0.92	-0.58	-0.17
Hurricane	-0.24	-0.52	-0.62
3 natural hazards (n=80)	**-0.78**	**-0.44**	**-0.18**
Task[b]			
Fire	-0.23	0.93	1.12
Flood	1.60	1.85	1.86
Hurricane	1.72	2.16	1.77
3 natural hazards (n=80)	**1.05**	**1.61**	**1.60**
Competence[c]			
Fire	1.85	0.90	0.64
Flood	1.08	1.35	0.97
Hurricane	0.76	0.92	0.92
3 natural hazards (n=80)	**1.21**	**1.05**	**0.85**

[a] For the unusualness question, we used a 7-point scale ranging from -3 "nothing unusual" to +3 "extremely unusual."
[b] The three attribution scales range from -3 (not in agreement with the causal explanation) to +3 (in complete agreement with the causal explanation).
[c] The Competence question scale ranges from -3 (both firms are not competent at all) to +3 (both firms are extremely competent). 0 indicates that participants feel that "at least one of the sources is not competent".

Regarding the prediction that *imprecise ambiguity* suggests that the forecasting task was difficult, responses to the task attribution question also significantly varied as a function of the hazard (F=10.24, p=0.000). More specifically insurers considered that the forecasting task was more difficult under *conflict ambiguity* (1.12) than under *imprecise ambiguity* (0.93) for fire (p=0.016) (Table 3)[10], presumably because, as discussed earlier, risk assessments for fires have been made on numerous occasions so that insurers felt that their advisors should have considerable knowledge of the risk. If the advisors were in conflict it implied that fire scenario was unusual and hard to forecast.

For flood, insurers considered the forecasting task as difficult under *conflict ambiguity* (1.86) as under *imprecise ambiguity* (1.85). This might be due to the fact that flood insurance is under the purview of the federal government in the United States so private insurers may not focus on the difficulty of this task. For hurricanes, which private insurers cover against, insurers tended to agree with the statement that the forecasting task was more difficult under *imprecise ambiguity* (2.16) than under *conflict ambiguity* (1.77) (the contrast is not statistically significant). As discussed above, for the hurricane hazard, insurers tended to be more averse to *conflict ambiguity* than to *imprecise ambiguity;* whereas for the fire hazard they were not more averse to conflict ambiguity than to imprecise ambiguity. This result tends to support the idea that aversion to conflict might be linked to the task causal attribution.

5. 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

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[10] MANOVA run with the three attribution variables and competence as dependent variables, and Source of Uncertainty as a fixed factor, in the fire case. The p value refers to the contrast between *imprecise ambiguity* and *conflict ambiguity* for the Task variable. The results of the next two contrasts come from similar MANOVA run in the flood case and hurricane case respectively.

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 much higher premiums under *conflict ambiguity* than under *imprecise ambiguity* for floods and hurricanes, but lower ones for fire.

We then asked whether that conflict aversion comes 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 would want to price the coverage higher 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, Smith and Kim 1995). We reasoned that insurers would normally expect risk-modeling firms to be in agreement and to communicate a precise probability (**H3**). Results of our field experiment support that assumption. We found that across natural hazards, the *risky* context was perceived as the most usual context, whereas *conflict ambiguity* was rated as the most unusual context. Then, we predicted that insurers expecting consensual and precise probability forecasts from their advisors (*risky* decision context) would consider that disagreeing advisors are less credible and competent than imprecise advisors (**H4**). We found that insurers indeed perceived the risk-modeling firms that provided the estimates as being less competent under *conflicting uncertainty* than under *imprecise uncertainty*. When receiving conflicting probability estimates, insurers were concerned that their advisors might not be trustworthy and competent whereas they did not have this feeling when the modeling firms communicating the same imprecise probability forecast.

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 scenarios associated with a perceived potential catastrophe (flood and hurricane) versus non-catastrophe (fire) ("perceived" because the expected loss is the same in the three scenarios). These systematic differences suggest that future research should address the correspondence between risk domain, availability of actuarial estimates, and experienced insurers' expectations about risk modelers' predictions. For example, the expectation that experts should converge to precise point estimates may only hold in cases where there is 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 only be seen as a cue to competence 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 could be better informed if they call on more competent advisors, whereas in the latter case they could not reduce the uncertainty by simply requesting the estimates of more advisors.

6. References

Abdellaoui, M., Baillon, A., Placido, L., & Wakker, P.P (2010). The rich domain of uncertainty: Source functions and their experimental implementation. *American Economic Review,* Forthcoming.

Budescu, D.V., Rantilla, A.K, Yu, H.-T., & Karelitz Y.M. (2003). The effects of asymmetry among advisors on the aggregation of their opinions. *Organizational Behavior and Human and Decision Processes, 90*, 178-194.

Cabantous, L. (2007). Ambiguity aversion in the field of insurance: insurers' attitude to imprecise and conflicting probability estimates. *Theory and Decision, 62*, 219-240.

Camerer, C., & Weber, M. (1992). Recent developments in modeling preferences: Uncertainty and ambiguity. *Journal of Risk and Uncertainty, 5*(4), 325-370.

De Marcellis, N. (2000). *Aux frontières de l'assurabilité des risques de l'entreprise, une analyse expérimentale des décisions de l'assureur. Thèse de Doctorat, ENS de Cachan*

Dean, M., & Shepherd, R. (2007). Effects of information from sources in conflict and in consensus on perceptions of genetically modified food. *Food Quality and Preference, 18*(2), 460-469

Einhorn, H., & Hogarth, R.M. (1985). Ambiguity and uncertainty in probabilistic inference. *Psychological Review, 92*, 433-461.

Ellsberg, D. (1961). Risk, ambiguity and the Savage axioms. *Quarterly Journal of Economics*, *75*, 643-669.

Frisch, D., & Baron, K. (1988). Ambiguity and rationality. *Journal of Behavioral Decision Making, 1,* 149-157.

Heath, C., & Tversky, A. (1991). Preference and belief: ambiguity and competence in choice under uncertainty. *Journal of Risk and Uncertainty*, *4*, 5-28.

Hilton, D.J. (2007) Causal explanation: From social perception to knowledge-based attribution. In A. Kruglanski & E.T. Higgins (Eds.). Social Psychology: Handbook of Basic Principles. (2nd edition). New York: Guilford Press. (pp. 232-253).

Hilton, D.J., & Slugoski, B.R. (1986). Knowledge-based causal attribution: the abnormal conditions focus model. *Psychological Review, 93*(1), 75-88.

Hilton, D.J., Smith, R.H., & Kim, S.H. (1995). Processes of causal explanation and dispositional attribution. *Journal of Personality and Social Psychology*, *68*(3), 377-387.

Hogarth, R.M., & Einhorn, H.J. (1990). Venture theory: a model of decision weights. *Management Science, 36*(7), 780-803.

Jaffee, D., Kunreuther, H. & Michel-Kerjan, E. (2008). Long Term Insurance (LTI) for Addressing Catastrophe Risk. NBER Working Papers, 14210. Cambridge, MA: National Bureau of Economic Research.

Kelley, H.H. (1973). The process of causal attribution. *American Psychologist, 28*(2), 107-128.

Hogarth, R.M, & Kunreuther, H. (1989). Risk, ambiguity, and insurance. *Journal of Risk and Uncertainty, 2*(1), 5-35.

Kunreuther, H & Michel-Kerjan, E. (2009). *At War with the Weather*. Cambridge, MA: MIT Press.

Kunreuther, H., Meszaros, J., Hogarth, R.M., & Spranca, M. (1995). Ambiguity and underwriter decision processes. *Journal of Economic Behavior & Organization*, *26*(3), 337-352.

McClure, J.L., Allen, M.W., & Walkey, F.H. (2001). Countering fatalism: Causal information in news reports affects judgments about earthquake damage. *Basic and Applied Social Psychology*, *23*, 109-121.

Shanteau, J. (2001). What does it mean when expert disagree? In E. Salas & G. Klein (Eds.), *Linking expertise and naturalistic decision making*. N.J.: Erlbaum.

Smithson, M. (1999). Conflict aversion: preference for ambiguity vs conflict in sources and evidence. *Organizational Behavior and Human Decision Processes, 79*(3), 179-198.

Taylor, K. (1995). Testing credit and blame attributions as explanation for choices under ambiguity. *Organizational Behavior and Human Decision Processes*, *64*(2), 128-137.

Viscusi, W.K. (1997). Alarmist decisions with divergent risk information. *Economic Journal, 107*, 1657-1670.

Viscusi, W.K., & Chesson, H. (1999). Hopes and fears: the conflicting effects of risk ambiguity. *Theory and Decision, 47*(2), 157-184.

Viscusi, K., & Magat, W. (1992). Bayesian Decision with Ambiguous Belief Aversion. *Journal of Risk and Uncertainty*, *5*, 371-387.

Weiner, B. (1985). “Spontaneous” causal thinking. *Psychological Bulletin, 109,* 74-84.

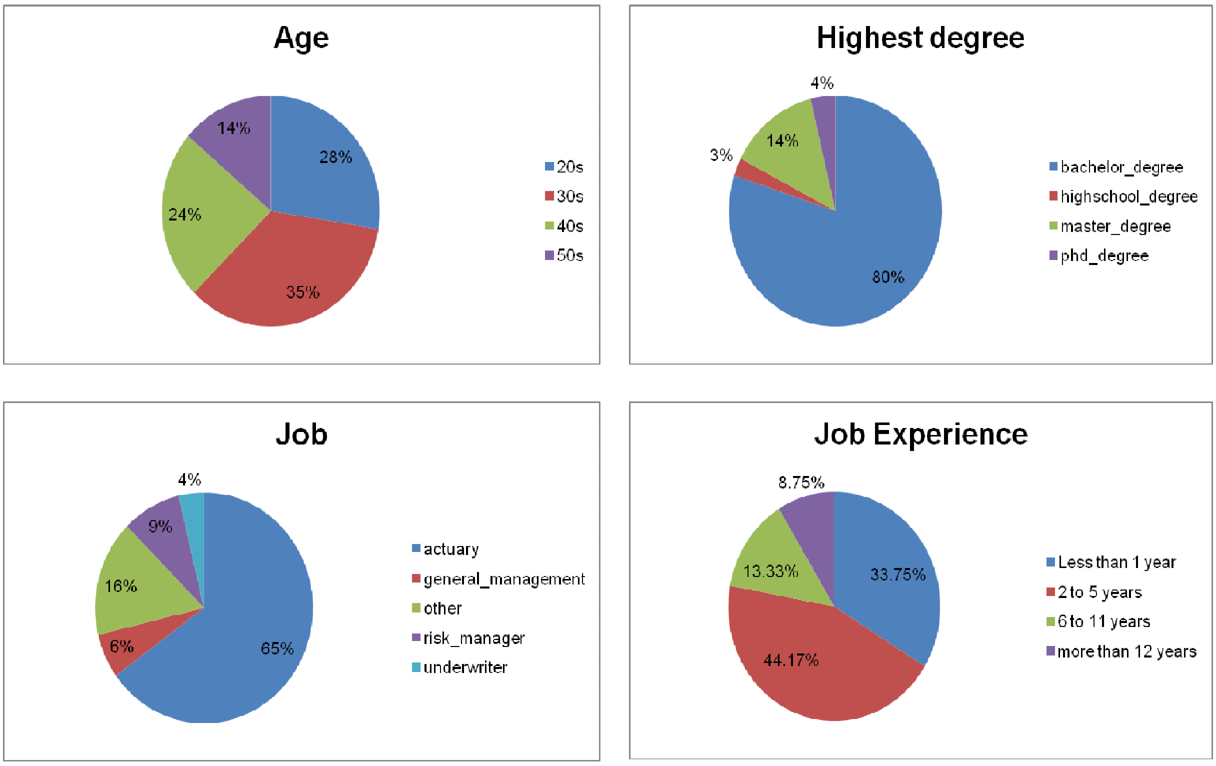
Appendix 1: Field Experiment Questions

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 un-usual at all" to +3 = "Extremely un-usual" the degree of "un-usualness" 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 participant: "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 participant: "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 participant: "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.

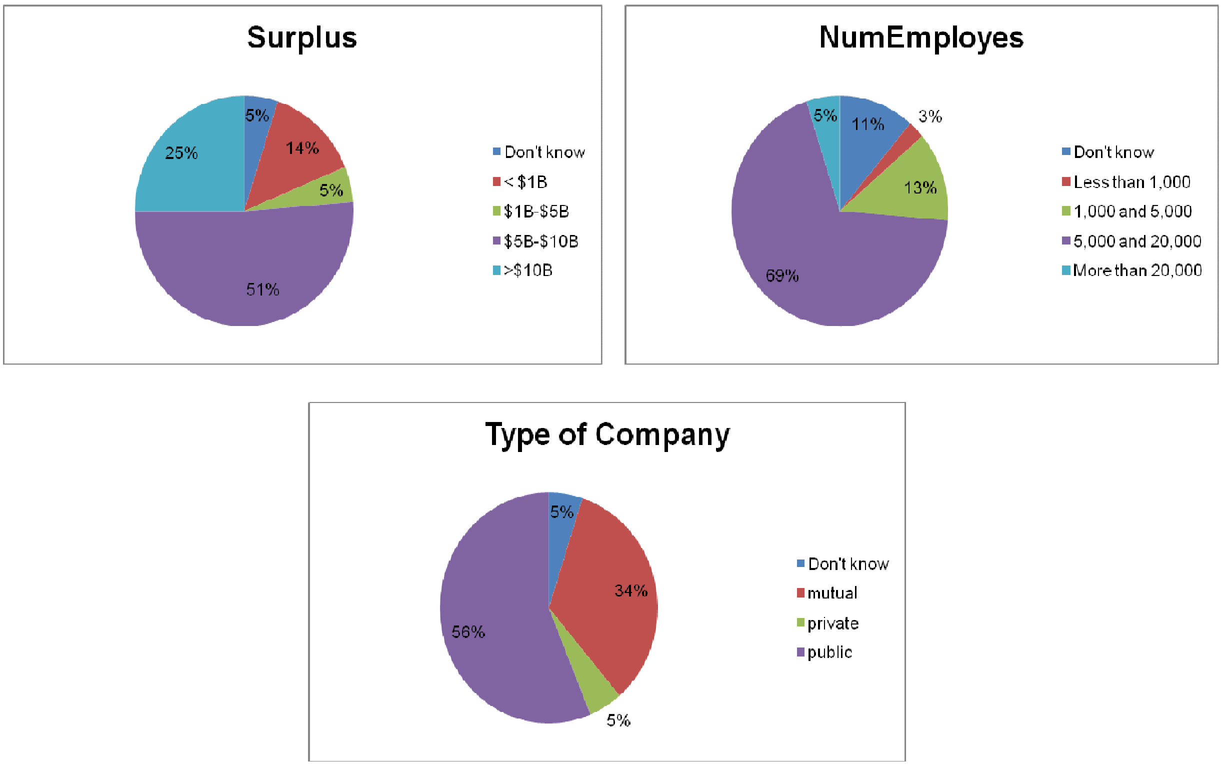
Appendix 2: Information about the participants and their company

The graphs below provide descriptive statistics on our random sample of 80 US 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…). Moreover, 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. 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 degree as their highest degree, and 13.75% had a master degree (n=11).



Graph 1: Descriptive statistics – Random Sample of 80 US insurers

On average, a majority of participants (56.25%) were working for public 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, and 25% of participants worked for a company having a surplus larger than $10B. 2% of the participants only worked for a company having a surplus between $1 and $5B. 5% 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