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Abstract:
Ambiguity may be high when there exists conflicting information regarding the probability model characterizing the randomness of a phenomenon. In this paper, we report the results of an experiment jointly eliciting the attitudes individuals exhibit towards risk and model uncertainty. Using a joint elicitation procedure, we are then able to quantify precisely the strength of individuals' attitude towards ambiguity and to characterize its main properties. Our results provide empirical evidence of decreasing absolute ambiguity aversion (DAAA) and constant relative ambiguity aversion (CRAA), and shed new light on the way ambiguity attitude may affect important decisions, such as the choice of health insurance policies or the optimal investement strategy in the face of climate change.

Submission to the Special Issue on Behavioral Insurance in the *Journal of Economic Behavior & Organization*

Dear François, Dear Prof. Corcos, Dear Prof. Montmarquette

Please find enclosed our article *"Characterizing ambiguity attitudes using conflicting information".*

This paper provides a methodological contribution to the experimental literature on ambiguity aversion, which could be of great interest for questions related, for example, to health insurance and to self-insurance/self-protection investments in the context of climate change.
Specifically, we propose a new experimental method to characterize more precisely the extent to which ambiguity aversion exists and to characterize its main properties.
Our approach explicitly makes use of the information provided by different *experts* regarding the probabilistic model to be used for characterizing a risk.

We contribute to the literature in several ways:

1) We find that the epistemic uncertainty concerning who is the "correct" expert to follow is not considered the same way as the aleatory uncertainty concerning the outcome of well-defined risk. More specifically, our subjects exhibit a stronger aversion towards epistemic uncertainty (model uncertainty) than towards aleatory uncertainty (risk).

2) The former result is interpreted as evidence of ambiguity aversion, which we are able to quantify precisely. In particular, our design enables us to elicit the degree of ambiguity aversion, which we estimate to be around 0.5 when considered in relative terms.

3) We find evidence of decreasing absolute ambiguity aversion (DAAA) and constant relative ambiguity aversion (CRAA).

As the properties of the ambiguity aversion function have been shown to be of great importance for determining the effect of ambiguity on optimal decision in insurance, self-insurance and self-protection problems (Alary, Gollier, Treich, 2013; Berger, 2016), we believe that our paper is particularly suitable for the Special Issue on Behavioral Insurance in the *Journal of Economic Behavior & Organization*.

We thank you very much for your time and effort and are looking forward to the evaluation.

Sincerely,

Loïc Berger and Valentina Bosetti

Characterizing ambiguity attitudes using conflicting information

Loïc Berger Valentina Bosetti*

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JEL Classification: D81

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*We thank Mohammed Abdellaoui, Aurélien Baillon, Han Bleichrodt, Itzhak Gilboa, Glenn Harrison, Ning Liu, François Pannequin, Massimo Tavoni, Peter Wakker and especially Massimo Marinacci for helpful comments and discussions. We acknowledge audiences at CEAR/MRIC Behavioral Insurance Workshop, the annual seminar of the European Group of Risk & Insurance Economists (EGRIE), the workshops "Uncertainty and public decision" (EconomiX) and seminar participants at Bocconi University, Rotterdam University, HEC Paris, Fondazione Eni Enrico Mattei, IESEG and EM-Lyon for their helpful comments. We thank Jacopo Crimi, Johannes Emmerling, Michele Peruzzi, Caterina Verrone and Stefano Zenobi for their help with the experiment. The research leading to these results has received funding from the European Union Seventh Framework Programme FP7/2007-2013 under grant agreement n°308329 (ADVANCE). Berger acknowledges the support of the French Agence Nationale de la Recherche (ANR), under grant ANR-17-CE03-0008-01 (project INDUCED). Bosetti gratefully acknowledges the financial support provided by the CASBS and the ERC-2013-StG 336703-RISICO. Logistic support from the Bocconi Experimental Laboratory in the Social Sciences (BELSS) for hosting our experimental sessions is kindly acknowledged. Some results of this research have previously circulated in a working paper entitled "Ellsberg Re-revisited: An Experiment Disentangling Model Uncertainty and Risk Aversion". Berger : IESEG School of Management (LEM-CNRS 9221), France, *E-mail address:* l.berger@ieseg.fr. Bosetti: Department of Economics and IGIER, Bocconi University, Italy and Fondazione Eni Enrico Mattei (FEEM), Italy.

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> "Ambiguity may be high [...] when there are questions of reliability and relevance of information, and particularly where there is *conflicting* opinion and evidence."
>
> Ellsberg (1961, p. 659)

1 Introduction

Almost sixty years ago, Ellsberg (1961) proposed a series of experiments whose results suggest that people generally prefer situations in which they know the probabilities of events occurrence to situations in which these probabilities are unknown. This behavior –which violates a key axiom of the classical model of choice under uncertainty– is known as *ambiguity aversion*. It has been the focus of a large body of literature, which has explored both the theoretical and experimental sides of the topic. According to Ellsberg himself, this preference is neither due to the relative desirability of the possible payoffs, nor to the relative likelihood of the events affecting them, but rather to "*the nature of one's information concerning the relative likelihood of events*". In particular, Ellsberg (1961) wrote:

> "*What is at issue might be called the ambiguity of this information, a quality depending on the amount, type, reliability and "unanimity" of information, and giving rise to one's degree of "confidence in an estimation of relative likelihoods.*"

Ambiguity aversion thus results from a preference for situations in which all events relevant to decision making are associated with obvious probability assignments, on which everyone agrees (i.e. what is generally called "risk" in economics) to situations in which some events do not have an obvious, unanimously agreeable, probability assignment (Ghirardato, 2004).

Ambiguity is present in virtually all real-life situations. It plays a major role in many problems policymakers and public authorities may face and thus directly affects their decision making processes. Ambiguity may, for example, result from the existence of conflicting expert opinions about the probability of a particular event (Cabantous, 2007; Cabantous et al., 2011). Or, it may arise from the existence of multiple, plausible and conflicting models predicting the probabilistic effects of alternative policies.

Health Insurance. As in Gilboa and Marinacci (2013); Marinacci (2015), consider the problem of a decision maker (DM) who has to choose whether to buy insurance against the risk of a heart disease. By browsing the internet and providing some personal information about herself (age, cholesterol level, blood pressure, smoking habits), the DM is confronted with different probability assessments of heart disease provided by the risk calculators of different hospitals. Thus different "experts"[1] provide different *probability models* for the same event, i.e. "suffering a heart attack in the next years". As illustrated in Gilboa and Marinacci (2013), the estimates may vary substantially from one expert to the other. The reason for this being that simple relative frequencies cannot be used as a definition of the probability of a heart disease since no two human bodies are perfectly identical. Instead, the calculators assess the probabilities for different individuals depending on their characteristics using more complex methods. As a consequence, the assessed probabilities are not perfectly objective: the team in charge of the calculator in each hospital has to choose the individual characteristics to be used, the database, as well as the estimation technique. Altogether, this results in the existence of a set of possible probability models rather than a unique probability distribution.

Environmental Disasters. A policymaker may have to design an investment strategy, entailing both mitigation and adaptation efforts, in response to climate change.[2] In this context, different probability distributions may exist to characterize the same event (Heal and Millner, 2014). This happens either because there is not enough information available; because different climate predictions exist –which depend on different data sets, different estimation techniques or numerical models– or because different experts provide different probabilities assessments for the same event occurence. As a consequence, we do not know, for example, how global warming will affect the probability of being confronted to a climate catastrophe (Lenton et al., 2008). Since these events have not been encountered in recent history, their likelihood of occurrence is extremely difficult to quantify precisely. Decisions are therefore generally made based on the advices of scientific experts –as those reviewing the available literature in the IPCC reports– whose probability assessments may vary significantly (Kriegler et al., 2009; Berger et al., 2017). In this case too, different probability models therefore exist to characterize the same event.

[1]Throughout the paper, we refer to *experts* as those individuals or entities who presumably have more information and/or expertise than the decision maker, and who are acting as advisors by providing information (Budescu et al., 2003).

[2]*Adaptation* is the process of "adjustment to actual or expected climate and its effects. In human systems, adaptation seeks to moderate harm or exploit beneficial opportunities" (IPCC, 2014a), while *mitigation* is "a human intervention to reduce the sources or enhance the sinks of greenhouse gases" (IPCC, 2014b).

Whether concerning health related issues or environmental questions, what is common to the above-mentioned examples is the idea that ambiguity and elements of insurance of different types are tightly intertwined. Specificaly, while the first example concerns the provision of market insurance in the presence of ambiguity, the second example deals with ambiguity and self-insurance/self-protection in the sense of Ehrlich and Becker (1972). These risk management tools are generally used to deal with the risk of a monetary loss when market insurance is not available. In both situations, the DM has the opportunity to undertake an effort to modify the distribution of a risk. In the case of self-insurance (SI), the effort is aimed at reducing the size of the potential loss, while in the case of self-protection (SP), the effort aims to reduce the probability of suffering from the loss. In that sense, and as mentioned by Berger (2016), investments in adaptation efforts in the face of climate change may seen as an example of SI, while mitigation efforts correspond to SP.

To what extend do ambiguity preferences affect the decisions to purchase health insurance policies, or to undertake SI/SP efforts in the presence of climate change? The answer to this question fundamentally depends on the strenght of ambiguity aversion, as well as on some behavioral properties of the function characterizing ambiguity preferences. In theoretical works, Snow (2011) and Alary et al. (2013) have for example shown, using single period models, that ambiguity aversion increases the insurance coverage rate and the optimal level of SI, while it may increase or decrease the optimal level of SP. In a two-period setting, Berger (2016) and Berger et al. (2017) have shown that ambiguity aversion alone is not sufficient to sign the effect ambiguity has on the decision to (self-)insure or self-protect. An additional condition of non-increasing absolute ambiguity aversion is also required in most usual situations where the degree of model disagreement among experts decreases with the effort. Yet, at an empirical level, the question has not been tackled in much details.

The aim of this paper is to provide a methodological contribution to this literature. Specifically, what we propose in this study is an experimental method able to quantify more precisely the extent to which ambiguity aversion exists and to characterize its main properties.[3] To do so, we decompose ambiguity into two distinct layers of analysis, following an approach proposed by Hansen (2014), Marinacci (2015) and Hansen et al. (2016). The first layer, commonly referred to *risk* (or *aleatory uncertainty),* features the probability measure associated with the ran-

[3]Few studies have actually attempted to quantify the strength of the ambiguity aversion effect. Notable exceptions, using various models, are Abdellaoui et al. (2011); Ahn et al. (2014); Dimmock et al. (2015).

domness of an event. It refers to the physical quantification of uncertainty by means of a probability model that specifies fully the outcome probabilities. This layer of *risk within a model* is the one typically studied by economists in problems involving decision making under uncertainty (see for example Dionne and Eeckhoudt (1985); Jullien et al. (1999); Eeckhoudt and Gollier (2005) in the context of SI-SP). The second layer, referred to as *model uncertainty* (or *epistemic uncertainty*), represents the uncertainty about which alternative probability model should be used to assign the probabilities.[4] This layer of analysis appears when the correct risk is itself unknown. This is for example the case when multiple expert assessments appear plausible in describing the randomness of a phenomenon.

In a controlled experimental environment which extends Holt and Laury's (2002) and Andersen et al.'s (2008) setups, we confront our subjects with various risk and model uncertainty situations. Using the distinction between the two, our design enables us to quantify precisely the degree of ambiguity aversion and to study its main properties by means of non-parametric statistics as well as structural econometric analyses of choice patterns.

There are two main findings emerging from our analysis. First, subjects tend to be both risk and model uncertainty averse, but exhibit stronger aversion towards model uncertainty than towards risk. This behavioral characteristic is interpreted as evidence of ambiguity aversion, which is then elicited via a joint estimation procedure. Second, and analogously to what has been previously reported for risk aversion (Holt and Laury, 2002, 2005), we find that model uncertainty aversion is decreasing when considered in absolute terms, and increasing when considered in relative terms. In terms of ambiguity attitude, we find evidence of decreasing absolute ambiguity aversion (DAAA) and constant relative ambiguity aversion (CRAA).

2 Experimental procedures

This section presents the procedures followed in the experiment. We study two different types of uncertain situations, represented by urns filled with balls that may be either red or black. The first situation is a simple risk situation in which the number of red and black balls –and therefore the probability model– is objectively known. The second situation is a model uncertainty situation where ignorance is first achieved by letting both the number and the color of the balls in

[4]Note that the term *"epistemic"* derives from the Ancient Greek ἐπιστήμη, which means "knowledge", while the term *"aleatory",* which originates from the Latin *alea*, refers to any game of chance involving dice.

the urn to be unknown before two experts provide their assessment –or probability models– of the urn composition. This situation presents uncertainty in two layers: two possible models (the two experts' assessments) representing two distinct risks are provided to the subjects. The experiment consists of a sequence of eight tasks. In each task, subjects are confronted with a series of binary choices, presented in the form of ordered tables, as popularized by Holt and Laury (2002).

2.1 The design

The two types of uncertain situation are represented by urns containing red and black balls. Each urn describes a particular type of uncertainty that we distinguish as follows:

- *Risk*: the proportion of red and black balls in the urn is known;
- *Model uncertainty*: the proportion of red, black and the total number of balls in the urn are unknown. However, information is provided by two "experts": each giving her own assessment of the composition of the urn.

The probability of drawing a red (black) ball $P(r)$ ($P(b)$) is thus objectively known in the case of risk, but not in the case of model uncertain. In this latter case however, subjects are still given information regarding the possible compositions of the urn, via the experts' assessments.

CE tasks The first set of tasks takes the form of certainty equivalent (CE) tasks. In these tasks, subjects are asked to make a series of choices between an uncertain prospect and sure amounts of money. The uncertain prospect is either represented by a risky lottery or by a situation of model uncertainty. Specifically, by letting O denote the set of monetary outcomes, and $\bar{o}_p\underline{o}$ the binary lottery yielding $\bar{o} \geq \underline{o} \in O$ with probability p and $\underline{o} \in O$ otherwise, subjects are asked to make a series of ten choices between $\bar{o}_p\underline{o}$ and different values of $o \in O$ ordered from $\bar{o}$ to $\underline{o}$.[5] In the case of model uncertainty, the lottery $\bar{o}_p\underline{o}$ is replaced by the uncertain situation denoted $\bar{o}_{\hat{p}_1\hat{p}_2}\underline{o}$, in which the subject is only given the two experts' assessed probabilities of winning $\hat{p}_1$ and $\hat{p}_2$. The design of the CE tasks is standard. It enables us to characterize the payoff that would leave the subject indifferent between the prospect and the sure amount of money in both situations of risk and model uncertainty. Ultimately, the CE tasks provide a direct measure of the strength of model uncertainty aversion relative to risk aversion. To ease

[5] We used the following values in our CE tasks: $\bar{o} = 25$, $\underline{o} = 4$, $p = 0.5$, and $o \in \{25, 18, 15, 14, 13, 12, 10, 8, 6, 4\}$.

comparisons, we only consider the case of *dogmatic experts* in the CE tasks: each expert's assessment is degenerate in the sense that a probability 100% is associated with a particular event. This enables us to isolate the effect of model uncertainty alone and to capture model uncertainty preferences (see hereafter).

PL tasks In the remaining tasks of the experiment, we use a double price list (PL) procedure to jointly elicit risk and model uncertainty attitudes. Two risky tasks are designed following Holt and Laury's (2002) PL standard procedure,[6] while in the four remaining uncertain tasks, subjects are asked to make a series of choices between risky situations $\bar{o}_p\underline{o}$ and situations of model uncertainty $\bar{o}_{\hat{p}_1\hat{p}_2}\underline{o}$. The PL procedure is one of the most commonly employed elicitation methods to represent choices between gambles (Andersen et al., 2006). It is widely considered as a transparent procedure that rarely confuses subjects about the incentives to respond truthfully (Harrison and Rutström, 2008). However, one of the main disadvantages of this method is that subjects typically have the possibility to switch freely between the two options as they progress down the decision tables. They may therefore make inconsistent choices either by switching more than once, or by making reverse choices (Charness, Gneezy, and Imas, 2013). While we recognize these inconsistent behaviors raise additional difficulties –given that they are difficult to rationalize under standard assumptions on preferences, and that the estimation technique and inference of risk and model uncertainty attitudes require a unique switching point– we decided not to enforce consistent choices in this experiment.[7] Rather, we view such behavior as indicative of failing to understand the instructions correctly, or of confusion on the part of the subjects, and discard this inconsistent data from the analysis of our results.

Discussion We aimed at a design that, at the same time, remains simple and yet emphasizes the difference between risk and model uncertainty. The design presents few caveats, that we discuss here. While two expert's assessments were provided in the model uncertainty tasks, it should be understood that these experts were not physically present in the lab during the experiment. Although this situation is close to many real-life situations in which expert opinions are presented without the physical presence of the experts themselves, this feature may have led

[6] In a nutshell, in each task subjects are asked to make a series of ten choices between two options (Option A and Option B), each presenting a different lottery (the full set of tasks can be found in the online supplemental Appendix).

[7] Several techniques have been proposed in the literature to enforce consistency in the subjects' choices (see for example Andersen et al. (2006)), but with the major drawback that they may significantly bias the results (Charness, Gneezy, and Imas, 2013).

subjects to downplay the experts' role or to partially ignore them (making the situation closer to a case of full ignorance). To minimize the potential bias, we gave particular attention to the way we presented the experts and their assessments.[8] We are confident that most of our subjects incorporated the information provided when making their choices. We are indeed able to show that subjects' choices monotonically follow the stochastic dominance criteria induced by the changes in assessments provided by the two experts (see Section 5.2). Relatedly, one could fear that the absence of physical experts in the room could have deceived our subjects, who could then have been tempted to suspect or mistrust the whole experiment.[9] Once again, we are able to show that this suspicion argument is inconsistent with the data we collected. However, to make sure we were on the safe side, we explicitly indicated in the instructions that were read aloud at the beginning of the experiment: "This experiment is about decision-making. There will be no deception in the experiment."

2.2 The randomness device

Since one of our main goals in the experiment is to characterize the way individuals behave in the presence of model uncertainty we need to make sure that, in the absence of experts' information, subjects are in a situation of perfect ignorance.[10] To mimic the situation of perfect ignorance, we construct the model

[8]For that purpose, we specifically mentioned the following in the instructions: "These experts are the best we could find for this situation. They are both experienced and both have excellent track records".

[9]While most experimental economists agree that deception should be avoided, nobody knows exactly and with certainty what deception is and is not (Krawczyk et al., 2013). Yet, a consensus has emerged across disciplinary borders that deception involves *intentional and explicit provision of misinformation* (Hertwig and Ortmann, 2008). Adair, Dushenko, and Lindsay (1985) for example define deception as "the provision of information that actively misled subjects regarding some aspect of the study", while Menges (1973) talks about instances where "the subject is given misleading or erroneous information". The main argument against the use of deception is that it jeopardizes future experiments if the subjects ever find out that they were deceived and report this information to their friends. Banning deception therefore ensures negative reputational spillover effects are avoided and maintains a "reputation among the student population for honesty in order to ensure that subject actions are motivated by the induced monetary rewards rather than by psychological reactions to suspected manipulation" (Davis and Holt, 1993). In that sense, our design was not subject to deception. In practice indeed, the way we constructed the model uncertainty urn is by randomly selecting one of the two models introduced by the experts in the design, and implementing her assessment.

[10]In other words, they could a priori consider any probability in the continuum $[0, 1]$. Remark that with a device like an urn, this situation would correspond to an urn containing an infinite number of balls. This is different from the canonical Ellsberg examples in which (objective) information is given concerning the total number of balls, thus enabling the decision maker to posit a restricted set of possible objective models M, making the Ellsberg case itself a situation of model uncertainty.

uncertainty urn in such a way that the total number of balls in the urn is itself unknown, and comprised between 1 and 100. We call this modification of Ellsberg's canonical example, that reduces the information bias due to the peculiarity of the urn representation, the *randomness device*. In such a situation, the total number of potential objective models is 3045, which is the cardinality of the Farey sequence of order 100.[11] To see this, consider Table 1 below. It presents the sets of potential models when the *maximum* number of balls N is known to be between 1 (first row) and 8 (last row). As can be seen, when the maximum number of balls is $N = 1$,

Table 1: Sets of models and their corresponding cardinality when the maximum number of balls in the urn is N

N	Set of possible models: $M_N = \{P(r)\}$																							$\lvert M_N \rvert$
1	$\frac{0}{1}$																						$\frac{1}{1}$	2
2	$\frac{0}{1}$											$\frac{1}{2}$											$\frac{1}{1}$	3
3	$\frac{0}{1}$							$\frac{1}{3}$				$\frac{1}{2}$				$\frac{2}{3}$							$\frac{1}{1}$	5
4	$\frac{0}{1}$					$\frac{1}{4}$		$\frac{1}{3}$				$\frac{1}{2}$				$\frac{2}{3}$		$\frac{3}{4}$					$\frac{1}{1}$	7
5	$\frac{0}{1}$				$\frac{1}{5}$	$\frac{1}{4}$		$\frac{1}{3}$		$\frac{2}{5}$		$\frac{1}{2}$		$\frac{3}{5}$		$\frac{2}{3}$		$\frac{3}{4}$	$\frac{4}{5}$				$\frac{1}{1}$	11
6	$\frac{0}{1}$			$\frac{1}{6}$	$\frac{1}{5}$	$\frac{1}{4}$		$\frac{1}{3}$		$\frac{2}{5}$		$\frac{1}{2}$		$\frac{3}{5}$		$\frac{2}{3}$		$\frac{3}{4}$	$\frac{4}{5}$	$\frac{5}{6}$			$\frac{1}{1}$	13
7	$\frac{0}{1}$		$\frac{1}{7}$	$\frac{1}{6}$	$\frac{1}{5}$	$\frac{1}{4}$	$\frac{2}{7}$	$\frac{1}{3}$		$\frac{2}{5}$	$\frac{3}{7}$	$\frac{1}{2}$	$\frac{4}{7}$	$\frac{3}{5}$		$\frac{2}{3}$	$\frac{5}{7}$	$\frac{3}{4}$	$\frac{4}{5}$	$\frac{5}{6}$	$\frac{6}{7}$		$\frac{1}{1}$	19
8	$\frac{0}{1}$	$\frac{1}{8}$	$\frac{1}{7}$	$\frac{1}{6}$	$\frac{1}{5}$	$\frac{1}{4}$	$\frac{2}{7}$	$\frac{1}{3}$	$\frac{3}{8}$	$\frac{2}{5}$	$\frac{3}{7}$	$\frac{1}{2}$	$\frac{4}{7}$	$\frac{3}{5}$	$\frac{5}{8}$	$\frac{2}{3}$	$\frac{5}{7}$	$\frac{3}{4}$	$\frac{4}{5}$	$\frac{5}{6}$	$\frac{6}{7}$	$\frac{7}{8}$	$\frac{1}{1}$	23

the set of possible models M consists of two elements: $M_1 = \{P(r) \in \{0, 1\}\}$, where $P(r)$ denotes the probability of drawing a red ball. When $N = 2$, the cardinality of M increases to $|M| = 3$, such that $M_2 = \{P(r) \in \{0, \frac{1}{2}, 1\}\}$, and so on. We view this device sufficiently complicated to prevent subjects from doing any calculation of probability distribution over the possible compositions of the urn and their corresponding weights.[12] In that sense, absent of any additional information from the experts, subjects will –most likely– be unable to compute the set of possible objective models, and end up in a situation close to one of perfect ignorance :

$$M_{100} = \{P(r) \in \{\mathfrak{F}_{100}\}\} \sim \{P(r) \in [0, 1]\}. \tag{1}$$

[11] A Farey sequence of order N, denoted $\mathfrak{F}_N$, is the ascending series of irreducible fractions between 0 and 1 whose denominators do not exceed N (Hardy et al., 1979).

[12] Note for example that even in the case in which all the possible total numbers of balls, and all their possible compositions are assumed to be equally probable, the possible models are not weighted uniformly. E.g., for a total number of balls comprised between 1 and 3, five different models exist: $M_3 = \{P(r) \in \{0, \frac{1}{3}, \frac{1}{2}, \frac{2}{3}, 1\}\}$. Assuming the number of balls in the urn is uniformly distributed between 1 and 3, and that for each case the different models are weighted equally, we end up with weights attached to the possible models that are respectively $q = \{\frac{13}{36}, \frac{1}{12}, \frac{1}{9}, \frac{1}{12}, \frac{13}{36}\}$.

We feel that such a setup, that emphasizes Frank Knight's (1921) original distinction between "measurable" and "unmeasurable" uncertainty (which cannot be represented by numerical probabilities) better reflects the actual state of individuals facing complex problems. Such is the case in a large fraction of modern science problems for example, where the level of abstraction and mathematical requirement to understand processes are such that individuals cannot have a mental construct of the problem they are facing.

2.3 Recruitment and administration

The experiment took place in the laboratory of Bocconi University (Italy). 189 subjects were recruited through an internal experimental economics recruitment system. Each subject was authorized to participate only once and had to sign up in advance for a particular time slot. The experiment was organized into 12 sessions taking place over four days. Each session lasted approximately 75 minutes, and comprised of 13 to 19 subjects. Subjects were provided with paper, pen and a calculator. A session typically started with silent reading of general instructions which were printed and provided to each subject in the cubicle to which she/he was assigned. The experimenter then read once more the instructions aloud and made sure everything was clear, before the subjects started a computerized training session that introduced them to the concepts of risky and model uncertain urns, and decision tables. The experiment was then performed on computers, with the order of tasks being randomized. Overall, the different tasks constituting our experiment were associated with a random incentive system to determine the final payoff. Once all subjects had answered all the questions, they were asked to fill in a short socio-economic questionnaire before being told their payoffs (i.e. which of their decisions had been randomly selected, what was the color of the ball drawn from the urn they chose (if any), and what was the corresponding amount they won). Subjects were then paid in cash a €5 participation fee, and the additional amount (up to €35) won on the basis of the choices they made. The average gain was about €18.50 per subject. The lab experiment was programmed and conducted with the experiment software z-Tree (Fischbacher, 2007). Details of the experimental procedure and instructions are provided in the Supplemental Material available online.

3 Theoretical predictions

In this section, we present our theoretical predictions. We use a specific model of choice which has been proposed by Marinacci (2015) building on Klibanoff et al. (2005). This model, known as the *smooth model*, is fairly general. It enriches and encompasses many of the recent theories of choice under uncertainty in cases where information is incorporated in the decision problem, while allowing for a distinction between the notions of aleatory and epistemic uncertainty.

3.1 The smooth model

The decision maker evaluates acts f whose outcome depends on the realization of an observable state. For each decision, the state may be associated with the color $c \in \{r, b\}$ of the ball (red r, or black b) drawn from the urn under consideration. In other words, each draw may be seen as the realization of a random variable that is characterized by an objective probability distribution, or *model,* corresponding to a specific composition of the urn. For a given model, the uncertainty on the outcome is of the *aleatory* type and is generally called *risk* in economics.[13] Conditionally on the model, the probability of drawing a red (black) ball is therefore *objective* and refers to a physical concept (in this case a specific composition of the urn).

As in many real-life decision problems, it might however be the case that multiple possible compositions of the urn exists, and that the decision maker (DM) is uncertain about which is the correct one. If this is the case, the probability model generating the observations is itself uncertain. We suppose that, following the ex-ante information, the DM is able to posit a set of potential models describing the likelihoods of the different states. This set M of possible compositions of the urn is assumed to be consistent with the available information, which is provided by the experts. In accordance with Wald (1950), it is taken as a datum of the decision problem.[14] In other words, the DM behaves as if she knows that states are generated by a probability model that belongs to the collection M. This therefore means that a second layer of uncertainty may add onto the first layer of risk. This additional layer of uncertainty is however not of the aleatory type. It has rather an *epistemic* nature: the DM does not know which is the most accurate model among the two, and the probability that may be attached to each of them

[13]Other denominations such as *physical*, *objective*, *inside*, or *measurable* uncertainty may also be found in the literature. They all refer to situations in which the probability distribution is are known.

[14]This set of models is analogous to what Ellsberg (1961) calls "reasonable" distributions in his subjective setting. In general, the set M is non-singleton, and the true model is assumed to belong to M (no misspecification issues).

is therefore nothing but a representation of the DM's degrees of belief. Altogether this makes the situation uncertain (or ambiguous) rather than risky. We will refer to this situation as *model uncertainty*. The smooth representation of preferences under model uncertainty assumes that epistemic uncertainty is quantified through a single prior probability measure over the set M of models (Marinacci, 2015). The different possible models –which may be fully characterized by their probability of drawing a red ball– are indexed by a parameter θ and noted $P_\theta(r)$. The DM attaches a probability $\mu(\theta)$ to each of them, reflecting the personal information she has on their likelihood.[15] The DM then chooses the act that maximizes her utility given by the two-stage criterion:

$$U(f) = \mathrm{E}_\theta(v \circ u^{-1}) \left(\sum_{c \in \{r,b\}} \tilde{P}_\theta(c) u\left(f(c)\right) \right). \tag{2}$$

In this expression, E_θ is the expectation operator taken over the prior distribution: $\mathrm{E}_\theta \tilde{X}_\theta = \int_M X(\theta) d\mu(\theta)$, u is the von Neumann and Morgenstern (1944) utility function capturing the DM's risk attitude (i.e. towards aleatory uncertainty), and v captures the attitude towards model uncertainty (i.e. towards epistemic uncertainty). These functions are assumed to be strictly increasing, continuous, and cardinally unique. Criterion (2) may be interpreted as follows. In the first stage, the DM evaluates the expected payoff per each possible model $P_\theta(r)$ and expresses it in monetary terms through a certainty equivalent $c_\theta \equiv u^{-1}\left(\sum_{c\in\{r,b\}} \tilde{P}_\theta(c) u\left(f(c)\right)\right)$. These certainty equivalents c_θ represent the amount of money which would make the DM indifferent between getting such amount for sure and facing the risk associated with the model. One certainty equivalent c_θ may be computed for each model. It only depends on risk attitude via the function u: the more risk averse the DM is, the lower c_θ. In the second stage, the DM addresses model uncertainty and summarizes the utility of the act by evaluating a global expected payoff $\mathrm{E}_\theta v\left(\tilde{c}_\theta\right)$ across the certainty equivalents using her attitude towards model uncertainty v and her prior belief μ. Remark that in the case where both attitudes towards the different types of uncertainty are identical (i.e. whenever v is equal –up to an affine transformation– to u), we recover the classical subjective expected utility model of Cerreia-Vioglio et al. (2013), which encompasses Savage's (1954) model. Representation 2 therefore encompasses both the Savagian subjective expected utility and the classical von Neumann-Morgernstern (when M is a singleton) representations.

[15] In that sense, the prior probability measure μ taken over the set of possible models is subjective: it reflects "personal information on models that the DM may have, in addition to objective information M" (Cerreia-Vioglio et al., 2013).

When attitudes towards risk and model uncertainty are different, representation (2) consists of a version of smooth ambiguity aversion (Klibanoff et al., 2005) where the ambiguity aversion function is recovered by letting $\phi \equiv v \circ u^{-1}$. In that sense, the DM is ambiguity averse if she is more averse to model uncertainty than to risk (i.e. v more concave than u).

3.2 Predictions

We now present the theoretical predictions for individual choices under risk and model uncertainty. We are particularly interested in characterizing the properties of the two functions u and v representing attitudes towards different types of uncertainty, and in confronting the smooth model uncertainty framework to previous results obtained in the literature.

Hypothesis 1. We expect subjects to be both risk and model uncertainty averse, in the sense that they generally prefer the degenerate lottery, giving $\sum_{c\in\{r,b\}} \bar{P}(c)f(c)$ with certainty, to any uncertain situation in which an act f yields $f(c)$ with (expected) probability $\bar{P}(c)$ $\forall c \in \{r, b\}$. By letting C^R and C^{MU} denote the certainty equivalents under risk and model uncertainty, respectively defined as

$$C^R \equiv u^{-1}\left(\sum_{c\in\{r,b\}} P(c)\, f(c)\right) \tag{3}$$

$$C^{MU} \equiv v^{-1}\left(\mathrm{E}_\theta(v \circ u^{-1})\left(\sum_{c\in\{r,b\}} \tilde{P}_\theta(c) u\left(f(c)\right)\right)\right), \tag{4}$$

and by letting $\bar{C}$ be the sure amount corresponding to the expected gain of the prospect, we expect to observe:

$$\bar{C} \geq C^R \tag{5}$$

$$\bar{C} \geq C^{MU}. \tag{6}$$

Expressed in terms of functional properties, these hypotheses simply become $u'' \leq 0$ and $v'' \leq 0$. While the first hypothesis is trivial and has been extensively documented (Holt and Laury, 2002, 2005; Andersen et al., 2008), it is useful for what we are testing next, which is whether ambiguity aversion may result from a stronger aversion towards model uncertainty than towards risk.

Hypothesis 2. Considering the decomposition of ambiguity into risk and model uncertainty, we expect our subjects to prefer risk to model uncertainty, in accordance with the results emphasized by Ellsberg (1961). Furthermore, we also predict that the degree of model uncertainty aversion (and of ambiguity aversion) are finite. In other words, we expect subjects not to behave according to a maxmin decision criterion in the sense of Wald (1950). In terms of certainty equivalents, these predictions may be written (under the assumption of equal expected values) as:

$$C^R \geq C^{MU} > \underline{C}, \tag{7}$$

where $\underline{C}$ refers to the certainty equivalent obtained under the worst possible model. In terms of functions u and v, the first part of (7) simply turns out to be v being more concave than u, in the sense of Arrow-Pratt (i.e. $-\frac{v''}{v'} \geq -\frac{u''}{u'}$), while the second part translates to $-\frac{v''}{v'} < \infty$.[16]

Hypothesis 3. Analogously to what is widely accepted in the risk theory literature, and given the similarity of our procedure with the one used in Holt and Laury (2002, 2005), we expect to observe decreasing absolute risk aversion (DARA) and increasing relative risk aversion (IRRA) for both functions u and v.[17] Specifically, by changing the values of the gains proposed and the probabilities that are associated with these gains, we expect to observe:

$$\frac{\partial}{\partial w_0}\left[-\frac{u''(w_0)}{u'(w_0)}\right] \leq 0 \quad \text{and} \quad \frac{\partial}{\partial w_0}\left[-\frac{u''(w_0)}{u'(w_0)}w_0\right] \geq 0, \tag{8}$$

where w_0 denotes the individual's wealth level, which is composed of the individual's background wealth ω, and the expected gain in each lottery $\bar{o}_p\underline{o}$: $w_0 = \omega + p\bar{o} + (1-p)\underline{o}$. Similarly, we expect the DARA and IRRA properties of function v to be translated to :

$$\frac{\partial}{\partial w_1}\left[-\frac{v''(w_1)}{v'(w_1)}\right] \leq 0 \quad \text{and} \quad \frac{\partial}{\partial w_1}\left[-\frac{v''(w_1)}{v'(w_1)}w_1\right] \geq 0, \tag{9}$$

[16] Or, equivalently $v^{-1}\left(\mathrm{E}_\theta(v \circ u^{-1})\left(\sum_{c\in\{r_i,b_i\}} \tilde{P}_\theta(c)u\left(f_i(c)\right)\right)\right) > u^{-1}\left(\min_\theta \sum_{c\in\{r_i,b_i\}} P_\theta(c)u\left(f_i(c)\right)\right)$.

[17] To be completely precise, we should talk about "decreasing absolute model uncertainty aversion" and "increasing relative model uncertainty aversion" in the case of function v, but for the sake of simplicity we prefer to refer to the widely used acronyms DARA and IRRA for the v function as well. While the DARA property seems well accepted in the literature, note however that the IRRA property is subject to debate when investigated outside of the lab environment (Harrison et al., 2007; Brunnermeier and Nagel, 2008; Chiappori and Paiella, 2011).

where the individual's wealth level w_1, in situations of model uncertainty, is an average of certainty equivalent wealth levels under the two expert's models.[18]

Hypothesis 4. Since ambiguity aversion in this setup results from the combination of attitudes towards risk and model uncertainty, we are able to indirectly characterize the properties of the ambiguity function. In particular, we are interested in knowing whether the absolute ambiguity aversion is constant or whether it is increasing or decreasing, in the sense that agents are willing to pay more or less to remove all source of uncertainty as their level of expected utility increases. Constant absolute ambiguity aversion (CAAA), as argued by Grant and Polak (2013), is an implicit characteristic of many of the ambiguity models proposed in the theoretical literature. It is for example implicitly assumed in the models of Gilboa and Schmeidler (1989); Hansen and Sargent (2001); Maccheroni et al. (2006). On the contrary, decreasing absolute ambiguity aversion (DAAA) is a condition that has been shown to play an important role in the determination of the precautionary saving motive under ambiguity (Gierlinger and Gollier, 2008; Berger, 2014), in the chances of survival of ambiguity averse investors (Guerdjikova and Sciubba, 2015), or in the choice of optimal abatement policies under scientific model uncertainty (Berger et al., 2017). We therefore expect to observe

$$\frac{\partial}{\partial U}\left[-\frac{\phi''(U)}{\phi'(U)}\right] \leq 0, \tag{10}$$

where U is the individual's expected utility level when the probabilities given by experts are averaged.[19] Note that the domain of the ambiguity function $\phi = v \circ u^{-1}$ is different than that of u and v, which are defined over monetary outcomes, while ϕ takes arguments that belong to a set of expected utilities.

4 General results

In this section, we report the results from the CE tasks. These results characterize attitudes towards risk and model uncertainty directly from the choices made by the subjects, and do not necessarily rely on the smooth representation of preferences. To facilitate the derivation of our results, we impose the following

[18] More precisely, in the uncertain situation characterized by $\bar{o}_{\hat{p}_1\hat{p}_2}\underline{o}$, w_1 is computed as $w_1 = \mu(1)u^{-1}\left(\hat{p}_1 u(\omega+\bar{o}) + (1-\hat{p}_1)u(\omega+\underline{o})\right) + \mu(2)u^{-1}\left(\hat{p}_2 u(\omega+\bar{o}) + (1-\hat{p}_2)u(\omega+\underline{o})\right)$. It is then obviously increasing in the background wealth ω, in the payoff outcomes $\bar{o}$ and $\underline{o}$, and in the expert's probabilities $\hat{p}_1$ and $\hat{p}_2$.

[19] Note that in a recent contribution, Baillon and Placido (2016) also tested the CAAA and DAAA hypotheses using a framework different from ours and found evidence of DAAA under Ellsberg's type of uncertainty.

assumption of symmetry that we briefly discuss.

Symmetry: For each model uncertainty situation, the decision maker assigns symmetric weights to the two experts.

This assumption is akin the one generally imposed in Ellsberg's type of experiments, stating that DMs are indifferent between betting on red or black balls. Its empirical validity has for example been supported by Abdellaoui et al. (2011) and Chew et al. (2017). The assumption relies on a symmetry of information argument. Given that the information on the two experts is perfectly symmetric (the experts only differentiate themselves by their names: "Expert 1" and "Expert 2" and their assessments of the urn composition), there should be no reason to attach more weight to one over the other. The prior distribution over the models in consequence reflects this symmetry, so that we have $\mu(1) = \mu(2) = 1/2$.[20]

The CE tasks enable us to obtain a direct measure of the strength of model uncertainty aversion relative to risk aversion. By considering *dogmatic experts* (i.e. experts who assess a probability 100% or 0% or winning), we are able to isolate the effect of model uncertainty alone from risk aversion and to capture directly model uncertainty preferences.[21] Table 2 reports the descriptive statistics of the certainty equivalents associated with the risky and model uncertainty prospects (i.e. $25_{.5}4$ and $25_{1\,0}4$, respectively). We use the decision item at which the subject switches from the sure outcome to the uncertain prospect to approximate her certainty equivalents. Formally, for a subject who switches from the sure outcome o_i after decision $i \in \{1, 2, ..., 10\}$, the certainty equivalent C^J, for $J \in \{R, MU\}$, is given by

$$C^J = \begin{cases} o_1 + \frac{1}{2}(o_2 - o_1) & \text{if} \quad i < 1 \\ \frac{1}{2}(o_{i+1} + o_i) & \text{if} \quad i \in \{1, ..., 9\} \\ o_{10} - \frac{1}{2}(o_{10} - o_9) & \text{if} \quad i > 9 \end{cases} \tag{11}$$

The reported certainty equivalents therefore correspond to the midpoint between

[20] Note that if it was not the case, we would observe subjects' choices to be biased in favor of model uncertainty situations. The results we obtain in this case would only represent a lower bound of what are individuals' exact preferences.

[21] To see this, remark that in the case of model uncertainty with dogmatic experts, the certainty equivalent collapses to $C^{MU} = v^{-1}\left(\sum_{c\in\{r,b\}} \frac{1}{2}v\big(f(c)\big)\right)$, while the certainty equivalent of the 50-50 risky situation is $C^R = u^{-1}\left(\sum_{c\in\{r,b\}} \frac{1}{2}u\big(f(c)\big)\right)$. Furthermore, the presence of dogmatic experts ensures that the results we obtain concerning model uncertainty aversion are, at worst, underestimated. Indeed, if subjects were to consider any other alternative model, the preferences associated with the observed choices would have to reflect a higher aversion to model uncertainty than what is presented in our results (since any other symmetric distribution in the space of expected utilities would consist in a mean preserving contraction of the dogmatic experts' distribution).

the highest outcome for which the uncertain prospect is preferred and the lowest outcome which is preferred to the uncertain prospect. The consistent sub-sample is made of 169 subjects. As can be observed from Table 2, the results confirm

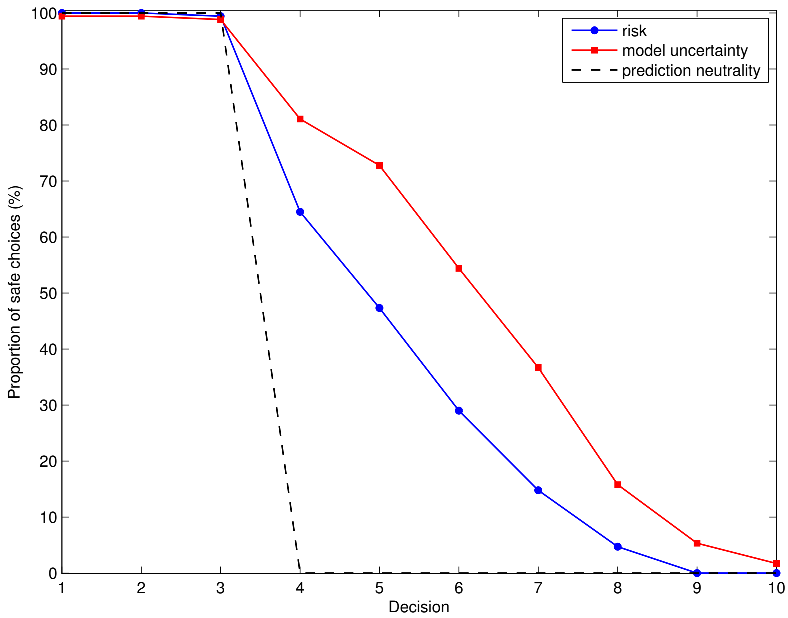
Table 2: Descriptive Statistics of the certainty equivalents

	Mean	**Std. Error**	**Median**	**Min**	**Max**	**Obs.**
C^R	12.57	0.17	13.5	7	16.5	169
C^{MU}	11.04	0.24	11	3	28.5	169

our first two predictions: subjects are on average ready to pay a higher premium –measured as the difference between the expected gain and the certainty equivalent ($\bar{C} - C^J$)– to avoid a situation characterized by epistemic uncertainty than to avoid a situation characterized by aleatory uncertainty. In particular, for an expected outcome $\bar{C} = 14.50$, the mean amount that our subjects deem equivalent to the risky situation is $C^R = 12.57$, while under model uncertainty it is only $C^{MU} = 11.04$. The difference between the certainty equivalents ($C^R - C^{MU}$) is significantly positive (p-value=8.9e-11), and both are higher than the certainty equivalent obtained under the worst possible model $\underline{C} = 4$.

The distribution of C^R second order stochastically dominates that of C^{MU}. While C^R does not first order stochastically dominate (FOSD) C^{MU}, this is only because there is one subject who systematically preferred the model uncertainty situation to the sure outcome (even when the choice was made between €25 for sure, and a situation in which one expert expressed a 100% probability the gain is €25, while the other expert expressed a 100% probability the gain is €4). We can only speculate what the preferences of this subject are. He/she could be a very optimistic subject who always trusts the expert predicting the highest outcome. In that sense, his/her first choice would express indifference between two situations yielding €25. Once we remove this subject from the sample, we recover the result that C^R FOSD C^{MU}. This result is illustrated in Figure 1 and Table 3, which display the proportions of safe choices –expressed by preference for the sure amount– for each of the ten decisions in the risky and model uncertainty situations, respectively. The dashed line represents the prediction under the assumption of neutrality (towards either risk or model uncertainty). In this case, the certainty equivalents of both situations are the same, and the probability that the sure outcome is chosen is 1 for the first three decisions, and 0 for the remaining ones. The blue line presents the observed choice frequency of the

Figure 1: Proportion of safe choices in the CE tasks



sure outcome option in the risk situation. As can be observed, it is at the right of the risk neutral prediction, indicating a tendency for risk aversion among subjects ($C^R \leq \bar{C}$). The red line represents the observed frequency in the case of model uncertainty. It lies to the right of the blue line, suggesting our subjects manifest a stronger aversion to model uncertainty than to risk ($C^{MU} \leq C^R \leq \bar{C}$). We finally note that our subjects did not express extreme model uncertainty aversion (which would have consisted in a proportion safe choice of 100% for each decision). In fact, only two subjects (i.e. 1.2% of the sample) expressed an extreme form of pessimism by systematically selecting the certain outcome when confronted to model uncertainty.[22] We can therefore confidently reject the maxmin expected utility hypothesis in which subjects only consider the worst possible model (Wald, 1950). A Wilcoxon signed-rank test statistically confirms (p-value=3.2e-12) that the risky alternative is valued differently than the corresponding model uncertainty prospect.[23] Table 3 provides the implied interval for the parameters of risk or model uncertainty aversion in the context of the smooth model. For this exercise, we consider the special case of power (or CRRA[24]) functions. Using an

[22]Note that a looser definition of extreme pessimism which considers those subjects who expressed nine safe choices before switching to the model uncertainty situation as being indifferent between the two options, leads to 5.3% of extreme model uncertainty averse individuals.

[23]The significance of the one-sided test, where the alternative hypothesis is that the median of the switching point in the model uncertainty task is greater than in the risk aversion task, is 4.2e-12.

[24]A utility function has the CRRA property if it takes the form $u(x) = \frac{x^{1-r}}{1-r}$, where r is the coefficient of relative risk aversion (when $r = 1$, this collapses to $u(x) = \ln x$).

Table 3: Classification of choices (CE tasks)

Number of safe choices	Range of relative risk or model uncertainty aversion: $u(x)$ or $v(x) = x^{1-r}/1-r$	Proportion of choices	
		Risk	Model Uncertainty
0-1	$r < -1.04$	0.00 %	0.59 %
2	$-1.04 < r < -0.12$	0.56 %	0.59 %
3	$-0.12 < r < 0.12$	34.91 %	17.75 %
4	$0.12 < r < 0.34$	17.16 %	8.28 %
5	$0.34 < r < 0.55$	18.34 %	15.38 %
6	$0.55 < r < 1$	14.20 %	20.71 %
7	$1 < r < 1.55$	10.06 %	21.89 %
8	$1.55 < r < 2.58$	4.73 %	9.47 %
9-10	$2.58 < r$	0.00 %	5.33 %

estimation procedure that will be described in the next section, we also find the best estimates for the coefficients of relative risk and model uncertainty aversion when both u and v are of CRRA type to be respectively $r_u = 0.42$ and $r_v = 0.83$ in the CE tasks.

At the individual level, we finally note that 88 (resp. 62, 19) subjects, representing 52% (resp. 37%, 11%) of the sample expressed a stronger (resp. equal, weaker) aversion towards model uncertainty than towards risk. Following the theoretical model presented above, these subjects may be considered as exhibiting ambiguity aversion, neutrality and loving, respectively.

5 Characterizing smooth preferences

In this section, we also use the choices made in the various PL tasks to further characterize preferences under uncertainty in the context of the smooth model. In particular, we use the 80 binary choices each subject typically provided to infer attitudes towards risk and model uncertainty, and then use this information to quantify the degree of ambiguity aversion. In total, 14% of the choices made in the eight PL tasks were deemed inconsistent (reverse choices or multiple switching points) and were discarded from the analysis. This is in line with what has been previously reported in other lab experiments (Holt and Laury, 2002).

5.1 Preliminary remark

Since the smooth model we study involves two distinct behavioral characteristics (i.e. risk and model uncertainty attitudes), the experimental procedure has to be designed such that it generates data that are rich enough to disentangle the different components and ultimately allows for estimating the subjects' attitude towards ambiguity. The double PL procedure, which presents choices in the presence of both aleatory and epistemic uncertainty, is designed for this purpose. It enables us to jointly elicit risk and model uncertainty attitudes. To see the importance of using a joint procedure, consider the identification of risk and model uncertainty under the smooth model. Assuming expression (2) correctly describes preferences over uncertain alternatives, a subject is indifferent between two options $\bar{o}_p\underline{o}$ and $\bar{o}_{\hat{p}_1\hat{p}_2}\underline{o}$ if and only if:

$$\begin{aligned}(v \circ u^{-1})\Big(pu(\omega+\bar{o}) + (1-p)u(\omega+\underline{o})\Big) = \frac{1}{2}\left(v \circ u^{-1}\right)\Big(\hat{p}_1 u(\omega+\bar{o}) + (1-\hat{p}_1)u(\omega+\underline{o})\Big) \\ + \frac{1}{2}\left(v \circ u^{-1}\right)\Big(\hat{p}_2 u(\omega+\bar{o}) + (1-\hat{p}_2)u(\omega+\underline{o})\Big),\end{aligned} \tag{12}$$

where ω represents background wealth. When considered in terms of attitude towards ambiguity, the identity $\phi = v \circ u^{-1}$ enables us to rewrite (12) as

$$\begin{aligned}\phi\big(pu(\omega+\bar{o}) + (1-p)u(\omega+\underline{o})\big) = \frac{1}{2}\phi\Big(\hat{p}_1 u(\omega+\bar{o}) + (1-\hat{p}_1)u(\omega+\underline{o})\Big) \\ + \frac{1}{2}\phi\Big(\hat{p}_2 u(\omega+\bar{o}) + (1-\hat{p}_2)u(\omega+\underline{o})\Big).\end{aligned} \tag{13}$$

From (12) and (13), it is clear that estimating model uncertainty aversion (v) or ambiguity aversion (ϕ) under the assumption of risk neutrality (u linear) may yield the same result. Ambiguity aversion is therefore significantly overestimated when risk neutrality is assumed.[25] If we relax the assumption of risk neutrality and let risk aversion $-u''/u'$ be positive, it becomes clear from the relationship $-\phi''/\phi' = (-v''/v' + u''/u')/u'$ that the implied degree of absolute ambiguity aversion is lower. One can therefore not capture the distinction between model uncertainty and ambiguity aversion without estimating the level of risk aversion, for which separated risky tasks also need to be performed.

5.2 The double PL tasks

In the double PL tasks, we exploit the comparisons between risk and model uncertainty prospects with experts that are no longer dogmatic. The purely risky tasks are based on Holt and Laury's (2002) mechanism, which has become a standard for elicitation of risk aversion. The model uncertain tasks are constructed analogously. Table 4 illustrates the type of choices proposed in this part of the

[25]We discuss the estimation results of this particular case in Appendix C.

experiment. In this example, Option A offers either €35 or €1 with equal probability, while Option B offers the same outcomes with unknown probabilities. In the latter case, respondents are given information in the form of the two experts' assessments. In the first decision for example, Expert 1 assesses the probability of obtaining €35 to be 50%, while Expert 2 is 100% sure the outcome will be €1. The expected value of Option A (EV^{A}), the expected value of Option B if either Expert 1 or Expert 2 is correct (respectively $\mathrm{EV}_1^{\mathrm{B}}$ and $\mathrm{EV}_2^{\mathrm{B}}$), the average expected value of Option B (EV^{B}) under the assumption of equal weights attached to each expert, and its standard deviation (SD^{B}), are also provided in Table 4, but were not given to subjects during the experiment. While the expected value of Option

Table 4: Payoff table in the model uncertainty aversion tasks

Option A			Option B				EV^{A}	$\mathrm{EV}_1^{\mathrm{B}}$	$\mathrm{EV}_2^{\mathrm{B}}$	EV^{B}	SD^{B}
$\bar{o}$	p	$\underline{o}$	$\bar{o}$	$\hat{p}_1$	$\hat{p}_2$	$\underline{o}$	(€)	(€)	(€)	(€)	(€)
35	0.5	1	35	0.5	0	1	18	18	1.0	9.5	8.5
35	0.5	1	35	0.9	0	1	18	31.6	1.0	16.3	15.3
35	0.5	1	35	0.9	0.09	1	18	31.6	4.1	17.8	13.8
35	0.5	1	35	0.8	0.19	1	18	28.2	7.5	17.8	10.4
35	0.5	1	35	0.8	0.21	1	18	28.2	8.1	18.2	10.0
35	0.5	1	35	0.7	0.31	1	18	24.8	11.5	18.2	6.6
35	0.5	1	35	0.6	0.41	1	18	21.4	14.9	18.2	3.2
35	0.5	1	35	0.55	0.46	1	18	19.7	16.6	18.2	1.5
35	0.5	1	35	0.51	0.50	1	18	18.3	18.0	18.2	0.2
35	0.5	1	35	0.61	0.60	1	18	21.7	21.4	21.6	0.2

Notes: Probabilities always refer to the outcome $\bar{o} \geq \underline{o} \in O$. $\mathrm{EV}^{\mathrm{B}} = \frac{1}{2}\mathrm{EV}_1^{\mathrm{B}} + \frac{1}{2}\mathrm{EV}_2^{\mathrm{B}}$; $\mathrm{SD}^{\mathrm{B}} = \left(\frac{1}{2}(\mathrm{EV}_1^{\mathrm{B}} - \mathrm{EV}^{\mathrm{B}})^2 + \frac{1}{2}(\mathrm{EV}_2^{\mathrm{B}} - \mathrm{EV}^{\mathrm{B}})^2\right)^{0.5}$

A is kept constant throughout the various choices, the expected value of Option B is increasing as one proceeds down the table. The standard deviation, on the other hand, is decreasing (except between the first and second decision). Overall, the decision table is constructed in such a way that, for any increasing utility function, Option B always stochastically dominates (in the first or second order sense) the previous decision as one proceeds down the table.[26] Under the smooth model, this feature should induce subject to switch only once, from Option A to Option B, while progressing down the table. The subjects went through four tasks similar to the one illustrated in Table 4, which vary in the proposed payoffs and probabilities. The set of payoffs and probabilities is designed in a way that the final payoffs span the range of income over which we are estimating model uncertainty aversion, which is the same as the one over which risk aversion is estimated.[27]

[26] It is for example easy to see that Option B in the second decision first order stochastically dominates Option B in the first decision, and that Option B in the fourth decision second order stochastically dominates Option B in the third decision.

[27] In particular, Option A in the three other uncertain tasks takes values as follows: $3.5_{0.5}0.1$, $35_{0.1}1$, $35_{0.9}1$, and Option B covers the space around these values analogously to what is pre-

5.3 Eliciting risk and model uncertainty attitudes

We use each of the subjects' binary choices to estimate the parameters of two latent utility functions that explain these choices. We allow for a stochastic error structure, as opposed to a strictly deterministic structural estimation procedure, as we want to allow for subjects to make some errors and, at the same time, to account for the panel structure of the data. Given the important support for the CRRA hypothesis in the empirical literature on risk aversion (Harrison, Lau, and Rutström, 2007; Brunnermeier and Nagel, 2008; Chiappori and Paiella, 2011), but at the same time the experimental evidence found in favor of increasing relative risk aversion (IRRA) (Holt and Laury, 2002), we maintain a generic parametric structure for the identification problem. We let both utility functions representing risk and model uncertainty attitudes be of the expo-power (EP) form (Saha, 1993). In the case of risk, this means that the utility function takes the following form:

$$u(x) = \frac{1 - \exp\left(-a_u(\omega + x)^{1-r_u}\right)}{a_u}. \tag{14}$$

This representation includes CRRA and constant absolute risk aversion (CARA) as special cases, and exhibits the desirable properties of decreasing absolute risk aversion and increasing relative risk aversion for positive values of the parameters a_u and r_u (Abdellaoui, Barrios, and Wakker, 2007).[28] Note the presence of ω, representing background wealth in expression (14). As is generally the case in the experimental literature, we assume $\omega = 0$. It should however be clear that in a situation in which $\omega > 0$, the same observed choices would imply higher risk aversion. Using the procedure proposed by Andersen et al. (2008), we then construct the expected utility of the two options comprising each decision by using candidate values of parameters a_u and r_u, and a linking index in order to infer the likelihood of the observed choice. The parameters of the latent utility function (14) are then chosen in order to maximizes the likelihood of getting the observed ranking of the different options, taking into account a Luce (1959) error specification with a structural noise parameter.[29] The first part of Table 5 presents the estimates obtained from the risky tasks. Given the prominent position

sented in Table 4. For a detailed description of our experimental design, please refer to the Online supplemental Appendix.

[28]As is well known, the Arrow-Pratt index of relative risk aversion of the EP function is $-u''(x)(\omega + x)/u'(x) = r_u + a_u(1 - r_u)(\omega + x)^{1-r_u}$. It is then easy to see that this function exhibits CRRA of value r_u when $a_u = 0$, and CARA of a_u when $r_u = 0$.

[29]The statistical specification we use allows for taking into account the correlation between responses given by the same subject. Robust estimates considering clustering corrections are provided in Appendix B. There is essentially no difference in the significance of our estimates in this case.

CRRA has achieved in the theoretical and empirical literature, we provide both the estimates for the cases in which u is of the CRRA and EP type. The estimate

Table 5: Estimates of risk, model uncertainty and ambiguity preferences

	u		v		ϕ	
	CRRA	EP	CRRA	EP	CRAA	EP
a		0.0294^{***} (0.00215)		0.152^{***} (0.0542)		-1.802 (0.9655)
r	0.279^{***} (0.0119)	0.135^{***} (0.0193)	0.738^{***} (0.0210)	0.467^{***} (0.0542)	0.534^{***} (0.0261)	0.86^{***} (0.0452)
noise parameter	0.103^{***} (0.00327)	0.105^{***} (0.00330)	0.0358^{***} (0.00237)	0.0534^{***} (0.00343)	0.0476^{***} (0.00213)	0.0363^{***} (0.00184)
Observations	5320	5320	7570	7570	7570	7570
Loglikelihood	-1550.3	-1516.8	-3682.5	-3682.1	-3680.6	-3675.1

Notes: Luce error specification is used in the estimation. Standard errors in parentheses. The EP risk specification is used to estimate v and ϕ. * $p - value < 0.05$, ** $p - value < 0.01$, *** $p - value < 0.001$

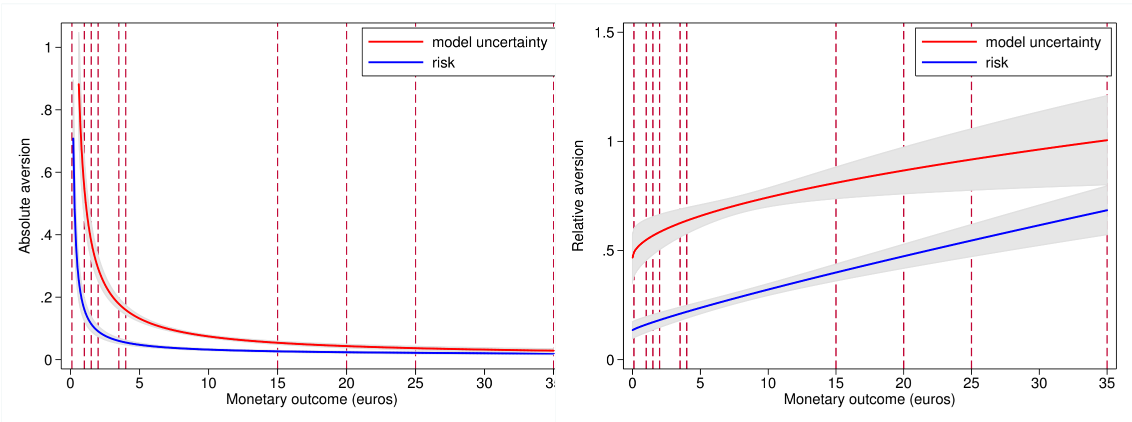
of the CRRA parameter we obtain is 0.28, which is lower than the one we found using the CE task only. When the EP specification is considered, we estimate $r_u = 0.135$ and $a_u = 0.029$, which implies IRRA. While the focus of our analysis is on comparing these estimates with the ones obtained for the model uncertainty function v, we note that their absolute magnitudes are consistent with the results obtained by Holt and Laury (2002); Andersen et al. (2008). We however recognize that the estimates we obtain only hold locally over the domain of stakes offered in our experiment. The last two rows of Table 5 present information about the data used (30 risk aversion choices for each of the 189 subjects, minus the inconsistent choices that are discarded) and the resulting log-likelihood values. As can be seen, the log-likelihood of the EP specification is slightly better than the CRRA one, but this should not be surprising given that the estimates are all significant, and the hypothesis $a_u = 0$ is therefore rejected. Given the superiority of the EP specification in explaining the observed choices in the risky tasks, this is the specification we consider in the remaining part of the estimation procedure. We then estimate the model uncertainty aversion function v, which takes the general EP form:

$$v(CE) = \frac{1 - \exp\left(-a_v (CE)^{1-r_v}\right)}{a_v}, \tag{15}$$

where CE represents the certainty equivalent wealth for a given model θ: $CE \equiv u^{-1}\Big(\hat{p}_\theta u(\bar{o}) + (1 - \hat{p}_\theta) u(\underline{o})\Big)$. The second part of Table 5 presents the estimates obtained from our five uncertain PL tasks. Estimates for the special cases of v being of the CRRA type ($a_v = 0$) are also provided for indicative purposes. In that case, the coefficient estimated is significantly higher than the one obtained in the case of risk. It should however be noted that this specification leads to a smaller log-likelihood value than the general expo-power formulation (15). Focusing on the EP specification, we remark that the estimates we obtain ($a_v = 0.152$ and $r_v = 0.467$) with the joint identification procedure are both significantly positive. This implies our subjects exhibit both decreasing absolute model uncertainty aversion and increasing relative model uncertainty aversion.

Our interest lies in comparing the estimates obtained for model uncertainty with the ones obtained for risk aversion. In Figure 2, we provide the paths of estimated absolute and relative aversion indexes for both risk and model uncertainty over the experimental prize domain. As predicted, we observe that the indexes are both decreasing in the monetary outcome when considered in absolute terms and increasing in relative terms (DARA and IRRA). Interestingly, we

Figure 2: Absolute (left) and relative (right) risk and model uncertainty aversion using EP estimates (95% confidence in grey).



also directly observe from Figure 2 that the degree of model uncertainty aversion is significantly higher (in both absolute and relative terms) than the one of risk aversion. This result confirms our main hypothesis that subjects are more averse to model uncertainty than to risk. Specifically, while the index of relative risk aversion is respectively 0.32 and 0.62 when the monetary outcome considered is either $x = 10$ or $x = 30$, the index of relative model uncertainty aversion takes values of 0.74 and 0.96 for the corresponding outcomes. Note that in the special case where both u and v are of the CRRA type, the indices of relative aversion to risk and model uncertainty are $r_u = 0.28$ and $r_v = 0.73$ when jointly estimated.[30] These differences observed between the attitudes towards objective and

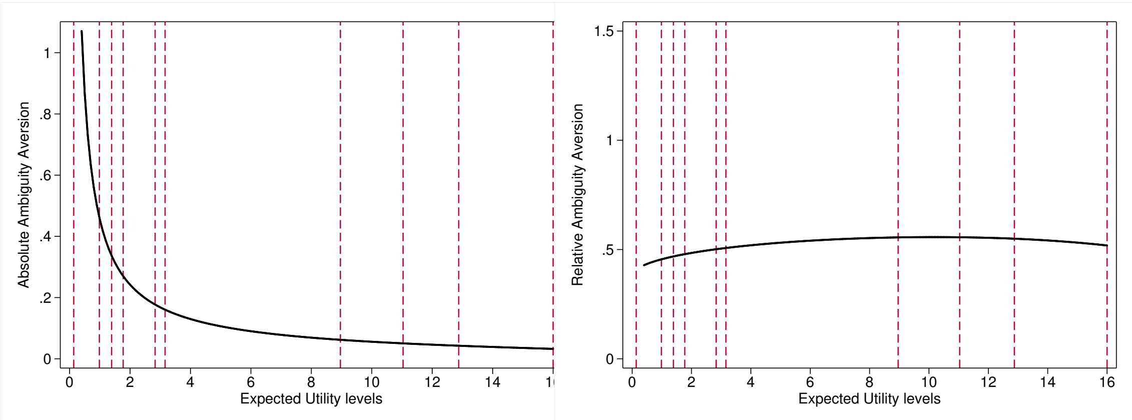
[30]In order to assess the sensitivity of the model uncertainty aversion index to variations in relative risk aversion, we also used the maximum likelihood procedure to estimate r_v using

subjective probabilities now enable us to quantify the attitude subjects manifest towards ambiguity.

5.4 The implications for ambiguity attitude

The joint characterization of functions u and v representing the subjects' attitudes towards two different types of uncertainty has an important direct implication for ambiguity aversion. Using the identity $\phi \equiv v \circ u^{-1}$ and the results obtained in the previous section, we are now able to characterize directly the attitude subjects manifest towards ambiguity, and to compute the parameters of absolute and relative ambiguity aversion (see Appendix A for the detailed analytical computations under the double EP specification). These parameters are represented in Figure 3. While we observe a clear decreasing trend in the degree of absolute ambiguity aversion, we remark that the degree of relative ambiguity aversion seems to be fairly constant over the domain considered. As already mentioned, it should however be clear that the domain of the ambiguity function ϕ is not the same monetary outcome domain as the one used in the study of u and v. Instead, ϕ is defined over expected utility levels U. In this sense, the vertical dashed red lines in Figure 3 represent the levels of utility obtained for the corresponding monetary outcomes in Figure 2, when the utility function u is of the EP type and coefficients are the ones reported in Table 5.

Figure 3: Absolute (left) and relative (right) ambiguity aversion obtained with EP function estimates



To assess the robustness of the constant relative ambiguity aversion (CRAA) result featured in Figure 3, we apply the joint estimation procedure directly to u

different (exogenously given) values of r_u. These additional results are presented in Appendix C.

and ϕ (both of which are of the EP type). In other words, we let the ambiguity aversion function be:

$$\phi(U) = \frac{1 - \exp\left(-a_\phi (U)^{1-r_\phi}\right)}{a_\phi}, \tag{16}$$

where U represents the expected utility obtained under a given model θ: $U \equiv \hat{p}_\theta u(\bar{o}) + (1 - \hat{p}_\theta) u(\underline{o})$, and u is defined as in equation (14). The estimated results are provided in the last two columns of Table 5. In this case, the coefficient a_ϕ of the EP formulation is not significant at the 5% level ($p - value = 0.062$). The function describing preferences towards ambiguity is therefore instead better represented by a CRAA function. Under this particular specification, the constant relative ambiguity aversion parameter is estimated to be 0.53. It does not perfectly match the value observed in Figure 3, but this should not be surprising given that the ambiguity functions do not share the same specifications in the two cases. If we instead consider the case of u being CRRA, we also obtain a non significant coefficient a_ϕ ($p - value = 0.093$) under the EP specification, and estimate the coefficient $r_\phi = 0.62$ under constant relative ambiguity aversion.[31]

6 Conclusion

Uncertainty is pervasive in collective as well as in individual decision making. During the past few years, a vast literature aiming at better formalizing the decision process in the face of uncertainty has been growing and encompassing multiple academic fields. This body of research investigates how individuals integrate available information in the process of decision making through the development of theoretical frameworks and experimental analyses. In particular, multiple decision models have been developed to account for attitudes towards ambiguity. These models have been adopted to explain individuals' behavior in multiple contexts and are increasingly applied to prescribe optimal strategies in the face of uncertainty.

The growing application of ambiguity aversion models calls for the development of experimental efforts enabling a better understanding of the underlying mechanisms at play and a more precise quantification of ambiguity preferences, similar to what has been done in the study of risk. In this paper, we provide new experimental evidence on ambiguity attitudes by means of attitudes towards

[31]In this case, the result could have been obtained directly from the twofold CRRA estimation results provided in Appendix A, given that ϕ is of the CRAA type with $r_\phi = \frac{r_v - r_u}{1 - r_u}$, when both u and v are CRRA (Berger et al., 2017).

model uncertainty in relation to risk. In particular, our design enables us to disentangle the role played by aleatory and epistemic uncertainty in determining individuals' ambiguity attitudes. We are then able to quantify, through a joint elicitation procedure, the extent to which ambiguity aversion exists as well as the properties of the ambiguity aversion function in the context of the smooth model (Klibanoff et al., 2005; Marinacci, 2015).

There are two main findings emerging from our analysis. First, we show that subjects tend to be both risk and model uncertainty averse, but exhibit stronger aversion to model uncertainty than to risk. Following the smooth model of choice under uncertainty, we interpret this behavioral characteristic as evidence of ambiguity aversion. Using a joint estimation procedure, we elicit the degree of ambiguity aversion, which we estimate to be around 0.5 when considered in relative terms. Second, investigating in more detail attitude towards model uncertainty, we find that model uncertainty aversion is decreasing in wealth when considered in absolute terms, and increasing when considered in relative terms. In regards to ambiguity attitude, we find evidence of decreasing absolute ambiguity aversion (DAAA) and constant relative ambiguity aversion (CRAA).

Appendix

A Absolute and relative ambiguity aversion

When the functions characterizing risk and model uncertainty preferences are both of the expo-power type, and are respectively defined as $u(x) = \frac{1-\exp(-a_u x^{1-r_u})}{a_u}$ and $v(x) = \frac{1-\exp(-a_v x^{1-r_v})}{a_v}$, the ambiguity function $\phi \equiv v \circ u^{-1}$ may be written as:

$$\phi(U) = \frac{1 - \exp\Big(- a_v \big(- \frac{\ln(1-a_u U)}{a_u}\big)^{\frac{1-r_v}{1-r_u}}\Big)}{a_v},$$

where U belongs to the space of expected utilities. In that case, it may be shown that the Arrow-Pratt absolute ambiguity aversion index is:

$$-\frac{\phi''(U)}{\phi'(U)} = \frac{a_v \big(\frac{1-r_v}{1-r_u}\big)\Big(\frac{-\ln(1-a_u U)}{a_u}\Big)^{\frac{r_u - r_v}{1-r_u}} + \big(\frac{a_u}{\ln(1-a_u U)}\big)\frac{r_u - r_v}{1-r_u} - a_u}{1 - a_u U}. \tag{A.1}$$

It is then easy to see that in the special case in which u and v are both of the CARA type (i.e. when $r_u = r_v = 0$), this index collapses to:

$$-\frac{\phi''(U)}{\phi'(U)} = \frac{a_v - a_u}{1 - a_u U}. \tag{A.2}$$

This index is positive whenever $a_v > a_u$, so that absolute ambiguity aversion results from higher absolute model uncertainty aversion than absolute risk aversion. Similarly, in the special case in which u and v are both of the CRRA type (i.e. when $a_u = a_v = 0$), the absolute ambiguity aversion becomes:

$$-\frac{\phi''(U)}{\phi'(U)} = \frac{r_v - r_u}{(1 - r_u)U}, \tag{A.3}$$

and is positive whenever $r_v > r_u$.

B Robust estimates of risk and model uncertainty preferences

Since each of our subjects provided multiple choices in the experiment, we may want to correct for the possible correlation of errors associated with a given subject (which may for example be due to unobserved individual effects). In this case, the residuals from the same subject are treated as potentially correlated, and the correction is made when calculating standard errors of estimates. As argued in Andersen et al. (2008), this procedure allows heteroskedasticity between and within clusters, as well as autocorrelation within clusters, and generalizes the "robust standard errors" approach popular in econometrics. The estimates of risk and model uncertainty aversion with robust standard errors are presented in Table B.1.

Table B.1: Robust estimates of risk, model uncertainty and ambiguity preferences

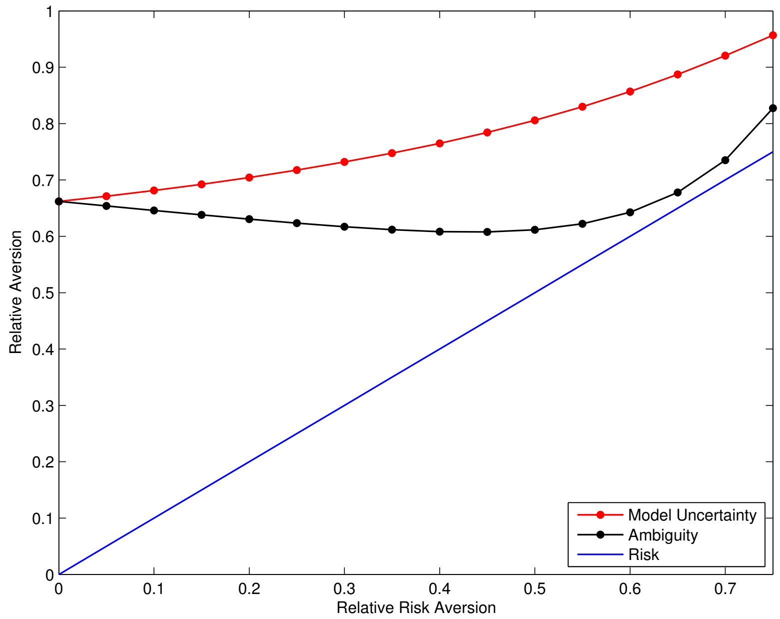
	u		v	
	CRRA	EP	CRRA	EP
a		0.0294*** (0.00398)		0.152*** (0.0252)
r	0.279*** (0.0281)	0.135*** (0.0278)	0.738*** (0.0444)	0.467*** (0.0842)
noise parameter	0.103*** (0.00378)	0.105*** (0.00384)	0.0358*** (0.00492)	0.0534*** (0.00643)
Observations	5320	5320	7570	7570 0
Loglikelihood	-1550.3	-1516.8	-3682.5	-3682.1

Notes: Estimation uses Luce error specification. Standard errors in parentheses. The EP risk specification is used to estimate v. * $p-value < 0.05$, ** $p-value < 0.01$, *** $p-value < 0.001$

C Sensitivity of model uncertainty aversion

In order to get further insight regarding the sensitivity of model uncertainty aversion to risk aversion, we used the results from our PL tasks to estimate the degree of relative model uncertainty aversion alone, for values of relative risk aversion ranging from 0 to 0.75. It should be clear that in this situation the estimation procedure is not anymore jointly realized (given the exogenously chosen values of risk aversion considered). In Figure C.1, we present the results of these estimations in the particular case where both u and v are of the CRRA type. For any value of relative risk aversion, we remark that the relative model uncertainty parameter estimated (represented in red) is significantly higher than the 45 degree line (in blue) representing relative risk aversion. In particular, it goes from $r_v = 0.66$ when $r_u = 0$ to $r_v = 0.96$ when $r_u = 0.75$. We also present in black the degree of relative ambiguity aversion implied by the twofold CRRA specification. Following Berger et al. (2017), the index of relative ambiguity aversion in this situation is given by $r_\phi = \frac{r_v - r_u}{1 - r_u}$. As can be observed, r_v and r_ϕ both coincide

Figure C.1: Relative model uncertainty aversion for different values of relative risk aversion when both u and v are of the CRRA type



when risk neutrality is considered (i.e. $r_u = 0$). Following the discussion provided in the main body of the paper, we claim that the level of ambiguity aversion is overestimated when measured in situations of risk neutrality, and remark that for positive values of r_u the index of relative ambiguity aversion is always lower than the one of relative model uncertainty aversion.

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