ARE POLICYMAKERS AMBIGUITY AVERSE?

(Short title: Policymakers and Ambiguity)*

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Abstract

We investigate the ambiguity preferences of a unique sample of real-life policymakers at the Paris UN climate conference (COP21). We find that policymakers are generally ambiguity averse. Using a simple design, we are moreover able to show that these preferences are not necessarily due to an irrational behavior, but rather to intrinsic preferences over unknown probabilities. Exploring the heterogeneity within our sample, we also show that the country of origin and the degree of quantitative sophistication affect policymakers' attitudes towards compound risk, but not towards ambiguity. Robustness results are obtained in a lab experiment with a sample of university students.

Keywords: Ambiguity aversion, experiment, policymakers, compound lotteries, non-expected utility, subjective probabilities

JEL Classification: D81

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Behavioral traits and preferences of decision makers affect the way they take their decisions. While this assertion is generally true for decisions taken at the individual level, it may also be important for collective decisions (depending on the way they are taken). Although it has long been argued that the behavioral traits of policymakers do not matter much at the time of making decisions –because of the broader interests these individuals are supposed to represent– in practice, these elites' preferences may ultimately affect policy choices and, therefore, have an impact on entire social groups (Hafner-Burton *et al.*, 2015).[1] In this context, it becomes crucial to better understand the behavioral traits and preferences characterizing these elites who actually make policy decisions, rather than extrapolating from convenience samples of university students.[2]

Given the pervasiveness of uncertainty in real-life decision problems and the wide interest decisions in the presence of uncertainty has attracted in economics and psychology, we focus our study on the attitude that policymakers exhibit towards one important type of uncertainty referred to as *ambiguity*. How do policymakers react to the presence of ambiguity? Does their behavior correspond to a form of irrationality, or does it represent intrinsic preferences? These questions are important as they help to understand and predict policymakers' behaviors in the face of ambiguity (for example, in the models we use to analyze public policies). In particular, ambiguity attitude may for instance impact the analysis of strategic interactions between policymakers regarding emissions or international environmental agreements (Harstad, 2012; Battigalli *et al.*, 2015). Besides these descriptive applications, a better understanding of what drives ambiguity preferences also bears important normative implications. In particular, the question concerning the ratio-

[1]In the real world indeed, political elites actually make many pivotal decisions affecting the course of economic policy (Hafner-Burton *et al.*, 2013). Think, for example, of the monetary policy decisions taken by the Governing Council of the European Central Bank or of the climate policy decisions taken at the international level.

[2]While most of the evidence about individuals' preferences has come from experimental works on –generally, Western– university students who are easily available at limited cost, little is known about the preferences of real-life experienced elites, who are more difficult to obtain as subjects (because they are generally busy and unwilling to reveal information about their decision-making processes and choices (Hafner-Burton *et al.*, 2013)).

nality of ambiguity aversion is of great importance, as ambiguity preferences have been shown to affect substantially the choice of optimal policies. In the context of climate change, for example, ambiguity aversion would imply more severe environmental policies under scientific ambiguity (Millner *et al.*, 2013; Berger *et al.*, 2017).

In this paper, we seek to provide formal answers to the above-mentioned questions by conducting a field experiment on real-life policymakers at a major UN conference. Leveraging on an extremely simplified design, we are able to show that policymakers are ambiguity averse and that this attitude has less to do with an irrational behavior (such as the inability to reduce compound lotteries) than with intrinsic preferences over unknown probabilities.

Background *Ambiguity* characterizes "situations in which a decision maker does not have sufficient information to quantify through a single probability distribution the stochastic nature of the problem she is facing" (Cerreia-Vioglio *et al.*, 2013a). It is distinct from the notion of *risk*, which refers to situations in which probabilities of random events are perfectly known. Ambiguity is present in virtually all real-life situations and plays a major role in most economic problems. For example, decisions concerning fiscal reforms of social security systems are made in the presence of demographic ambiguity, while central banks' responses to inflation and unemployment are designed under structural economic ambiguity. Ambiguity is also at the heart of climate decision-making, where it arises from the science of climate itself and from various socioeconomic and technological drivers. Since Ellsberg's (1961) seminal article, it has been widely recognized that people are in general *ambiguity averse* in the sense that they prefer situations in which probabilities are perfectly known to situations in which they are unknown. Whether the driving force at the heart of ambiguity aversion corresponds to an irrational behavior comparable to the one highlighted by Allais (1953), or a rational response to situations of uncertainty, however, remains an open question.

In a context where an increasing number of criticisms have been raised against the use of classical techniques originally developed to deal with risk in problems involving ambiguity[3] and that has seen the emergence of various calls for integrating alternative approaches for issues relevant to policy choices in the presence of ambiguity,[4] it becomes crucial to better understand what are the ambiguity preferences of the individuals actually making policy decisions and what drives these preferences. These insights ultimately determine the status and the role ambiguity models can play in informing policymaking.

This paper Given that devising policy strategies in the context of climate change is an activity strongly affected by the presence of ambiguity,[5] we specifically focus on *climate* policymakers. We ran our experiment at the 21st session of the Conference of the Parties (COP21) to the United Nations Framework Convention on Climate Change (UNFCCC).[6] Our respondents comprise a unique sample of 80 policymakers directly involved in climate negotiations. Most of them are elite bureaucrats who have a substantial influence

[3]The standard way to deal with ambiguity when designing policies has, until now, remained to follow the Subjective Expected Utility (SEU) approach proposed by Savage (1954), which states that any source of uncertainty can be quantified in probabilistic terms and hence *considered as a risk*, which can then be analyzed using the expected utility framework.

[4]In the context of climate change, Kunreuther *et al.* (2013) for example wrote: *"Studies of climate change and its impacts rarely yield consensus on the distribution of exposure, vulnerability or possible outcomes. Hence policy analysis cannot effectively evaluate alternatives using standard approaches, such as expected utility theory and benefit-cost analysis. [...] For most issues relevant to policy choices, the solution is to use more robust approaches to risk management that do not require unambiguous probabilities. Risk management strategies designed to deal with the uncertainties that surround projections of climate change and their impacts can thus play an important role in supporting the development of sound policy options."* While in the context of macroeconomic policy, Caballero (2010) wrote: "*The reaction of human beings to the truly unknown is fundamentally different from the way they deal with the risks associated with a known situation and environment. In realistic, real-time settings, both economic agents and researchers have a very limited understanding of the mechanisms at work. This is an order-of-magnitude less knowledge than our core macroeconomic models currently assume [...] A number of researchers have sought to design policy frameworks that are robust to small modeling mistakes by the policymaker. [...] This strategy is clearly a step in the right direction, although I suspect the deviations they consider from the core models are still too local to capture the enormous uncertainties and confusion that policymakers face in realistic nontrivial scenarios. But this literature has many of the right words in it. The natural next step for this robustness literature is to incorporate massive uncertainty.*"

[5]It requires dealing with ambiguity on many dimensions (Heal and Millner, 2014) and concerns events that have never been encountered before, for which our lack of knowledge (in the form of a lack of data or little empirical information) renders the assessment of precise probabilities difficult.

[6]The COP is the supreme decision-making body of the UNFCCC. All States that are Parties to the Convention are represented at the COP, at which they review the implementation of the Convention and any other legal instruments that the COP adopts and take decisions necessary to promote the effective implementation of the Convention, including institutional and administrative arrangements (see more on www.unfccc.int).

over what their respective governments ultimately agree on in the game of international negotiations. They sit at the negotiation table and have substantial autonomy, as well as formal or informal permissions.

The objective of this paper is twofold. *(i)* First, it aims to characterize the ambiguity preferences of those individuals who actually make policy decisions (in a supposedly rational way), and *(ii)* second, it aims to determine whether these preferences are associated with irrational behavior arising, for example, from an inability to reduce compound lotteries (i.e. failing to perform basic probability computations). By interviewing subjects originating from 49 countries and with different backgrounds, and by running a second experiment in the laboratory with university students, we are furthermore able to achieve a third objective, which consists in *(iii)* investigating how general the findings concerning ambiguity preferences and their behavioral foundations are across groups of individuals, cultures and contexts.

Two main findings emerge from our analysis: *(i)* policymakers are generally ambiguity averse, and *(ii)* this attitude is not necessarily associated with the inability to reduce compound lotteries. The combination of *(i)* and *(ii)* has important policy implications: the individuals actually making policy decisions are ambiguity averse for a reason which is not necessarily related to a form of irrational cautiousness, but may stem from a specific treatment of probabilities that are not objectively known. One additional finding then emerges while investigating the sources of heterogeneity in the policymakers' responses and comparing them with those of the students: *(iii)* the country of origin of the policymakers and their degree of quantitative sophistication significantly affect the way they deal with compound lotteries, but not their ambiguity attitude. More specifically, policymakers originating from OECD countries, or exhibiting a relatively higher degree of quantitative sophistication, share similar patterns of preferences towards uncertainty as the students. In other words, the main results obtained in the field experiment are maintained in the lab with a totally different group of individuals, provided that some specific characteristics are controlled for.

1 Related literature

This article is closely related to three strands of literature. The first is experimental research on individuals' attitudes towards ambiguity. Ambiguity aversion has been and continues to be one of the most intensively experimentally investigated phenomena in economics. Existing studies replicating Ellsberg's (1961) experiment have typically confirmed the conjecture of widespread ambiguity aversion (see e.g. Trautmann and van de Kuilen, 2014 for a recent survey). While most of these studies have generally considered Western university students as subjects, the same overall findings have been replicated with people from the general population (Dimmock *et al.*, 2015; Dimmock *et al.*, 2016), business owners (Viscusi and Chesson, 1999), trade union leaders (Maffioletti and Santoni, 2005), managers and actuaries (Hogarth and Kunreuther, 1989; Ho *et al.*, 2002), farmers (Akay *et al.*, 2012; Bougherara *et al.*, 2017), and children (Sutter *et al.*, 2013; Prokosheva, 2016). To our knowledge, our study is the first that investigates ambiguity preferences of a pool of overconfident and experienced elites, such as real-life policymakers, who moreover come from all over the world (see Bosetti *et al.*, 2017).

The second is a literature that has studied the rationality of Ellsberg choices using various approaches. From a theoretical point of view, Cerreia-Vioglio *et al.* (2011) analyze preferences in the presence of ambiguity that satisfy two basic tenets of rationality (weak order and monotonicity), and Gilboa *et al.* (2010); Cerreia-Vioglio (2016) characterize two notions of rationality under different models of ambiguity aversion. Specifically, they suggest that a choice may either be *objectively rational* (if the decision maker –DM– can convince others that she is right in making it) or *subjectively rational* (if others cannot convince the DM that she is wrong in making it), and proposed a set of axioms capturing the regularities satisfied by these two notions of rationality. From a philosophical point of view, Al-Najjar and Weinstein (2009) provide a critical assessment of the ambiguity aversion literature, arguing that ambiguity aversion leads to irrational behaviors as, for example, aversion to information. On the contrary, Gilboa *et al.* (2008, 2009, 2012) and Gilboa and Marinacci (2013) argue that rational DMs may violate Savage axioms by expressing ambiguity aversion. These authors argue that this type of behavior does not necessarily imply that the DMs are unable to think probabilistically or fail to compute probabilities correctly, but rather that they acknowledge that the expected utility theory requires more information than they actually have. Finally, from an experimental point of view, Halevy (2007) and Chew *et al.* (2017) report the results of experiments suggesting that attitudes towards compound risk and ambiguity are tightly associated. However, Halevy (2007) also shows that people, on average, prefer compound risk situations to ambiguous ones. Qualitatively similar results were obtained by Armantier and Treich (2016), who show that not only was attitude to compound risk tightly associated to attitude towards ambiguity, but so was attitude towards complex risk.[7] Abdellaoui *et al.* (2015); Aydogan *et al.* (2018) also find an association between compound risk reduction and ambiguity neutrality, but the association they find is, however, weaker than in Halevy's data. Interestingly, these authors show that, for mathematically more sophisticated subjects, compound risk reduction is compatible with ambiguity non-neutrality, suggesting that failure to reduce compound risk and ambiguity non-neutrality do not necessarily share the same behavioral grounds. Relatedly, Prokosheva (2016) obtains a significant relationship between arithmetic test scores and compound risk reduction in an experiment with adolescents (no such relationship is found between ambiguity neutrality and these test scores). By exploring the relationship between preferences towards ambiguity and compound risk using a design, which, at the same time, makes explicit the distinction between objective and subjective probabilities and remains extremely sim-

[7]Complex risk in Armantier and Treich's (2016) design refers to a situation in which the probabilities associated with the different events are non-trivial to compute. For example, if a pair of colored balls draw simultaneously from two transparent urns (one from each urn).

ple, we contribute to this literature in providing experimental evidence that ambiguity aversion may not be due to an inability to perform basic probability computations.

Finally, our paper also relates to a literature which studies the way international interactions are affected by individual preferences and behavioral traits. From an economic perspective, Bramoullé and Treich (2009) analyze the effect of risk and risk aversion in a strategic global pollution context. Boucher and Bramoullé (2010) study how risk and risk aversion affect international agreements regarding the supply of global public goods. In international studies, Hafner-Burton *et al.* (2015) study the impact of patience and strategic skills of policy elites on international treaty outcomes, while Hafner-Burton *et al.* (2017) study how patience and risk aversion help to explain actual policymakers' variations in their willingness to cooperate in the face of uncertainty. By studying the ambiguity attitude of the individuals directly involved in international negotiations, we open the way for going beyond the study of risk aversion and for integrating ambiguity aversion directly into models of international negotiation.

2 Experimental design

In this section, we present the framework used in our experiments. Our study consists of a main experiment with policymakers at the climate convention COP21 and a supplementary experiment with students. The main experiment is an artefactual field experiment that enables us to investigate the policymakers' attitude towards ambiguity and towards two other types of uncertainty presented in two stages. The supplementary experiment is a standard laboratory experiment. It enables us to examine the robustness of the findings from the main experiment under different conditions and with distinct subjects. We leverage on an extremely simplified design that we implement in a simple context of decision-making, ruling out other potential confounding factors.[8]

Having a simple, unframed design, which can be easily understood and incentivised,

[8]The experimental instructions, data and programmes used are available online.

is particularly important in such an experiment. Yet, it comes at a cost of remaining far from the decision context policymakers face in their professional life, where they might be subject to the competence hypothesis (Heath and Tversky, 1991). While the presence of widespread scientific and socioeconomic uncertainties surrounding climate change ensures that the climate policymakers' decision problems are comparable to the ones used in our experiment (Chambers and Melkonyan, 2017), the evidence supporting the external validity of Ellsberg measures is however relatively scarce. Some recent studies support the idea that experimental measures of ambiguity predict behavior outside the lab (see for example Engle-Warnick *et al.*, 2007; Muthukrishnan *et al.*, 2009; Ross *et al.*, 2010). Overall, Abdellaoui *et al.* (2011) have shown that positive and significant correlations exist between the pessimism indexes (encompassing ambiguity aversion) in different sources of ambiguity, suggesting that that there exists a correlation between the attitudes towards natural and Ellsberg type events.

2.1 The choice situations

Our subjects may be confronted with four different uncertain situations across the experiment. These situations are represented by urns containing balls that can be either red (R) or black (B). Each urn describes a particular type of uncertainty. They are characterized as follows:

- *Urn 1 (risk)*: the number of red and black balls is perfectly known;
- *Urn 2 (compound risk)*: the number of red and black balls is determined by flipping a fair coin in the air;
- *Urn 3 (model uncertainty)*: the number of red, black and the total number of balls in the urn are unknown (reflecting therefore a situation of ignorance), but information is provided by two "experts", each giving her own assessment of the composition of the urn;

- *Urn 4 (Ambiguity à la Ellsberg)*: the total number of balls in the urn is known, but the exact composition of the urn is unknown.

In our experiment, the particular urn compositions (R,B) are as follows: Urn 1 is (50,50); Urn 2 is either (100,0) or (0,100) (flipping a fair coin determines which of the two); Urn 3's composition is unknown, but Expert 1's assessment is that there are only red balls, while Expert 2's assessment is that there are only black balls; Urn 4 is composed of 100 balls (there could therefore be between 0 and 100 red (or black) balls in it). The graphical representation of these urns is illustrated in Figure 1. The urns are presented two-by-

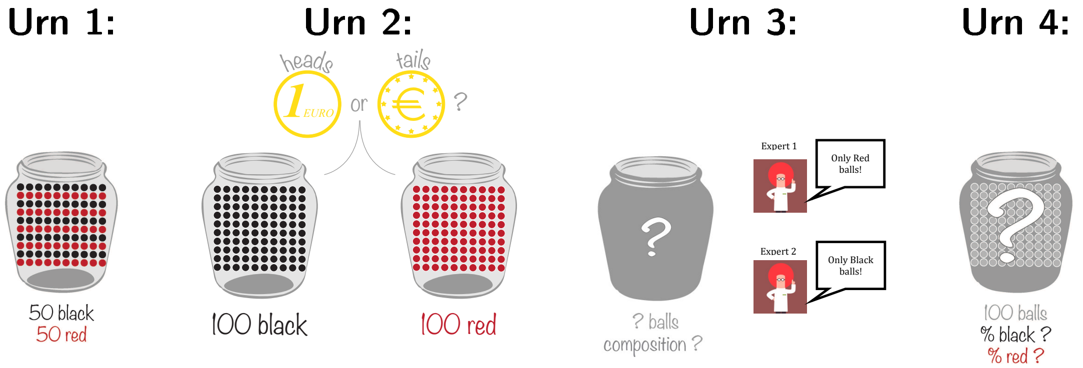


Figure 1: *The different uncertain situations represented by urns*

two in a randomized sequence (random lottery pairs –or RLP– design, see Harrison and Rutström, 2008). In order to replicate results previously obtained in the literature while introducing the model uncertainty framework, the risky Urn 1 is kept as a reference and systematically paired with the other three urns. In each task, subjects are required to place a bet on the color of the ball drawn from each urn (R or B), and to decide on which urn to place their bet (allowing for indifference).[9] The bet is said to win the subject a given amount in euros and to entail no losses otherwise.

This set of choices enables us to test the predictions of expected utility (EU) theory and directly detect potential deviations from it in situations of uncertainty. In the first

[9]Allowing for indifference when eliciting ambiguity aversion was for example recently used by Dimmock *et al.* (2015). Note that we did not give information about the way the urn were selected in the case of a choice expressing indifference. This ensures that the subjects who report to be indifferent between urn A and urn B were indeed exhibiting indifference and not a preference for a mixture between the two urns.

two urns, the probability of drawing, say a red ball $P(R)$, is objectively known to be 1/2. The only difference between the two is that Urn 1 corresponds to a simple risk, while Urn 2 is presented as a compound risk. In Urns 3 and 4, the probabilities are unknown. However, subjects are still given some information taking the form of the experts' assessments of the urn's composition (in Urn 3), or the total number of balls (in Urn 4). In both Urn 2 and Urn 3, the uncertainty is presented in two stages. The main difference being that the probabilities associated with the different compositions of the urn are objectively known in the case of compound risk, but not in the case of model uncertainty.

2.2 Main experiment

We conducted the main experiment as an artefactual field experiment at the COP21 to the UNFCCC, held in Paris in December, 2015. The experiment consisted of a sequence of tasks using a RLP procedure. In each task, subjects faced pairs of uncertain alternatives (represented by the urns) and were asked to pick one of two, or to express indifference. The payoff was set to €50 for a correct bet. The 80 subjects who participated in this experiment originated from 49 different countries. In individual in-person interviews lasting about 15 minutes, we prompted respondents who volunteered for the study with a few questions framed in the context of climate change,[10] before confronting them with the RLP tasks. The experiment was conducted with pen and paper. Subjects gave written consent to participate in the experiment. In order to elicit meaningful and reliable choice behaviors, while at the same time limiting logistical complications going together with the monetary transactions, we offered payment to only a subset of the subjects (between-subjects random incentive system).[11]

[10]Specifically, we asked them their assessed probability distribution over 2100 temperature increases based on current nationally determined contributions (see Bosetti *et al.*, 2017).

[11]We mentioned at the beginning of the questionnaire: "1 in every 50 respondents will be chosen randomly to play for real money and once you are finished you will find out whether it is you! For the rest of you the decisions will be hypothetical, but since you all have a chance to be selected, it is in your best interest to make choices according to your true preferences." This incentivises subjects to make

2.3 Supplementary experiment

The robustness round was run as a laboratory experiment with university students. It took place at BELSS (Bocconi Experimental Laboratory for the Social Sciences). 189 subjects were recruited through an internal recruitment system. Each subject was authorized to participate only once and had to sign up in advance for a particular time slot. Subjects were provided with paper, pen and a calculator. The experiment was performed on computers, with the order of tasks being randomized. The experiment was incentivised on the basis of a within-subjects random incentive system[12] and the payoff reached €15 if the bet was correct. Once all subjects had answered 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, and what was the corresponding amount they won). Subjects were then paid in cash a €5 participation fee and the additional amount won on the basis of the choices they made. The laboratory experiment was programmed and conducted with the experiment software z-Tree (Fischbacher, 2007).

2.4 Discussion of the design

Cognizant of the limited time policymakers would be able to dedicate to the experiment, we opted for a design of minimal complexity, that was yet able to explore the crucial differences between various types of uncertain situations. We here discuss the design simplifications.

Incentive system While recognizing there is potentially a fundamental psychological difference between facing a set of tasks with one being payed with certainty (within-

honest and non-arbitrary choices

[12]This means that each subject was paid on the basis of only one of the choices made, drawn at random at the end of the experiment. Note that the RLP tasks were part of a broader experiment on model uncertainty consisting in 9 tasks and lasting about 75 minutes. Overall, the average gain in this experiment was about €18.50 per subject.

subjects random incentive system) and a set of tasks with one being payed only with some probability (between-subjects random incentive system), results in the literature suggest that the two random incentive methods lead to substantially similar results (Beaud and Willinger, 2015; Charness *et al.*, 2016). The potential loss of motivation or effort induced by the between-subjects random incentive system that we used in the main experiment is moreover mitigated by the nature of the respondents, who agreed to spend time in their busy schedule, manifesting thereof sufficient intrinsic motivation to perform well for the purpose of the scientific study.[13]

Degenerate compositions The second stage of uncertainty in Urns 2 and 3 is structured so that one of the two events is associated with a degenerate 100% probability. The reason for this is to keep the problem's computational complexity minimal. Moreover, this also allows us to isolate the effect of model uncertainty alone and to minimize the potential role played by cognitive skills in the reduction of compound lotteries. While risk has *stricto sensu* disappeared in the second stage, we argue that subjects still need to make *some* computational effort to find out the final probability of winning the prize. This is reinforced by the fact that our subjects are given the choice of the color on which to bet, which requires them to consider the different possibilities depending on the outcome of the coin toss in Urn 2. We are not the first to consider compound risk with a degenerate second stage. For example, Halevy (2007) also uses this specific form to test for reduction of compound lotteries. He finds differences in the way subjects value it relative to simple risk, rejecting, therefore, any systematic reduction. To make the "model uncertainty" situation fully comparable with the objective compound risk, experts are presented as being dogmatic (in the sense that they both assign a 100% probability to one particular event). This allows us to isolate directly the impact of model uncertainty

[13]For example, the proportion of subjects making combinations of choices that could be considered as a priori irrational (i.e. any of the 6 possible combinations with an averse attitude towards one type of uncertainty, neutral attitude towards another and loving towards the last one) is lower for policymakers than for students (4.4% vs 10.1%).

aversion from risk aversion (see below). While this simplification in the design might partly reduce the realism of the task, overall any concern associated with the incompleteness of the extremely simplified design should then equally influence both Urn 2 and Urn 3.

Model misspecification While two experts' assessments were provided in Urn 3, it should be clear that the experts were not physically present during the experiment. This is close to many real life situations in which expert opinions are presented without the physical presence of the experts themselves. However, this feature may lead subjects to downplay the experts' role and to (partially) ignore them, making the situation closer to that of full ignorance. Given our design, we cannot guarantee that subjects did not have an alternative urn composition in mind other than the ones given by the experts when making decisions involving Urn 3 (i.e. misspecification issues). To minimize the potential bias, we paid particular attention to the way we presented the experts and their assessments.[14] Yet, the presence of dogmatic experts ensures that the results we obtained concerning model uncertainty aversion are at worst underestimated. Indeed, if subjects were to consider any other possible composition of the urn (i.e. any other probabilities between 0% and 100%, as a possibility), then preferences associated with the observed choices would reflect a higher aversion to model uncertainty than what is presented in our results, given that any other symmetric distribution in the space of expected utilities would consist of a mean preserving contraction of the dogmatic experts' distribution.

[14]For that purpose, we specifically mentioned the following in the instructions: "These experts are the best we could find for this problem. They are both experienced and both have excellent track records". Overall, we are confident that most of our subjects incorporated the information provided by the experts when making their choices, as we are able to show, using data from Berger and Bosetti (2018), that subjects' choices monotonically follow the stochastic dominance criteria induced by changes in assessments provided by the two experts.

3 Theory and predictions

This section analyzes how recent theories of decision-making under uncertainty predict individual's choices in our different tasks. We follow the decomposition of uncertainty into distinct layers proposed by Marinacci (2015); Hansen and Marinacci (2016) and make the distinction between the notions of aleatory and epistemic uncertainty. Since our design enables us to measure attitudes directly from behavior, we express our predictions from a general point of view, abstracting from any specific model of choice. In Appendix A, we add some structure by considering a version of the smooth model proposed by Klibanoff *et al.* (2005). To facilitate the derivation of our predictions in the analysis that follows, we make the assumption that subjects are indifferent between betting on Red or Black. Under this assumption, subjects assign symmetric probabilities to the two experts in Urn 3 and to the possible compositions of the urn in Urn 4. This assumption relies on a symmetry of information argument: since the information about the experts is perfectly symmetric in Urn 3, there is a priori no reason to believe that one of them may deserve more weight than the other. The prior distribution over the models should, in consequence, reflect this symmetry. The same argument holds for Urn 4 in which there is symmetry in the absence of information. These arguments mirror what Schmeidler (1989) calls an "unwritten rule saying that symmetric information with respect to the occurrence of events results in equal probabilities" or, more generally, to the *principle of insufficient reason* (or *principle of indifference)*.[15]

3.1 The setting

The DM evaluates bets whose outcome depends on the realization of an observable state of the world. In the experiment, there are only two events of importance for each

[15] In practice, it might well be the case that some of the subjects unequally weighted the two experts, for example by over-weighting the most optimistic or pessimistic expert. If this were indeed the case, we would expect subjects' choices to be biased in favor of model uncertainty situations, given that subjects are given the choice of the color on which to bet. In that case, the results concerning model uncertainty aversion we found would only represent a lower bound of what might be individuals' real preferences.

bet on a specific Urn i: either a red ball is drawn or a black ball is drawn. In this context, each ball draw may be seen as the realization of a random variable that can be described by a specific objective *model*.[16] The uncertainty about the outcome of a given model is of the aleatory type and generally called *risk* in economics. This risk is directly relevant to the DM since it determines the probability with which each event realizes. Probabilities of the different events can, in this case, be defined as *objective* (they refer to a physical concept, represented by a specific composition of the urn).

As is the case in the vast majority of decision problems, when facing Urns 2, 3 and 4, the DM does not know exactly which probability model generates the observations. In such a situation, another layer of uncertainty adds to the layer of risk. This layer of uncertainty, which concerns the possible compositions of the urn, may have different natures. It may be another layer of risk, in which case the uncertain situation is simply an instance of compound risk, as in Urn 2. Or, as in Urns 3 and 4, it may be characterized by *epistemic* uncertainty, if multiple compositions of the urn are possible, but the DM does not know how likely each of them is. When this is the case, the probabilities in this extra layer of uncertainty are not objective anymore, but represent the DM's degree of belief in each potential model.[17] As in Cerreia-Vioglio *et al.* (2013b) and Marinacci (2015), we assume that the DM knows that the possible alternative models belong to a subset M of the collection of all probability measures. In our case, this is the information given to subjects that allows them to posit this subset. Elements of M are seen as possible compositions of the urn that are consistent with the available information and that could hence be selected by Nature to generate observations. In accordance with Wald (1950), the set M is assumed to be taken as a datum of the decision problem.[18]

[16]The term *"model"* here refers to a probability model (or distribution). In our experiment, a model corresponds to a possible composition of the urn.

[17]As such, these probabilities are *subjective*. This is in line with Schmeidler (1989), who interprets subjective probabilities of an event as the number used in calculating the expectation of a random variable. Remark that this definition includes objective probabilities as a special case, where we know exactly which number to use.

[18]Note that in general incompleteness of information makes the set M non-singleton, contrary to what is assumed in the standard subjective expected utility theory. The true model is assumed to belong to

3.2 Predictions

Following Ellsberg's (1961) seminal idea and the subsequent experimental literature that has implemented it,[19] we predict that our subjects will generally be ambiguity averse, in the sense of preferring the risky urn (Urn 1) over the ambiguous one (Urn 4). This behavioral characteristic, which violates key axioms of classical models of choice under uncertainty, has however been subject to heated debates among scholars, questioning whether preferences emerging from observed choices in Ellsberg's type of experiments should be considered as a deviation from rationality, or instead, should be seen as a rational way of coping with ambiguity. Considering a possible instance of ambiguity, composed by model uncertainty and risk, we also expect this behavior to be related to a preference for risk (Urn 1) over model uncertainty (Urn 3). In that sense, we expect our subjects not to reduce model uncertainty. On the contrary, we posit that, given an instance of compound risk sufficiently easy to reduce, subjects will be indifferent between the simple risk (Urn 1) and compound risk (Urn 2) situations. In that sense, we expect them to reduce compound risk. These predictions may be summarized as follows:[20]

$$Urn\,1 \succ Urn\,4, \tag{1}$$

$$Urn\,1 \succ Urn\,3, \tag{2}$$

$$Urn\,1 \sim Urn\,2. \tag{3}$$

We also expect an association between expressions (1) and (2). Statement (3) says that different layers of objective sources of uncertainty are reducible: people are indifferent between risk and compound risk when the expected values of the lotteries are identical.

M, abstracting therefore from misspecification issues.

[19]See Trautmann and van de Kuilen (2014) for a recent survey of this literature.

[20]As is standard in economics, we assume DMs have a preference $\succeq$ over situations that describe how they rank the different alternatives. In particular, we write $a \succeq b$ if the DM prefers situation a to situation b in the sense that she either strictly prefers situation a to situation b, $a \succ b$, or is indifferent between the two, $a \sim b$.

This rational behavior of subjects has, however, been seriously challenged in the literature, which has usually found that subjects often manifest aversion towards compound risks, and that this behavior is to some extent associated with that towards ambiguity (Halevy, 2007; Chew *et al.*, 2017, see Section 1).[21] Although we do not explicitly test any specific theory that might explain why compound risk may be associated with ambiguity, we leverage on our extremely simplified design to shed new light on this issue. If cognitive inability is at the basis of failures to reduce compound probabilities (Abdellaoui *et al.*, 2015; Harrison *et al.*, 2015; Prokosheva, 2016) –reflecting a deficiency of the 'human intuitive statistician' (Budescu and Fischer, 2001)– then by designing a situation where compounding is extremely simple, as in Urn 2, we can rule out instances purely based on this limited cognitive ability. We therefore expect subjects to correctly reduce compound risk if the probabilities of the two layers of uncertainty are objectively given: $Urn\,1 \sim Urn\,2$, but not if the probability assessments are given by experts (Urn 3). In this case indeed, the second layer of uncertainty is no longer objective and we expect to observe $Urn\,1 \nsim Urn\,3$ if the subjects perceive objective and subjective probabilities differently. In particular, while an expected utility maximiser would be indifferent between the two uncertain situations, we expect subjects in our experiment not to evaluate the two 50%-50% distributions of $Urn\,1$ and $Urn\,3$ in the same way. Specifically, we expect a majority of subjects to opt for the risk rather than the model uncertainty situation ($Urn1 \succ Urn3$), revealing in this way higher aversion towards model uncertainty than to risk.

4 Results

This section reports the results from both experiments with policymakers and students. We start by providing a short description of our data and then compare the

[21]Note also that Harrison *et al.* (2015) test the reduction of compound lotteries with objective probabilities in both a setup with multiple choices associated with a random incentive system and in one with a unique choice. They find evidence of violation of reduction of compound lotteries in the first case, but not in the second.

results from different uncertain situations. We provide additional details and analyses in Appendix B.

4.1 The data

In the main experiment the subject pool consists of 80 policymakers originating from 49 different countries.[22] Most of them are climate negotiators (43 subjects, of which 3 are heads of delegation), while 19 subjects are representatives of NGOs (21%), 10 subjects are researchers/academics, 4 subjects are representatives of the private sector and 4 subjects self-identified with a different category.[23] An interesting characteristic of this sample is that the subjects involved are, a priori, used to being confronted with uncertainty (in the form of ambiguity or model uncertainty) in their professional activities.[24] Climate policymakers should indeed be accustomed to work with alternative models and probabilistic projections that are essential for policy evaluation. The average respondent in the main experiment is a 40 year-old man, with one child, holding at least a master's degree. The subject sample in the supplementary experiment consists of 189 university students. Their average age is around 21 years and 46% of them are female. They either study economics (33%), management (32%), finance (10%), marketing (6%), law (5%), or have identified themselves as following another major.

Figure 2 presents the data collected in the two experiments, classifying subjects into different types, depending on the choices they made in the three RLP tasks.

With three options per pairwise comparison, there are in principle 27 combinations of choices possible based on the attitude (averse, neutral or loving) exhibited towards

[22]The term *policymaker* is here defined in its broadest sense as characterizing individuals who take part in the process of consultation and negotiations. In particular, the set includes negotiators, who have access to all negotiation tables and represent their countries in the negotiation of international climate agreements; and delegates, who represent the civil society (special interest groups, NGOs, academics and other researchers, etc.) and have access to some of the discussion and negotiation rooms.

[23]Further descriptive statistics of the sample are presented in Appendix B.1.

[24]This sophistication constitutes a major difference with the convenience samples typically used in experiments. Elites such as climate policymakers tend to have large amounts of context-specific experience, which possibly affects the way they make decisions (Hafner-Burton *et al.*, 2013).

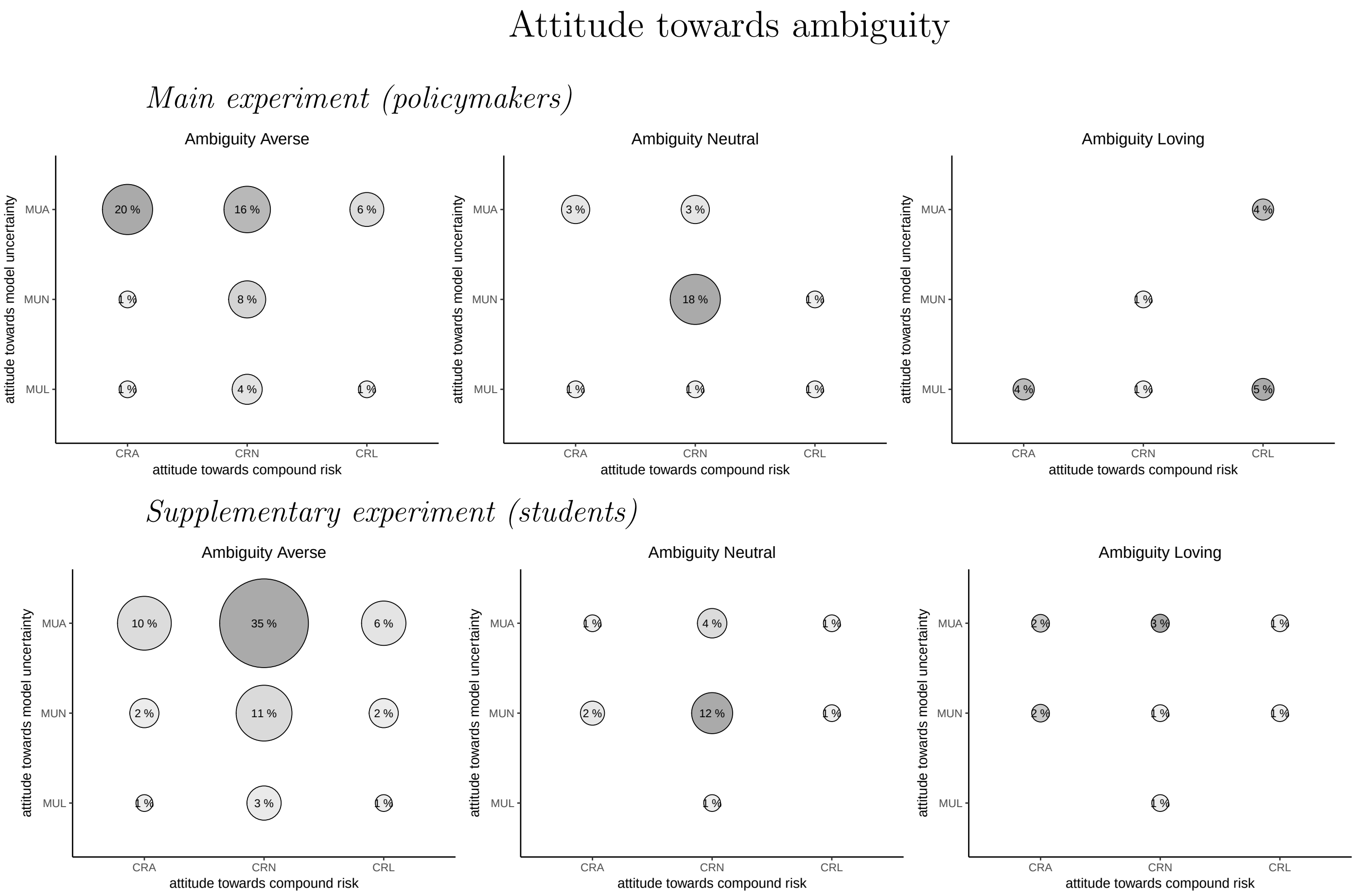


Figure 2: *Classification of subjects depending on their attitudes towards different types of uncertainty*

Notes: N=80 in the main experiment. N=189 in the supplementary experiment. MUA, MUN, MUL refer to, respectively, an averse, neutral or loving attitude towards model uncertainty. CRA, CRN, CRL refer to, respectively, an averse, neutral or loving attitude towards compound risk.

each type of uncertainty (ambiguity, model uncertainty and compound risk). As can be observed in Figure 2, the majority of subjects are located in the left panels, representing ambiguity aversion. In what follows, we analyze in more details the nature of these choices and the association that may exists between attitudes towards different types of uncertainty.

4.2 Ambiguity neutrality, reduction and the nature of probabilities

We are first interested in assessing whether subjects behave in accordance with the EU axioms (and as a consequence are indifferent between the four uncertain urns). As can be observed in Figure 2, this is the case for 18% of the policymakers and 12% of the students. Table 1 reports the results of the association between ambiguity neutrality and reduction of both compound risk and model uncertainty in the two experiments. It sheds light on our predictions and compares the results with the ones expected under the EU theory. The rows in the table distinguish subjects who are ambiguity neutral (i.e. $Urn\ 1 \sim Urn\ 4$) from those who are not. A non-neutral attitude may either express ambiguity aversion or ambiguity seeking. The first two columns distinguish between subjects who either reduce compound lotteries (ROCL) and are, therefore, classified as compound risk neutral (i.e. $Urn\,1 \sim Urn\,2$) and those who do not reduce them. The second two columns divide subjects between those who reduce model uncertainty (ROMU) (i.e. $Urn\ 1 \sim Urn\,3$) and those who do not. The results reveal the anticipated pattern: 72% (58 subjects out of 80) of the policymakers are ambiguity non-neutral, 51% (41 out of 80) reduce compound lottery, and 71% (57 out of 80) express a different attitude towards risk than towards model uncertainty. A similar pattern emerges from the results of the supplementary experiment, shown in the bottom part of Table 1, where 79% of the students (150 out of 189) reveal a non-neutral attitude towards ambiguity, 71% (134 out of 189) reduce compound risk, and 69% (130 out of 189) do not reduce model uncertainty. Similarly to preceding studies, we observe an association between ambiguity neutrality and the reduction of compound risks. However, several subjects who are ambiguity non-neutral *do* reduce compound lotteries (24 out of 58 policymakers and 102 out of 150 students), so that preferences towards ambiguity cannot simply be interpreted as an inability to handle uncertainty presented in different stages. In particular, while 79% of the ambiguity neutral policymakers reduce compound risks (22 out of 28 subjects),

Table 1: *Association between ambiguity neutrality, ROCL and ROMU in the two experiments*

Ambiguity neutral		ROCL No	ROCL Yes	ROMU No	ROMU Yes	Total
*Main experiment (policymakers)**						
No	Count	34	24	50	8	**58**
	Expected	*28.3*	*29.7*	*41.3*	*16.7*	
Yes	Count	5	17	7	15	**22**
	Expected	*10.7*	*11.3*	*15.7*	*6.3*	
Total		**39**	**41**	**57**	**23**	**80**
*Supplementary experiment (students)***						
No	Count	48	102	118	32	**150**
	Expected	*43.7*	*106.3*	*103.2*	*46.8*	
Yes	Count	7	32	12	27	**39**
	Expected	*11.3*	*27.7*	*26.8*	*12.2*	
Total		**55**	**134**	**130**	**59**	**189**

Notes: * Fisher's exact test (2-sided) with ROCL: 0.006; Fisher's exact test (2-sided) with ROMU: < 0.001
** Fisher's exact test (2-sided) with ROCL: 0.113; Fisher's exact test (2-sided) with ROMU: < 0.001

only 41% (17 out of 41) of the policymakers who reduce compound risk are also ambiguity neutral (17 out of 41). In comparison with the expected frequency under a null hypothesis of independence, the observed number of subjects indifferent between Urns 1, 2 and 4 is increased by 50%. Interestingly, Table 1 reveals instead a strong association between attitudes towards model uncertainty and ambiguity. Out of the 23 policymakers who reduce model uncertainty, 65% of them (15 subjects) also expressed ambiguity neutrality, representing 68% of the 22 ambiguity neutral subjects. The observed frequency of policymakers implicitly expressing $Urn\,1 \sim Urn\,3 \sim Urn\,4$ is therefore 2.4 times more than the expected frequency under the null hypothesis of independence. Similarly, out of the 57 subjects who did not reduce the two layers of uncertainty when confronted with model uncertainty, only 12% of them (7 subjects, which represents less than half of the expected frequency under the hypothesis of independence) were also ambiguity neutral. Finally, out of the 58 subjects who did not express ambiguity neutrality, 34 did not reduce the compound risk with objective probabilities, while 50 did not reduce the model uncertainty (this corresponds respectively to an increase of 25% and 21% with respect to the independence hypotheses).[25] The association between ambiguity neutrality and ROMU, therefore, seems stronger than with ROCL. In the case of policymakers, however, this result needs confirmation given that a Fisher exact test rejects both the independence hypothesis between ambiguity neutrality and ROCL (p-value=0.006) and the one between ambiguity neutrality and ROMU (p-value<0.001). In the case of students, the Fisher exact test rejects (p-value<0.001) the independence hypothesis between ambiguity neutrality and ROMU, but not the one (p-value=0.113) between ambiguity neutrality and ROCL. In total, the share of ambiguity non-neutral policymakers (students) who did not reduce model uncertainty is 86% (79%), while the share of ambiguity non-neutral subjects who did not reduce compound risk is 59% (32%).

We then perform a couple of logistic regressions to examine further the ambiguity preferences of our subjects. The dependent variable AN_i in the regressions is ambiguity neutrality (i.e. indifference between Urn 1 and Urn 4). We estimate the following equation

$$\Pr(AN_i) = \exp(z_i)/\left(1 + \exp(z_i)\right), \tag{4}$$

where

$$z_i = \beta_0 + \beta_1 ROCL_i + \beta_2 ROMU_i + \beta_3 X_i. \tag{5}$$

In this expression, the main variables of interest are $ROCL_i$ and $ROMU_i$, binary-coded variables reporting whether the subject reduces compound risk and the model uncertainty situation, respectively. X_i are other characteristics of subject i such as her gender and age (and in the case of policymakers, her number of children). The results of the logistic regressions are reported in Table 2. In regressions (1) and (2), ROCL and ROMU are in

[25] Similarly, the observed frequency of students implicitly revealing indifference between Urns 1, 2 and 4 is 16% higher than the expected frequency under a null hypothesis of independence, while the frequency of subjects implicitly revealing indifference between Urns 1, 3 and 4 is 2.2 times the expected frequency under the null hypothesis.

Table 2: *Characteristics of Ambiguity Neutrality: Logistic analysis*

	Ambiguity neutrality					
	Policymakers			Students		
	(1)	(2)	(3)	(1)	(2)	(3)
Reduction of compound lottery (ROCL)	2.056***		0.654	0.902		0.977
	(0.708)		(0.892)	(0.470)		(0.524)
Reduction of model uncertainty (ROMU)		2.978***	2.640***		2.203***	2.226***
		(0.692)	(0.804)		(0.416)	(0.424)
Observations	77	77	77	189	189	189

Notes: The table reports coefficients estimates from logistic regressions with ambiguity neutrality as the outcome variable. Gender, age (and the number of children in the main experiment) are control variables in all regressions.
Standard errors in parentheses
** $p < 0.05$, *** $p < 0.01$

turn used as predictors of ambiguity neutrality. As can be observed, both coefficients are significantly positive in the main experiment, suggesting that an identical attitude towards aleatory and epistemic uncertainty enables us to predict ambiguity neutrality with statistical significance. The odds of being ambiguity neutral when expressing ROMU corresponds to 19.6 times the odds when it is not the case (p-value<0.001). Similarly, ROCL alone also has a significant impact on ambiguity neutrality (p-value=0.004). However, we can infer from Table 2 that the odds ratio is much lower than the one corresponding to the attitude towards model uncertainty (indeed the odds ratio in this case is 7.8). As we adjust the logistic regression to account for the two effects simultaneously in (3), the effect of compound risk attitude becomes non-significant (p-value = 0.46) and the only significant effect comes from the attitude towards model uncertainty (odds ratio=14, p-value=0.001). In the supplementary experiment with students, ROMU predicts ambiguity neutrality (odds of being ambiguity neutral are 8.3 times higher, p-value<0.001), while ROCL does not (p-value = 0.06).

The probability of being ambiguity neutral in the sample of policymakers (students) is 27.5% (20.6%). It increases to 62% (44%) when the individual exhibits the same attitude towards risk and model uncertainty and drops to 10% (8%) when this is not the case (when model uncertainty attitude is considered in isolation). This means that the change in probability increases by 51 (36) percentage points and is significant (p-

value<0.001) when attitude towards model uncertainty goes from 'the same attitude as the one towards risk' to 'a different attitude than the one towards risk'. In comparison, compound risk neutrality only increases the predicted probability of ambiguity neutrality by 34 (12) percentage points when considered in isolation, going from 9% to 43%, with a p-value=0.067 (from 11% to 23%, p-value =0.008). These results confirm the stronger association between ambiguity neutrality and a similar attitude towards risk and model uncertainty, rather than between ambiguity neutrality and compound risk reduction.

4.3 Beyond neutrality vs. non-neutrality

In this section, we move beyond the dichotomous analysis of neutral/non-neutral attitudes. In Table 3, we present the results of the experiments when the distinction is made between the different attitudes towards the type of uncertainty j: aversion ($Urn\ 1 \succ Urn\ j$), neutrality ($Urn\ 1 \sim Urn\ j$), and loving ($Urn\ 1 \prec Urn\ j$), where $j = \{2, 3, 4\}$ refers to compound risk, model uncertainty and ambiguity, respectively. As before, results are presented for the main experiment in the upper panel and for the supplementary experiment in the lower panel. As can be observed, 57.5.% (70.4%) of the policymakers (students) exhibit ambiguity aversion, 51.2% (70.9%) reduce compound risk, and 51.2% (62.4%) are more model uncertainty averse than risk averse.[26] As previously observed, there is an association between attitudes towards ambiguity and compound risk, but this association is weaker than the one between ambiguity and model uncertainty. Comparing the observed frequencies with the ones obtained under the null hypothesis of independence, we observe that the number of ambiguity averse policymakers that are also compound risk averse increases by 30.4%, while this number rises to 44.1% when ambiguity aversion is considered together with having a stronger aversion to model uncertainty than to risk. The same pattern arises when considering neutral and loving attitudes. The associations we found between the different attitudes towards

[26] A decomposition of these attitudes by geographical areas for the policymakers is provided in Appendix B.2.

Table 3: *Association between attitudes towards ambiguity, compound risk and model uncertainty*

Ambiguity		**Compound risk** $Urn1 \succ Urn2$	**Compound risk** $Urn1 \sim Urn2$	**Compound risk** $Urn1 \prec Urn2$	**Model uncertainty** $Urn1 \succ Urn3$	**Model uncertainty** $Urn1 \sim Urn3$	**Model uncertainty** $Urn1 \prec Urn3$	**Total**
*Main experiment (policymakers)**								
$Urn1 \succ Urn4$	Count	18	22	6	34	7	5	**46**
	Expected	*13.8*	*23.6*	*8.6*	*23.6*	*13.2*	*9.2*	
$Urn1 \sim Urn4$	Count	3	17	2	4	15	3	**22**
	Expected	*6.6*	*11.3*	*4.1*	*11.3*	*6.3*	*4.4*	
$Urn1 \prec Urn4$	Count	3	2	7	3	1	8	**12**
	Expected	*3.6*	*6.2*	*2.3*	*6.2*	*3.5*	*2.4*	
Total		**24**	**41**	**15**	**41**	**23**	**16**	**80**
*Supplementary experiment (students)***								
$Urn1 \succ Urn4$	Count	23	93	17	98	26	9	**133**
	Expected	*23.2*	*94.3*	*15.5*	*83*	*41.5*	*8.4*	
$Urn1 \sim Urn4$	Count	4	32	3	10	27	2	**39**
	Expected	*6.8*	*27.7*	*4.5*	*24.3*	*12.2*	*2.5*	
$Urn1 \prec Urn4$	Count	6	9	2	10	6	1	**17**
	Expected	*3*	*12.1*	*2*	*10.6*	*5.3*	*1.1*	
Total		**33**	**134**	**22**	**118**	**59**	**12**	**189**

Notes: * Fisher's exact test with compound risk: 0.001; Fisher's exact test with model uncertainty: < 0.001

** Fisher's exact test with compound risk: 0.188; Fisher's exact test with model uncertainty: < 0.001

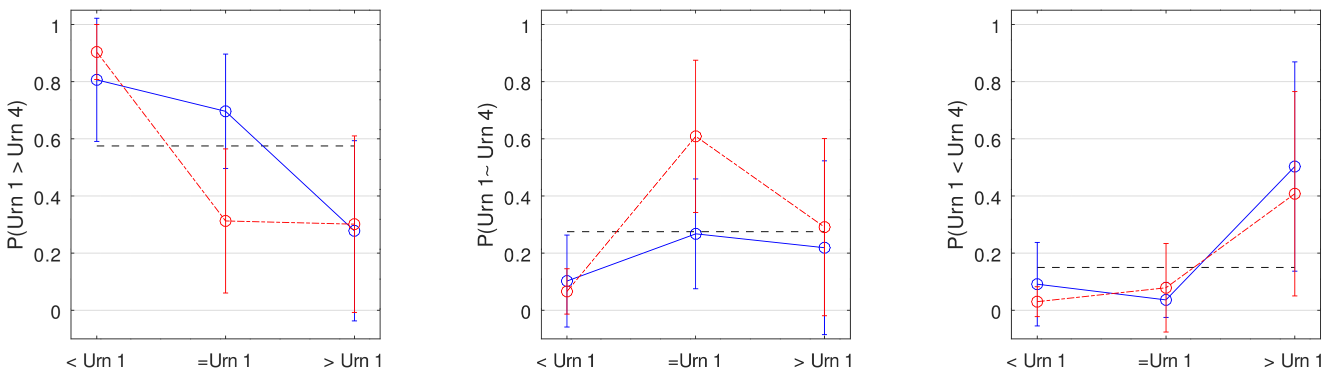
different types of uncertainty are confirmed by Fisher's exact tests, which enable us to statistically reject the independence hypotheses between ambiguity and both compound risk and model uncertainty, respectively. Considering the pool of students, we remark that, among the subjects manifesting a stronger aversion to model uncertainty than to risk, 83% (98 out of 118 subjects) also exhibit ambiguity aversion. Looking at compound risk attitude, we remark that 69.4% of our subjects (93 out of 134) who reduce compound risks are also ambiguity averse, suggesting separate attitudes towards these two types of uncertain situations. Comparing the observed frequencies with the expected ones under the null hypothesis of independence with respect to ambiguity attitude, we do not observe significant differences in the case of compound risk, but do observe differences in the case of model uncertainty.[27] Interestingly, we do not observe any kind of pattern between ambiguity loving and either compound risk loving or having less aversion to model uncertainty than to risk in the robustness round with students.

To further investigate the association between the attitudes towards the different types of uncertainty, we run a series of multinomial logistic regressions. The detailed results are provided in Appendix B.3. Figure 3 summarizes the results by presenting the predicted probabilities of exhibiting each type of attitude towards ambiguity (aversion, neutrality, loving in the column dimension), at each corresponding attitude towards compound risk (in blue) and model uncertainty (in red). To ease comparisons, we also provide the predicted probabilities of ambiguity attitudes irrespective of the attitudes towards compound risk and model uncertainty (dashed black lines).[28] Looking at the results for policymakers, we observe a tight association between ambiguity aversion and model uncertainty aversion. For example, the probability of exhibiting ambiguity aversion is 90% for a more model uncertainty averse than risk averse policymaker. It falls to 31% if the subject exhibits the same or a weaker attitude towards risk and model uncertainty. Similarly, the predictive probability of ambiguity neutrality goes from 27.5% for the whole sample to 66% once the subject exhibits a similar attitude towards model uncertainty as towards risk. Once we consider attitudes towards compound risk, the association only exists between compound risk aversion and ambiguity aversion, but this association is weaker than that with model uncertainty aversion. The same pattern emerges in the experiment with students. In this case, exhibiting a stronger aversion towards model uncertainty than towards risk increases the probability of being ambiguity averse to 85%, while the probability decreases to 46% if the subject exhibits the same attitude towards risk and model uncertainty. Similarly, exhibiting an analogous aversion to risk and model

[27] The Fisher exact tests confirm (p-value<0.001) the predictions that attitude towards model uncertainty and towards ambiguity are tightly associated, while we cannot reject the independence hypothesis between the attitudes towards compound lottery and ambiguity (p-value=0.19).

[28] Note that these probabilities exactly correspond to the total proportions of ambiguity averse, neutral and loving subjects that can easily be computed from the last column of Table 3.

Main experiment (policymakers)



Supplementary experiment (students)

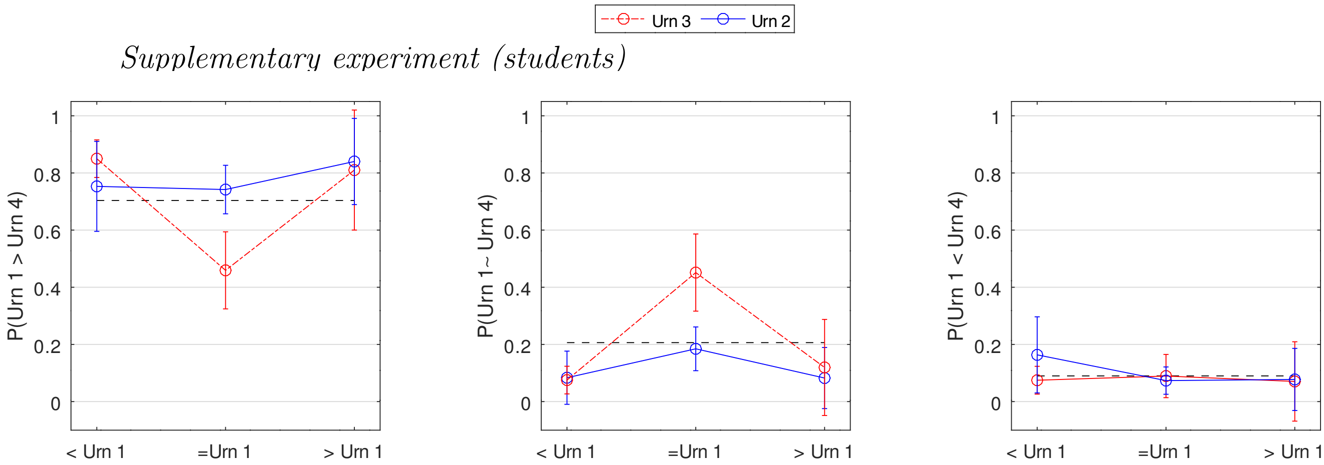


Figure 3: *Adjusted predictions of model uncertainty and compound risk on ambiguity attitudes*

Notes: First row represents results of the main experiment with policymakers (N=77), second row represents results of the supplementary experiment with students (N=189). Bars represent 95% confidence levels

uncertainty significantly increases the probability of being ambiguity neutral. Compound risk attitude on the contrary does not significantly affect the probabilities associated with the different ambiguity attitudes in any consistent way.

4.4 Heterogeneity

In this section, we investigate further the sources of heterogeneity in preferences within and between our different samples of subjects.

4.4.1 Sample: policymakers vs. students

Although similar patterns of preferences emerge from both experiments with policymakers and students, the results highlighted in the previous sections also suggest some systematic differences in the distribution of preferences. Specifically, students seem to be at the same time more ambiguity averse (70.4% vs 57.5%), more prone to reduce compound lotteries (70.9% vs 51.3%), and more model uncertainty averse (62.4% vs 51.3%) than policymakers. These differences are statistically significant at 5% level. More generally, the distribution of preferences appears relatively more dispersed for policymakers than for students in all three binary comparisons. The key result concerning the association between ambiguity and model uncertainty attitudes rather than that with compound risk attitudes is more clear cut for the student sample than for policymakers. At the individual level, we observe some differences between the two samples in the way subjects are distributed across the 27 combinations of attitudes (see Figure 2), especially for what concerns ambiguity averse subjects.

We can only speculate what are the drivers of these differences between the two samples. They may reflect differences in preferences, but they also may be driven by differences in statistical training and quantitative skills (note that 127 students, representing 67% of the sample in the supplementary experiment, reported to have attended classes on decision making under uncertainty). An alternative explanation might be that the policymaker pool is more heterogeneous. In the next sections, we explore the heterogeneity in the sample of policymakers. Finally, although we did our best to replicate exactly the same design, we cannot rule out that small differences between the two experiments (i.e. incentive structure and magnitude of the monetary payoff for a correct bet) may also have introduced some noise.[29]

[29] Note however that this latter possibility should be carefully considered in the light of the existing literature. Following Camerer and Hogarth (1999) –who review 74 studies comparing behavior of experimental subjects who were not paid, or were paid low or high financial incentives– the effect of incentives magnitude appears not to substantially alter the average behavior. Similarly, the effect of a random incentive system where only a fraction of the subjects are randomly selected to be actually paid, seems

4.4.2 Role at the conference: negotiators vs. non-negotiators

We here examine whether the role played by the policymakers at UN conference on Climate (COP21) has an impact on the preferences they exhibit. In particular, we draw a distinction between climate negotiators (who sit at the negotiation table and as such are officially representing their government in the decision-making processes) and delegates (non-negotiators who are still part of countries delegation, but may represent special interest groups, civil society or science).

Table 4 reports the results of the association between ambiguity neutrality and reduction for the two groups of policymakers. Both sub-samples exhibit ambiguity non-

Table 4: *Association between ambiguity neutrality, ROCL and ROMU distinguishing negotiators and non-negotiators*

		ROCL		**ROMU**		
Ambiguity neutral		No	Yes	No	Yes	**Total**
*Negotiators**						
No	Count	23	7	28	2	**30**
	Expected	*19.5*	*10.5*	*24.4*	*5.6*	
Yes	Count	5	8	7	6	**13**
	Expected	*8.5*	*4.5*	*10.6*	*2.4*	
Total		**28**	**15**	**35**	**8**	**43**
*Non-negotiators***						
No	Count	11	17	22	6	**28**
	Expected	*8.3*	*19.7*	*16.6*	*11.4*	
Yes	Count	0	9	0	9	**9**
	Expected	*2.7*	*6.3*	*5.4*	*3.6*	
Total		**11**	**26**	**22**	**15**	**37**

* Fisher's exact test (2-sided) with ROCL: 0.034; Fisher's exact test (2-sided) with ROMU: 0.006
** Fisher's exact test (2-sided) with ROCL: 0.036; Fisher's exact test (2-sided) with ROMU: < 0.001

neutrality (70% of negotiators and 76% of non-negotiators) and non-reduction of model uncertainty (81% of negotiators and 60% of non-negotiators). However, only 35% of the negotiators reduce compound risk, while more than 70% of the non-negotiators reduce it. We reject the hypothesis of independence between ambiguity neutrality and ROCL for

not to matter for the overall behavior of subjects (Beaud and Willinger, 2015).

both groups (p-value=0.03 in both cases), but results from a couple of logistic regressions (Table 5, rows (1)) reveal that being a negotiator significantly decreases the probability of reducing compound risk, while it does not affect the probability of being ambiguity neutral. Said differently, the odds of reducing the compound risk are almost 4 times higher for non-negotiators delegates than for negotiators (p-value=0.008).

This latter finding shows a similarity between non-negotiator delegates and students (p-values of equal proportions tests are respectively 0.62, 0.94 and 0.27 for ambiguity neutrality, ROCL and ROMU), while emphasizing a stark difference between these groups of individuals and climate negotiators. Looking more closely at the overall sample of policymakers, we are able to identify two main drivers of these observed differences.

Table 5: *The impact of heterogeneity on attitudes towards ambiguity and compound risk: logistic regressions*

	Ambiguity neutrality			ROCL		
	(1)	(2)	(3)	(1)	(2)	(3)
Role at the conference: negotiator	0.218 (0.536)			-1.360*** (0.511)		
Country of origin: OECD		0.106 (0.574)			1.821*** (0.541)	
Quantitative sophistication: "more"			-0.353 (0.581)			1.089** (0.519)
Observations	77	76	76	77	76	76

Notes: The table reports coefficients estimates from logistic regressions with, in turn, ambiguity neutrality or ROCL as the outcome variable. Gender, age and the number of children are control variables in all regressions.
Standard errors in parentheses.
** $p < 0.05$, *** $p < 0.01$

4.4.3 Country of Origin: OECD vs. non-OECD

The first driver we identify is the geographical origin of the policymaker. As can be observed in Table **??** (Appendix B.1), none of the 43 negotiators represents a North American country, while only 19.5% of them represent a country from Western Europe. In contrast, the total proportion of representatives of these two geographical areas among delegates reaches 56.8% (21.6% representing North America and 35.1% representing Western Europe). Splitting the variable "country of origin" into members of the Organisation for Economic Co-operation and Development (OECD) and non members, we observe that

37% of the negotiators are from a OECD country, while this is the case for 73% of the non-negotiators. In general, as we argue in this section, being originated from a OECD country significantly affects the attitude towards compound lotteries, but not towards ambiguity.

In Table 6, we present the contingency tables by making explicit the difference between policymakers coming from a country member of the OECD and those who are not. As we show, this variable affects attitudes towards ambiguity and the ability to reduce compound lotteries differently. In particular, we observe that the two groups of policymakers are ambiguity non-neutral (respectively, 71% and 75% of OECD members and non-members) and do not reduce model uncertainty (60% of OECD members and 83% of non-OECD members). However, for what concerns attitude towards compound risk, we observe an important difference between the two groups, with 74% of OECD member policymakers reducing compound risk, while 72% of non-OECD members do *not* reduce compound risk. Looking at the association between ambiguity neutrality and reduction of

Table 6: *Association between ambiguity neutrality, ROCL and ROMU distinguishing policymakers from OECD and non-OECD countries*

		ROCL		**ROMU**		
Ambiguity neutral		No	Yes	No	Yes	**Total**
*OECD countries**						
No	Count	10	20	23	7	**30**
	Expected	*7.9*	*22.1*	*17.9*	*12.1*	
Yes	Count	1	11	2	10	**12**
	Expected	*3.1*	*8.9*	*7.1*	*4.9*	
Total		**11**	**31**	**25**	**17**	**42**
*Non-OECD countries***						
No	Count	23	4	26	1	**27**
	Expected	*19.5*	*7.5*	*22.5*	*4.5*	
Yes	Count	3	6	4	5	**9**
	Expected	*6.5*	*2.5*	*7.5*	*1.5*	
Total		**26**	**10**	**30**	**6**	**36**

* Fisher's exact test (2-sided) with ROCL: 0.133; Fisher's exact test (2-sided) with ROMU: 0.001

** Fisher's exact test (2-sided) with ROCL: 0.006; Fisher's exact test (2-sided) with ROMU: 0.002

compound risk, we can confidently reject the null hypothesis of independence in the case of OECD non-member policymakers (p-value=0.006) but not in the case of OECD members (p-value=0.133). As shown in the rows (2) of Table 5, a couple of logistic regressions confirm that OECD origin enables to predict reduction of compound risk with statistical significance (odds ratio=6.2, p-value=0.001), but not ambiguity neutrality (odds ratio=1.1, p-value=0.854). In that sense, the probability of reducing compound risk for the average policymaker goes from 30% if she originates form a non-OECD country, to 72% if she is from a OECD country (43 percentage points increase, p-value<0.001). These results therefore confirm that the origin of a policymaker is a key driver of her preferences towards compound risk, but not towards ambiguity. Overall, the results obtained with policymakers originating from a OECD country are moreover in line with the ones obtained in the lab experiment with students.

4.4.4 Degree of quantitative sophistication

The second driver we identify is the level of quantitative sophistication of the subjects. Using data collected for the purpose of a study on policymakers' responses to climate forecasts (Bosetti *et al.*, 2017), we are able to compute different indices of quantitative sophistication that we use to distinguish between relatively more/less quantitatively sophisticated subjects. Specifically, we use the data concerning the way subjects incorporate scientific information to update their beliefs. Our index of quantitative sophistication takes the value 1 if the Euclidean distance between the reported conditional probabilities and the provided scientific information is lower than a given threshold, and 0 otherwise.[30] This index therefore synthesizes the way policymakers understand, interpret and report statistical evidence that was provided to them. Alternatively, it could be used as a proxy for the attention paid to the survey they were taking. In Appendix B.4, we replicate the analysis with two alternative measures of quantitative sophistication, and show that the same conclusions can be drawn.

Table 7 presents the associations between ambiguity neutrality and reduction for the two groups of relatively "more" and "less" quantitatively sophisticated subjects. Our intuition is that subjects who handle in a more sophisticated way quantitative tasks tend to reduce compound risk more often, while this sophistication has no effect on their attitude towards ambiguity. We observe that, among the 39 more sophisticated subjects, 31 (79%) are ambiguity non-neutral, while this is the case for 27 (68%) out of the 40 less sophisticated subjects (the difference is not significant at the 5% level, p-value=0.23). Turning to the attitude towards compound risk, we see that 67% of the more sophisticated subjects are indifferent between the simple and the compound risk, while it is the case for only 35% of the less sophisticated subjects (this difference is statistically

[30] As explained in Bosetti *et al.* (2017), subject were asked for their estimates of the expected future global temperature increases after having received a range of predictions made by major climate models associated with a specific emission pathway. The associated projected temperature was shown to policymakers by means of a box-plot. The threshold for the Euclidean distance is fixed to 0.25 in what follows.

Table 7: *Association between ambiguity neutrality, ROCL and ROMU distinguishing "more" and "less" quantitatively sophisticated policymakers*

Ambiguity neutral		**ROCL** No	**ROCL** Yes	**ROMU** No	**ROMU** Yes	**Total**
*More quantitatively sophisticated**						
No	Count	12	19	26	5	**31**
	Expected	*10.3*	*20.7*	*22.3*	*8.7*	
Yes	Count	1	7	2	6	**8**
	Expected	*2.7*	*5.3*	*5.7*	*2.3*	
Total		**13**	**26**	**28**	**11**	**39**
*Less quantitatively sophisticated***						
No	Count	22	5	24	3	**27**
	Expected	*17.6*	*9.4*	*19.6*	*7.4*	
Yes	Count	4	9	5	8	**13**
	Expected	*8.4*	*4.5*	*9.4*	*3.6*	
Total		**26**	**14**	**29**	**11**	**40**

* Fisher's exact test (2-sided) with ROCL: 0.229; Fisher's exact test (2-sided) with ROMU: 0.003

** Fisher's exact test (2-sided) with ROCL: 0.004; Fisher's exact test (2-sided) with ROMU: 0.002

significant, p-value=0.005). In terms of association, we only observe an association between ambiguity neutrality and the reduction of compound risk for the less quantitatively sophisticated subjects (Fisher exact test, p-value=0.004), but not for the more sophisticated ones (p-value=0.229). These results are in line with Abdellaoui *et al.* (2015) and Prokosheva (2016) who show that, for mathematically more sophisticated subjects, compound risk reduction is compatible with ambiguity non-neutrality, suggesting that failure to reduce compound risk and ambiguity non-neutrality do not necessarily share the same behavioral grounds. Finally, as shown in rows (3) of Table 5, a couple of logistic regressions enables us to assess that our quantitative sophistication index has a significant impact on the probability of reducing compound risk, which increases by 27 percentage points (p-value=0.028), while it does not affect the probability of ambiguity neutrality (p-value=0.54). Interestingly, we find a larger proportion of relatively less sophisticated subjects within the climate negotiator group (60.5%) than within the non-negotiator delegates (38.9%). This difference in the proportions is statistically significant (p-value=0.028 for one-sided test and p-value=0.056 for 2-sided test).

5 Conclusion

Although the application of the standard expected utility model to deeply uncertain situations has received increasing criticisms, ambiguity models have until now rarely been used to analyze public policies, or to prescribe optimal strategies in the face of ambiguity. Possible reasons for these shortcomings are the limited knowledge we have about preferences of some specific categories of individuals (and particularly, the elites actually making the decisions), and the lack of consensus concerning the normative status of non-expected utility models.

In this paper, we provide new experimental evidence on the ambiguity attitudes exhibited by a unique sample of real-life policymakers. Leveraging on an extremely simplified design, we are able to disentangle preferences for objective or subjective probabilities in association with individuals' ambiguity attitudes. Two main findings emerge from our analysis. First, the majority of policymakers are ambiguity averse. Second, this attitude is not necessarily due to an irrational behavior such as the inability to reduce compound lotteries, but rather to intrinsic preferences over unknown probabilities. Provided that the compound probabilities are simple enough, we find that most subjects reduce compound risk. Exploiting the richness of our data, we are moreover able to show that other variables such as the country origin, or the degree of sophistication of the subjects affect their ability to reduce compound risk while leaving their ambiguity attitudes unchanged. Moreover, we show that the preferences of policymakers originating from OECD countries, or exhibiting a relatively higher degree of sophistication are remarkably close to those of the students.

These results reveal inconsistencies with the classical model of choice under uncertainty and call for a new reading of some important findings previously obtained in the literature, when trying to explain the behavioral mechanisms underneath individuals' attitudes towards ambiguity. Perhaps most importantly, these results also shed light on the role ambiguity models can play in informing policymaking. In particular, our results have important implications for the way attitude towards ambiguity is perceived and treated in economic models. Considering ambiguity aversion as a rational way to deal with uncertainty, rather than as a departure from rationality (sharing the same behavioral ground as the violation of independence in risky choices) strengthens the potential for ambiguity models to provide normative policy guidances. In the context of climate change, for example, taking ambiguity attitudes into account would lead to larger reductions of greenhouse gas emissions when the probability distribution of important climate parameters –such as the climate sensitivity– is unknown (Millner *et al.*, 2013), or when experts disagree about the probability of a potential climate catastrophe (Berger *et al.*, 2017). In that sense, neglecting ambiguity attitudes leads to underestimate the benefits of more stringent climate policy decisions. On the descriptive side, the data we collect on policymakers make possible a better representation of policymakers' preferences when modeling them in economic settings. As such, our results also contribute to a vast literature that is emerging at the frontier of psychology and economics, for which non-standard preferences constitute the bulk of the empirical research (DellaVigna, 2009) and within which behavioral political economy –which considers the (psychologically informed) economic analysis of behavior and its effects in the political arena (Schnellenbach and Schubert, 2015)– is emerging. According to this literature, the processes generating political outcomes should be understood as relying on the same motivational assumptions that guide the economic analysis of market behavior. As such, policymakers should be considered self-interested and prone to honing their behavioral rules according to their preferences to match the incentives they face, unlike the benevolent planner of traditional welfare economics (Levitt and List, 2007).

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