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Measuring strategic-uncertainty attitudes*

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ABSTRACT

Strategic uncertainty is the uncertainty that players face with respect to the purposeful behavior of other players in an interactive decision situation. Our paper develops a new method for measuring strategic-uncertainty attitudes and distinguishing them from risk and ambiguity attitudes. We vary the source of uncertainty (whether strategic or not) across conditions in a ceteris paribus manner. We elicit certainty equivalents of participating in two strategic 2x2 games (a stag-hunt and a market-entry game) as well as certainty equivalents of related lotteries that yield the same possible payoffs with exogenously given probabilities (risk) and lotteries with unknown probabilities (ambiguity). We provide a structural model of uncertainty attitudes that allows us to measure a preference for or an aversion against the source of uncertainty, as well as optimism or pessimism regarding the desired outcome. We document systematic attitudes towards strategic uncertainty that vary across contexts. Under strategic complementarity [substitutability], the majority of participants tend to be pessimistic [optimistic] regarding the desired outcome. However, preferences for the source of uncertainty are distributed around zero.

Keywords: risk attitudes, ambiguity attitudes, strategic-uncertainty attitudes, stag-hunt game, market-entry game

JEL Codes: C72, C91, C92, D81

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1. Introduction

Strategic uncertainty is the uncertainty that players face with respect to the purposeful behavior of other players in an interactive decision situation. While economic theory mostly applies equilibrium concepts like Nash or rational expectations equilibria that are based on the absence of strategic uncertainty, experiments show that real decision makers are sensitive to strategic uncertainty. Laboratory experiments have indicated that many humans exhibit strategic uncertainty aversion: they are ready to waive a part of their expected payoff in order to avoid that their payoff depends on the decisions made by others.[1] This behavioral phenomenon has far-reaching consequences for economic efficiency, because it implies coordination failures and suboptimal levels of investment and risk taking in markets.

From early experiments, we know that humans tend to prefer situations with known probabilities of outcomes to "ambiguous" situations in which these probabilities are unknown (Camerer and Weber, 1992). This attitude is called ambiguity aversion. Tests of ambiguity aversion traditionally compare choices between lotteries with given probabilities and lotteries for which the probabilities are exogenously given but unknown to subjects. Ambiguity aversion might also apply to strategic interaction. However, the beliefs about the strategic behavior of other humans are also affected by the theory of mind: agents may put themselves in the shoes of other decision makers and form beliefs about their reasoning processes. This idea has been taken to the extreme by the Nash equilibrium concept in which each player's strategy is a best response to the other players' strategies. As a descriptive theory, Nash equilibrium assumes that players are able to guess the strategies of others either by simultaneously solving the others' decision problems or by relying on experience (as in repeated games). Such reasoning processes may reduce perceived strategic uncertainty, so that strategic uncertainty aversion may have lower effects on behavior than ambiguity aversion in lotteries with completely unknown probabilities. On the other hand, strategic interactions are also more complex to analyze than lotteries. Humans try to avoid complexity and may doubt the logical consistency of their own reasoning processes or the logical consistency of other players' reasoning processes or decisions.

This paper develops a method for measuring strategic-uncertainty attitudes and distinguishing them from risk and ambiguity attitudes. The main idea is to elicit and exploit the information contained in certainty equivalents (willingness to accept) for lotteries under three different sources of uncertainty: strategic uncertainty, risk and ambiguity. We provide a structural model of uncertainty attitudes that allows us to measure two dimensions of uncertainty attitudes: a preference for, or aversion against, the source of uncertainty, modelled by an additional [dis]utility depending on the source, and optimism or pessimism[2] regarding the outcome, which we formalize as a shift of the subjective weight that is put on the higher outcome.

We conduct an experiment with interactive games and interaction-free lottery tasks. Unlike previous experiments, our novel methodology allows for a variation of the source of uncertainty (whether strategic or not) across conditions in a *ceteris paribus* manner. This means that we keep the potential payoffs constant but consider different mechanisms (random or strategic) that determine the realized payoff. Since strategic uncertainty typically characterizes coordination problems, we focus on two coordination games: one with strategic

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[1] See, for example, Greiner (2016).

[2] One might also interpret these as excitement or fear about the other player's behavior.

complementarities in agents' actions and one with strategic substitutability (anti-coordination). Following the literature on strategic uncertainty (see below), we apply our methodology to two classic 2x2 games: stag-hunt and market-entry games.[3]

For the different sources of uncertainty – each of the two games, as well as the corresponding ambiguous lottery environments – we identify two subject-specific parameters of a model of uncertainty attitudes. We investigate two ways in which strategic uncertainty may affect behavior in a game. First, following Baillon et al. (2017), we define ambiguity as a situation where subjects have information about possible outcomes of a lottery but not about probabilities. Whether these given – *exogenous* to the decision maker – unknown probabilities are resulting from human decisions or nature does not affect this definition of ambiguity. We investigate whether, all other things being equal, attitudes towards uncertainty differ between strategic uncertainty and ambiguity conditions. Second, strategic uncertainty is related to conscious behavior of human players whose interaction exhibits common or opposite interests, and as such involves decisions based on strategic thinking. We study how the nature of the game (strategic complements versus substitutes) affects these uncertainty attitudes.

We document systematic attitudes toward uncertainty. These attitudes vary across contexts and across subjects. The median participant exhibits neither a preference for, nor an aversion against ambiguity or strategic uncertainty. In the game with strategic complements [substitutes], the median participant is found to be pessimistic [optimistic] regarding the outcome that leads to a higher payoff given the player's own choice. Comparing uncertainty attitudes across treatments, we observe more optimism in the entry game than in the stag-hunt game or under ambiguity (both of which, in turn generate similar results).

The next section describes our contribution to the literature. Section 3 presents the experimental design and procedures. Section 4 lays out the theoretical underpinnings of our design. Section 5 shows the results and Section 6 concludes the paper.

2. Related literature

Brandenburger (1996) defines strategic uncertainty as uncertainty about the purposeful behavior of players in an interactive decision situation. Experimental evidence reported in Beard and Beil (1994) can hardly be explained without assuming that players dislike situations in which their payoffs depend on the decisions made by other players. Camerer and Karjalainen (1994) attribute this behavior to ambiguity aversion, because there are no given probabilities for other players' strategies. They use non-additive probabilities as in Gilboa and Schmeidler (1989) to model ambiguity aversion and argue that ambiguity aversion may be responsible for players not reaching an efficient equilibrium in coordination games with strategic complements (like the median effort game). Camerer and Karjalainen (1994) conduct an experiment on the median effort game, in which they elicit bounds on subjective probabilities for complementary and exhaustive events defined on the outcomes of the game. If the sum of these probabilities is smaller than one, a subject can be said to be ambiguity averse. Unfortunately, their method of

[3] Stag-hunt games provide a useful paradigm to analyze a wide range of economic phenomena, such as macroeconomic fluctuations (Cooper and John, 1988), bank runs, debt and liquidity crises, speculative attacks (Morris and Shin, 2003; Heinemann, 2012), and commercial production processes (Brandts et al., 2015). Market-entry games describe the prototypical situation of conflicting interests, such as Cournot competition or location choice.

eliciting subjective probabilities seems rather fragile as it may produce contradictory results and does not allow a clear distinction between subjective beliefs about others' behavior and aversion against strategic uncertainty.

Greiner (2016) is the first to clearly identify aversion against strategic uncertainty by comparing behavior in dictator, ultimatum, and impunity games. He shows that behavior in these games indicates a substantial aversion against strategic uncertainty that may be higher than ambiguity aversion. Subjects pay high prices for avoiding that their payoff depends on the decisions of their partners, even though they attribute high subjective probabilities to their partners' decisions being favorable for them.

Bohnet and Zeckhauser (2004) find similar evidence in a trust game, where the second mover could either be another subject or a lottery. They attribute subjects' reluctance to depend on human second movers as betrayal aversion, but strategic uncertainty aversion might have played some role. Li et al. (2020) find that ambiguity preference affects the decision to trust a trustee. Note that the games used by Greiner (2016) and Bohnet and Zeckhauser (2004) all have a unique equilibrium and equilibrium choices of the second movers can be derived simply by eliminating dominated strategies.

Kelsey and le Roux (2015) analyze behavior in an extended battle of the sexes game and find further evidence indicating that strategic uncertainty aversion may exceed ambiguity aversion in non-strategic games. They also conjecture that not only strategic uncertainty, but also strategic uncertainty aversion may depend on the nature of the game. However, they have no means to test this hypothesis. Nevertheless, this conjecture has to be taken seriously, because Ivanov (2011) finds that in a game that is solvable by iterative elimination of dominated strategies, 32 percent of subjects are strategic uncertainty loving, while only 22 percent are averse to strategic uncertainty.

Nagel (1995) provides an experimental test of a game with strategic complements and shows that behavior can be described by assuming that subjects follow distinct levels of reasoning, where Level zero is defined as random choice of a strategy and Level k is defined as best response to Level k-1. Camerer et al. (2004) develop a cognitive hierarchy model based on levels of reasoning. Uncertainty about other players' strategies can be modelled as uncertainty about the levels of reasoning applied by other players. In games with strategic complements, the number of levels of reasoning is in a monotone relationship with actions and, thus, experiments on such games can be used to measure the distribution of levels among players, but also the beliefs about others' levels of reasoning. In games with strategic substitutes, however, the optimal strategy for a given number of levels of reasoning is non-monotonic. In entry games, for example, the optimal decision is to enter for any odd number of levels and to stay out for any even number of levels (or vice versa). This raises the question whether perceived strategic uncertainty or strategic uncertainty aversion differ between games with strategic complements and substitutes.

Heinemann et al. (2009) propose a method to measure strategic uncertainty in coordination games with strategic complements. They let subjects play a variety of games, each consisting of a choice between two options A and B. Option A is associated with a safe payoff X, while Option B paid 15€ if at least a fraction k of the other subjects were choosing B in the same game and zero otherwise. The safe payoff was varied from 1.50€ to 15€ and subjects typically switched from B to A at some value of the safe payoff. The safe payoff at the switching point can be interpreted as certainty equivalent for the uncertain option in this game and, thus, be used as a measure for strategic uncertainty. Subjective probabilities for success of Option B can be elicited directly or derived from comparing the certainty equivalent of a strategic game with certainty equivalents of lotteries with given probabilities. As the safe payoffs are part of the game and any pair A-B is a different game, switching points only provide precise measures of strategic uncertainty for games in which subjects are indifferent between A and B. Thus, this method can only give upper or lower bounds for strategic uncertainty in games in which subjects reveal their preference for one or the other option by choosing it.

Following the same method as Heinemann et al., recent work by Chierchia et al. (2018) elicits certainty equivalents for choosing the uncertain option in coordination games with strategic complements (stag-hunt games) and substitutes (entry games). They find that most subjects have a unique switching point in stag-hunt games, but multiple switching points for entry games, which is in line with higher levels of reasoning.[4] The observed multiple switching points in entry games indicate, however, that levels of reasoning and strategic uncertainty may be related, for which reason we focused on games with strategic complements and substitutes to measure strategic uncertainty aversion. In addition, many simultaneous-move games are characterized by strategies being either complements or substitutes, and games with these characteristics are applied in many domains of economics to model competition, monetary policy, financial crises, network externalities in growth, and political economy issues, to name just a few.

While multiple price lists used by Heinemann et al. (2009) and others allow for measuring strategic uncertainty, the authors do not clearly distinguish strategic-uncertainty attitudes from ambiguity attitudes.[5,6] At best, the existing methods suffice to distinguish whether a subject likes or dislikes strategic uncertainty. While the general conclusion is that subjects dislike strategic uncertainty, Ivanov (2011) provides evidence that strategic uncertainty may be preferred to risk. We thus reckon that the literature lacks a clear methodology to measure strategic-uncertainty attitudes. We fill this void by developing a method that can be used to measure strategic-uncertainty attitudes for any strategic binary-choice game and distinguish

[4] Nagel et al. (2018) explain multiple switching points in entry games by the higher demand for strategic reasoning compared to a stag-hunt game. They analyze the brain activity of subjects during decision-making in an fMRI scanner. They show that strategic games activate the brain network that also mediates risk during lottery decisions (anterior insula, dorsomedial prefrontal cortex and parietal cortex) which indicates that strategic uncertainty is treated in a similar way as other forms of uncertainty. The activation of the risk mediating network is highest when subjects chose the risky action in the entry game which indicates that entry games are associated with a higher perceived strategic uncertainty. The level of strategic thinking is reflected in the activity of the dorsomedial and dorsolateral prefrontal cortex. These regions are more active among players with non-threshold strategies in the entry game, indicating higher levels of reasoning.

[5] Heinemann et al. (2009) compare strategic uncertainty to risk. Apart from the research question itself, many design features of our experiment differ from theirs (e.g. elicitation of certainty equivalent and subjective beliefs). In their experiment, subjects choose between a safe payoff and a risky payoff that they get if and only if a sufficient number of subjects chooses the risky option. Thus, the safe payoff was not a certainty equivalent for the game, but part of the game itself. Hence, the method employed by Heinemann et al. (2009) cannot identify any attitudes towards or against strategic uncertainty. In contrast, we elicit certainty equivalents for each potential action in the game without the stated certainty equivalents affecting payoffs in the game.

[6] A comparison of risk and ambiguity driven either by human behavior or computer is proposed by Farjam (2019). However, he focuses on non-strategic human-driven uncertainty and shows that computerized uncertainty is preferred.

optimism or pessimism regarding the outcome of the game from a preference for or aversion against the source of uncertainty.

3. Experimental design and procedures

We develop a method for measuring attitudes towards strategic uncertainty. We use a within-subject design based on three distinct experimental conditions. The main condition of interest is STRATEGICUNCERTAINTY, in which the uncertainty that players face in the game stems from other players' behavior. We also include two control conditions: RISK (the aim of which is to establish a behavioral benchmark for a pre-determined structure of uncertainty, where possible outcomes and associated probabilities are known) and AMBIGUITY (which captures behavior under uncertainty, where possible outcomes are known but associated probabilities are unknown).

Each subject acts in all of the three decision-making environments in the following order: RISK, AMBIGUITY, and finally STRATEGICUNCERTAINTY. The STRATEGICUNCERTAINTY treatment is played for two distinct 2-player, 2-strategy settings: one with strategic complements, the stag-hunt game (see Game 1 in Table 1 below), and one with strategic substitutes, the entry game (see Game 2 in Table 2 below). The order, in which subjects face the two games, varies. In half of the sessions, the STRATEGICUNCERTAINTY treatment starts with subjects facing Game 1 before Game 2, and conversely in the other half of the sessions. The payoff structure in Tables 1 and 2 is such that in each game each player decides between two "lotteries" (one lottery pays either 20€ or 15€, the other either 5€ or 25€) in which the outcome depends on the other player's decision. We elicit the certainty equivalents for both of these "lotteries" along with subjective beliefs, and compare them with certainty equivalents of analogous binary lotteries with exogenously given probabilities.

Table 1. Game 1 and associated payoffs.

		The other player	
		L	R
You	L	20€, 20€	15€, 5€
	R	5€, 15€	25€, 25€

Table 2. Game 2 and associated payoffs.

		The other player	
		L	R
You	L	5€, 5€	25€, 20€
	R	20€, 25€	15€, 15€

Prior to the RISK treatment, subjects take part in five unpaid lotteries under the same design as the RISK treatment. The goal of this training part is to accustom subjects with the basic mechanisms at play, and especially to let them gain experience with the Becker-DeGroot-Marschak procedure (Becker et al., 1964). Unlike the main part of the experiment that follows, in this preliminary part subjects receive feedback after each lottery.

The three treatments are summarized in Section 3.1. The key feature of our experimental design is that it varies the source of uncertainty, keeping the remaining aspects of the decision-making process as identical as possible across treatments. This, in turn, allows for isolating and measuring the behavioral effect of strategic uncertainty as compared to other sources of uncertainty. The experimental procedure is outlined in Section 3.2.

3.1. Treatments

While the STRATEGICUNCERTAINTY is played last in our experiment, we present it first because it is our main treatment. We then present the two control treatments, which are played first.

Main treatment: STRATEGICUNCERTAINTY

This treatment consists of two consecutive parts, each involving a different game (either Game 1 or Game 2). The order of games is balanced across sessions. Subjects are randomly and anonymously matched into pairs for each game.

In each session there are 12 subjects. This allows us to consistently use frequency-based framing ("how many times out of 10") when eliciting beliefs about others' behavior.

In the STRATEGICUNCERTAINTY treatment, each subject makes 4 decisions:

- **Decision 1**: The choice between L and R in the game.
- **Decision 2**: Subjective beliefs about the behavior of the other subjects. We ask the following question: Out of the 10 other participants (not including the own counterpart) in this session, how many would choose R? Beliefs are incentivized using a binarized quadratic scoring rule.[7]
- **Decision 3**: The certainty equivalent (WTA) for not playing the game if Decision 1 is implemented.
- **Decision 4**: The certainty equivalent (WTA) for not playing the game if the alternative of Decision 1 is implemented.

We allow WTAs in Decisions 3 and 4 to be stated on [0, 30€]. This exceeds the range of potential payoffs so as to detect strong aversion against or strong preference for strategic uncertainty. Payoffs are determined as follows:

[7] Note that quadratic scoring rules are incentive compatible only for expected-payoff maximizers. Biases may occur for non-risk-neutral subjects (Offerman et al., 2009). Schotter and Trevino (2014) provide a survey on experimental belief elicitation. The binarized quadratic scoring rule (Hossain and Okui, 2013) (BSR) incentivises truthful reporting of beliefs independently of risk-preferences and the (non-linear) form of probability weighting. Danz et al. (2020) have recently shown that in practice subjects misreport their beliefs even with the BSR. However, they also show that "*false reporting and pull-to-center effects arise only when participants are informed of the BSR's quantitative incentives*" (Danz et al., 2020, p. 2). For this reason, we apply the binarized quadratic scoring rule, but in the instructions, we present the details only on demand and solely tell subjects the principle of this mechanism and that it is in their own interest to state their true beliefs. Alternatively, we could correct the stated beliefs from a standard quadratic scoring rule using the estimated relative risk aversion along the lines laid out in Offerman et al. (2009). However, this exercise also requires structural assumptions that, if mis-specified, may bias the findings even more than using the stated beliefs without correction. See the experimental instructions in Online Appendix A1 for implementation details of the BSR in our study.

A. With 1/3 probability, the game is played and payoffs are determined by both subjects' Decision 1.

B. With 1/3 probability, subjects are paid for their stated beliefs.

C. With 1/3 probability, a subject's own payoff depends on her own stated WTAs and on the other subject's Decision 1. Here, each subject's payoffs are determined as follows:

   1. One of two possible actions – either L or R – is drawn at random (with 50% chance for the own preferred action) and replaces the subject's own Decision 1.
   2. For that action, the BDM procedure takes place. The computer draws a random integer from 1 to 30€. All integers are equally likely. If the drawn integer is larger than or equal to the stated WTA for that action, then the subject's payoff equals the randomly drawn number.
   3. If the drawn integer is smaller than the stated WTA for that action, the subject's payoffs are determined by that action and by Decision 1 of the other subject.

With this design, a subject's own Decision 1 is only payoff-relevant for her if the game is actually played (Situation A). Thus, each subject's Decision 1 is not affected by her choice of WTAs. Hence, beliefs about the other's Decision 1 are not affected by beliefs about the other's WTA either. Thereby, we provide the highest incentive for subjects to activate their theory of mind as intended for Game 1 or Game 2. The decision on WTAs depends solely on beliefs about the Decision 1 of the other subject and it requires the same considerations. Our procedure elicits the WTAs for the action that the subject would have chosen herself and also for the counterfactual non-preferred decision. This allows us to identify two parameters of a model of strategic uncertainty that can be interpreted as uncertainty aversion and optimism (see Section 4). Theoretically, the higher of the two stated WTAs is the WTA for the entire game.

For comparability purposes, we design the two control treatments in a similar frame as the STRATEGICUNCERTAINTY treatment. These two treatments vary the source of uncertainty. In the RISK treatment, uncertainty is generated by a random process with known probabilities. In the AMBIGUITY treatment, the outcome is determined by an unknown probability distribution.

Control treatment 1: RISK

In this treatment, each subject is faced with 11 pairs of lotteries (lotteries 15€/20€ or 5€/25€ associated with 11 given probabilities p). Here, we only ask for 22 WTAs for the respective 22 lotteries.

A subject's own payoff depends on her own stated WTAs and is determined as follows. The computer determines which of the 22 lotteries is carried out. Each lottery is equally likely to be selected. Then, the BDM procedure takes place. The computer draws a random amount from 0 to 30€ with 2 decimals. If the drawn amount is larger than or equal to the stated WTA for the selected lottery, then the subject's payoff is equal to the randomly drawn amount. Otherwise, the lottery is played. Altogether, each subject makes 22 decisions using a table of contingent choices similar to Table 3 below.

The 11 lotteries on the left-hand side of the table pay either 15€ or 20€, the 11 lotteries on the right-hand side pay either 5€ or 25€. In any lottery, the computer determines randomly which of the two possible payments is made. Subjects receive information about which part of the experiment and eventually which lottery is selected for payoffs only at the end of the experiment after all decisions are completed.

Table 3. Decision table in the RISK treatment.

Probability with which the computer selects the higher payoff	WTA for lottery that pays either 15€ or 20€	WTA for lottery that pays either 5€ or 25€
0%		
10%		
20%		
30%		
40%		
50%		
60%		
70%		
80%		
90%		
100%		

Control treatment 2: AMBIGUITY

In this treatment, each subject is faced with one pair of lotteries that are presented in the same way as potential payoffs in the previous treatment, but this time, subjects are not told the likelihood that the higher payoff is chosen. Subjects are informed that the computer selects one of the 11 distributions from the RISK treatment before their own decision. We inform them that the 11 distributions are not equally likely to be selected.[8] As in the RISK treatment, each subject states WTAs. Here, we ask for two WTAs, one for each lottery. In addition, each subject states her belief about the selected probability distribution. The computer randomly decides whether subjects get paid according to the BDM procedure, or according to their stated beliefs (with 1/2 probability each). The computer selects the probability for the higher payoff and, if the BDM procedure is payoff-relevant, one of the lotteries (L/R) is selected with 50% chance. As a next step of the BDM procedure, the computer draws a random amount from 0 to 30€. If the random amount is larger than or equal to the stated WTA for that lottery, then the subject's payoff is equal to the randomly drawn amount. Otherwise, the lottery is played with the probability distribution selected by the computer.

[8] For the sake of implementation, the random process generating probability distributions in lotteries played under ambiguity is based on 2019 weather data from Berlin.

3.2. Implementation details

The design of the experiment was approved by the local GATE-Lab (Lyon) ethic committee. We ran 19 sessions (including the pilot session) with 12 participants each (maximal capacity during the COVID pandemic) at the Experimental Economics Laboratory of the Technische Universität Berlin, Germany, between September and October 2021.[9,10] Participants were recruited through ORSEE (Greiner, 2015) and 95% of them were students from various disciplines – engineering (41.7%), economics (8.8%), and business administration (6.6%) representing the largest groups. The experiment was programmed using z-Tree (Fischbacher, 2007).

Participants were randomly seated in front of PCs. Throughout the sessions, they were not allowed to communicate with one another and could not see each other's screens. All questions were answered in private.

Only one of the four parts (risk, ambiguity, stag-hunt game, entry game) was chosen for final payoffs. The probability was 0.25 for each part. Within the selected part, the payoff was determined as specified in Section 3.1. This means that only one decision of a player was payoff relevant, but each decision could be the one. This procedure rules out incentives for hedging and provides the highest incentive to consider the uncertainty of the outcome associated with each decision. The average payoff was about 21.80€ (minimum 6.60€, maximum 34.80€) including the fixed show-up fee of 5€. Sessions lasted for around 70 minutes on average. Examples of instructions, questionnaires, and screens are given in Appendices A.1, A.2 and A.5.

4. Theoretical framework

Let us start our theory considerations by observing that any choice in a simultaneous-move game may be interpreted as a choice between lotteries whose outcomes depend on the choices of other players. Our 2x2 games involve the choice between a lottery L with payoff 20€ or 15€ and lottery R with payoff 5€ or 25€. Note that the probability of receiving 15€ after choosing L is the same as the probability of receiving 25€ when choosing R. It is the probability that the other player chooses R. In the *stag-hunt* game (Game 1), a player gets the higher payoff of her chosen lottery, if her partner chooses the *same* lottery. In the *entry* game (Game 2), a player gets the higher payoff, if her partner chooses the *other* lottery.

The value of a lottery k for a subject i can be written as

$$W_i^k(\bar{x}|\pi_i) = E(u_i(x)|\pi_i) + \Delta_i^k(\bar{x}|\pi_i),$$

[9] In the pre-results reviewed report, we planned to run sessions with a minimum of 14 participants at the GATE-Lab, Lyon, France. This initial plan could not be implemented due to the pandemic conditions.

[10] The minimal sample size determined by the power analysis is N = 208. Our power calculations (GPower software, version 3.1) are based on the nonparametric two-sided Wilcoxon signed rank test. We assume normal parent distribution. We apply the following criteria. First, a test attains the statistical power of at least 0.8 (which is a common-place reference value in the literature) with the conventional threshold for rejecting a null hypothesis of 5%. Second, the minimal effect size (as measured by Cohen's d) a test can pick up on is small (d = 0.2). The resulting actual power equals 0.801. Given our initial sample of N = 228 (i.e., prior to applying both the pre-registered and the ex post data selection criteria, as explained in Section 5.1) and d = 0.2, the resulting statistical power is even higher and equals 0.836 at the 5% significance level. Conversely, with a reference minimal power of 0.8 (the actual one being 0.801), this sample size is enough to pick up on a treatment effect of magnitude d = 0.191.

where $u_i(x)$ is subject i's utility function, $\bar{x}$ is the vector of potential monetary payoffs and π_i is the subject's probability distribution over outcomes. For an expected-utility maximizer, $\Delta_i^k(x|.) = 0$ for all x. If we assume that subjects evaluate lotteries with exogenously given probabilities by expected utility, the attitude towards or against ambiguity or strategic uncertainty can be written as a deviation of the evaluation from expected utility, denoted by $\Delta_i^k(\bar{x}|\pi_i)$. A theory of ambiguity attitudes specifies this deviation.

We propose to model ambiguity attitudes for binary lotteries and strategic-uncertainty attitudes for a 2x2 game by two parameters α_i^k and δ_i^k such that the utility value that subject i attaches to the possible outcomes from her own choice is

$$W_i^k(x_1, x_2, \pi_i) = (\pi_i + \alpha_i^k)\, u_i(x_1) + \left(1 - \pi_i - \alpha_i^k\right) u_i(x_2) - \delta_i^k, \quad (1)$$

where $x_1 \geq x_2$ are the potential monetary payoffs and π_i is the subjective probability for receiving x_1. The parameter δ_i^k may be interpreted as an aversion against strategic uncertainty if it is positive, or as a preference for strategic uncertainty if it is negative. The higher δ_i^k, the lower is the value of the lottery, in line with the interpretation of an increasing aversion against uncertainty. The parameter δ_i^k affects the value of a lottery independent of the perceived risk that is associated with it. The second parameter, α_i^k, establishes the weight that the subject puts on the higher outcome given her own choice. If $\alpha_i^k > 0$, the subject puts a weight on the *higher* payoff that exceeds her subjective probability for this outcome. If $\alpha_i^k < 0$, the subject puts a weight on the *lower* payoff that exceeds her subjective probability for this outcome. We may interpret this parameter as optimism, where $\alpha_i^k = 0$ is the unemotional Bayesian view on the lottery, while subjects with $\alpha_i^k > 0$ may be called optimists and subjects with $\alpha_i^k < 0$ pessimists. Optimism [pessimism] may arise from the excitement [fear] about the prospect of getting the high [low] amount when it is determined by another human playing strategically (strategic uncertainty) or by an unknown process (ambiguity). Note that the value of the lottery rises with increasing optimism. Thereby, our model allows for a clear interpretation of both parameters.

The value of an ambiguous lottery or a game may be higher [lower] than the value of the highest [lowest] possible realization under certainty. From the standard economic perspective, it may seem odd that the value of an uncertain situation could be higher than the highest possible payoff or lower than the lowest one. However, this may reflect particular attitudes towards strategic interactions with other human players: a person may be generally uncomfortable with depending on other humans, or may derive utility from playing a game with somebody else on top of the utility generated by the monetary payoffs in this game.

In our experiment, we also elicit the certainty equivalent of participating in the game, if the player's chosen action is replaced by the opposing action. If the subject is optimistic about getting x_1=25€ in the game with his chosen action, she must be pessimistic about receiving $\bar{x}_1$=20€ under the replaced choice. Thus, for this counterfactual choice, the value of the implied lottery is

$$\overline{W}_i^k(\bar{x}_1, \bar{x}_2, 1 - \pi_i) = (\pi_i + \alpha_i^k)\, u_i(\bar{x}_2) + \left(1 - \pi_i - \alpha_i^k\right) u_i(\bar{x}_1) - \delta_i^k, \quad (2)$$

where $\bar{x}_1 > \bar{x}_2$ are the payoffs implied by the counterfactual choice.

An alternative theory of ambiguity attitudes is the Choquet-expected utility with neo-additive capacities that specifies a value function (cf. Chateauneuf et al., 2007)

$$V_i(\bar{x}, \pi_i) = \sum_x (1 - \delta_i)\, \pi_i(x)\, u_i(x) + \delta_i \left[\alpha_i\, u_i(x^{max}) + (1 - \alpha_i)\, u_i\big(x^{min}\big)\right].$$

For a lottery with only two possible outcomes $x_1 \geq x_2$,

$$V_i(x_1, x_2, \pi_i) = \big(\pi_i + \delta_i(\alpha_i - \pi_i)\big)u_i(x_1) + \big((1 - \pi_i) - \delta_i(\alpha_i - \pi_i)\big)u_i(x_2).$$
$$= E(u_i(x)|\pi_i) + \delta_i(\alpha_i - \pi_i)[u_i(x_1) - u_i(x_2)].$$

The interpretation, given in the literature (see e.g., Greiner (2016)), is that δ_i is the ambiguity of a player ($1 - \delta_i$ is her trust in her own beliefs) and α_i is optimism. By this interpretation, an increasing ambiguity may raise or lower the value of the lottery, depending on whether optimism exceeds or stays below the subjective probability for the higher payoff. The interpretation of α_i may also cause a problem. For $\delta_i > 0$, the evaluation rises in α_i, but for $\delta_i < 0$, increasing "optimism" reduces the value of the lottery. Restricting α_i and δ_i to be in [0,1] avoids this, but may be inconsistent with large deviations of the value of a lottery from the expected utility that it implies. Finally, the parameters are not identified from the evaluations of the two lotteries that a subject can choose in a 2x2 game, if she assigns $\pi_i = 0.5$ to the other player's choices. For these reasons, we use the model described by Equations (1) and (2) for further analysis.

4.1. Identification of uncertainty attitudes

For identification, we assume that α_i^k and δ_i^k are the same for all lotteries with the same source of uncertainty. With the data from our experiment, we compare these parameters for three sources of uncertainty: we denote $k = A$ in the AMBIGUITY treatment, $k = S$ in the stag-hunt game, and $k = E$ in the entry game.

Utility function and risk aversion

In order to estimate uncertainty attitudes, we assume that subjects have CRRA utility functions, $u_i(x) = x^{1-r_i}/(1 - r_i)$ for $r_i \neq 1$ and $u_i(x) = \ln(x)$ for $r_i = 1$, where r_i is the Arrow-Pratt measure of relative risk aversion (RRA). We use the 22 stated WTAs in the RISK treatment to estimate r_i for each subject *i*. If all 22 WTAs are equal to the expected monetary payments of the respective lotteries, we set $r_i = 0$. For further details, see Section 5.3.

Identification of parameters

Let π_i be a subject *i*'s probability to receive x_1 in a binary lottery *k* with payoffs $x_1 > x_2$. Then, the subject's WTA for an ambiguous lottery or for the chosen lottery in a game is given by the value $W_i^k(x_1, x_2, \pi_i)$.

Our 2x2 games involve the choice between a lottery L with payoff 20€ or 15€ and lottery R with payoff 5€ or 25€. In the *stag-hunt* game (Game 1), a player gets the higher payoff of his chosen lottery, if her partner choses the *same* lottery. In the *entry* game (Game 2), a player gets the higher payoff, if her partner choses the *other* lottery. Thus, in both games, we observe the values of two lotteries where the probability π_i to win the higher payoff in the chosen lottery equals the probability of getting the lower payoff in the counterfactual lottery. In the stag-hunt game, π_i is the subject's probability that her partner chooses the same action. In the entry game, π_i is the subject's probability that her partner chooses the opposite action.

Setting the utility of the stated WTA for the chosen strategy in game k equal to $W_i^k(x_1, x_2, \pi_i)$ and the utility of the stated WTA for the opposing strategy in game k equal to $\bar{W}_i^k(\bar{x}_1, \bar{x}_2, 1-\pi_i)$, while assuming a CRRA utility function with RRA r_i as estimated from decision in the RISK treatment, yields two equations that identify α_i^k and δ_i^k.

As we assumed that subjects evaluate lotteries as expected-utility maximizers, the WTA for a lottery with payoffs 20€ or 15€ and a probability p for the higher payoff should yield a utility that equals $Eu_i(20,15|p)$.

If a subject chooses the strategy that leads to potential payoffs (x_1, x_2) in a game with $x_1 > x_2$, and for a subjective probability π_i of getting x_1, the value of this game is given by Equation (1). Using this,

$$\begin{aligned} W_i^k(x_1, x_2, \pi_i) &= (\alpha_i^k + \pi_i)\, u_i(x_1) + \left(1 - \alpha_i^k - \pi_i\right) u_i(x_2) - \delta_i^k \\ &= Eu_i(x_1, x_2|\pi_i) + \alpha_i^k\, (u_i(x_1) - u_i(x_2)) - \delta_i^k, \end{aligned}$$

and replacing expected utility by utility from stated WTA in the risky lottery (WTA_i^R), we get[11]

$$\frac{\left(WTA_i^k(x_1, x_2, \pi_i)\right)^{1-r_i} - \left(WTA_i^R(x_1, x_2, p = \pi_i)\right)^{1-r_i}}{1 - r_i} = \alpha_i^k[u_i(x_1) - u_i(x_2)] - \delta_i^k$$

$$\Leftrightarrow \delta_i^k = \frac{\left(WTA_i^R(x_1, x_2, p = \pi_i)\right)^{1-r_i} - \left(WTA_i^k(x_1, x_2, \pi_i)\right)^{1-r_i} + \alpha_i^k[x_1^{1-r_i} - x_2^{1-r_i}]}{1 - r_i}. \quad (3)$$

For the lottery with the alternative payoffs $(\bar{x}_1, \bar{x}_2)$, the probability of achieving the higher payoff is $1 - \pi_i$. Thus,

$$\begin{aligned} \bar{W}_i^k(\bar{x}_1, \bar{x}_2, 1 - \pi_i) &= \left(1 - \pi_i - \alpha_i^k\right) u_i(\bar{x}_1) + \left(\pi_i + \alpha_i^k\right) u_i(\bar{x}_2) - \delta_i^k \\ &= Eu_i(\bar{x}_1, \bar{x}_2|1 - \pi_i) - \alpha_i^k\, (u_i(\bar{x}_1) - u_i(\bar{x}_2)) - \delta_i^k. \end{aligned}$$

Replacing the value of the lottery by the utility of the certainty equivalent, WTA_i^k, and EU by WTA under risk, we get:

$$\frac{\left(WTA_i^k(\bar{x}_1, \bar{x}_2, 1 - \pi_i)\right)^{1-r_i} - \left(WTA_i^R(\bar{x}_1, \bar{x}_2, p = 1 - \pi_i)\right)^{1-r_i}}{1 - r_i}$$

$$= -\alpha_i^k\, [u_i(\bar{x}_1) - u_i(\bar{x}_2)] - \delta_i^k$$

$$\Leftrightarrow \delta_i^k = \frac{\left(WTA_i^R(\bar{x}_1, \bar{x}_2, 1 - \pi_i)\right)^{1-r_i} - \left(WTA_i^k(\bar{x}_1, \bar{x}_2, 1 - \pi_i)\right)^{1-r_i} - \alpha_i^k[\bar{x}_1{}^{1-r_i} - \bar{x}_2{}^{1-r_i}]}{1 - r_i}. \quad (4)$$

Setting (3) equal to (4) yields

$$\left(WTA_i^R(x_1, x_2, p = \pi_i)\right)^{1-r_i} - \left(WTA_i^k(x_1, x_2, \pi_i)\right)^{1-r_i} + \alpha_i^k[x_1{}^{1-r_i} - x_2{}^{1-r_i}]$$

[11] Note that, alternatively, we could calculate the expected utility of this lottery by inserting monetary payments in the estimated CRRA utility function. We prefer the more direct comparison between stated WTAs, because this is less affected by assumptions on the utility function.

$$= \left(WTA_i^R(\bar{x}_1, \bar{x}_2, 1-\pi_i)\right)^{1-r_i} - \left(WTA_i^k(\bar{x}_1, \bar{x}_2, 1-\ \pi_i)\right)^{1-r_i} - \alpha_i^k[\bar{x}_1{}^{1-r_i} - \bar{x}_2{}^{1-r_i}]$$

$$\Leftrightarrow \left(WTA_i^R(x_1, x_2, p=\pi_i)\right)^{1-r_i} - \left(WTA_i^R(\bar{x}_1, \bar{x}_2, 1-\pi_i)\right)^{1-r_i} + \left(WTA_i^k(\bar{x}_1, \bar{x}_2, 1-\ \pi_i)\right)^{1-r_i} - \left(WTA_i^k(x_1, x_2, \pi_i)\right)^{1-r_I} = -\alpha_i^k\left[x_1{}^{1-r_i} + \bar{x}_1{}^{1-r_i} - x_2{}^{1-r_i} - \bar{x}_2{}^{1-r_i}\right]$$

$$\Leftrightarrow \alpha_i^k = \frac{A}{B} \quad \text{for } k = S, E, \tag{5}$$

with

$$A = \left(WTA_i^R(x_1, x_2, \pi_i)\right)^{1-r_i} - \left(WTA_i^R(\bar{x}_1, \bar{x}_2, 1-\pi_i)\right)^{1-r_i} + \left(WTA_i^k(\bar{x}_1, \bar{x}_2, 1-\ \pi_i)\right)^{1-r_i} - \left(WTA_i^k(x_1, x_2, \pi_i)\right)^{1-r_i}$$

and

$$B = -\left[x_1{}^{1-r_i} + \bar{x}_1{}^{1-r_i} - x_2{}^{1-r_i} - \bar{x}_2{}^{1-r_i}\right] < 0 \quad \text{for } k = S, E.$$

For subjects with $r_i = 1$, $A = \ln WTA_i^R(x_1, x_2, \pi_i) - \ln WTA_i^R(\bar{x}_1, \bar{x}_2, 1-\ \pi_i) + \ln WTA_i^k(\bar{x}_1, \bar{x}_2, 1-\ \pi_i) - \ln WTA_i^k(x_1, x_2, \pi_i)$, $B = -[ln\, x_1 + ln\, \bar{x}_1 - ln\, x_2 - ln\, \bar{x}_2]$, and $\delta_i^k = \ln(WTA_i^R(x_1, x_2, p=\pi_i)) - \ln(WTA_i^k(x_1, x_2, \pi_i)) + \alpha_i^k[\ln(x_1) - \ln(x_2)]$.

Note that $(x_1, x_2) = (20{,}15) \Leftrightarrow (\bar{x}_1, \bar{x}_2) = (25{,}5)$ and $(x_1, x_2) = (25{,}5) \Leftrightarrow (\bar{x}_1, \bar{x}_2) = (20{,}15)$. In both games, if $(x_1, x_2) = (25{,}5)$, π_i is the probability that the other player chooses R. If $(x_1, x_2) = (20{,}15)$, π_i is the probability that the other player chooses L.

Under ambiguity (*k* = *A*), we elicit the WTAs for two lotteries with payoffs (25,5) and (20,15) along with a subjective probability π_i for receiving the higher payoff in both of these lotteries. Setting utility of stated WTAs equal to $W_i^A(25{,}5, \pi_i)$ and $W_i^A(20{,}15, \pi_i)$, respectively, identifies parameters (α_i^A, δ_i^A). To see this, define $(x_1, x_2) = (20{,}15)$ in Equation (3) and use the same equation also for $(x'_1, x'_2) = (25{,}5)$. Then, by setting the right-hand sides of these equations equal to each other, we get

$$\left(WTA_i^R(20{,}15, p=\pi_i)\right)^{1-r_i} - \left(WTA_i^A(20{,}15, \pi_i)\right)^{1-r_i} + \alpha_i^k\ [20^{1-r_i} - 15^{1-r_i}] = \left(WTA_i^R(25{,}5, p=\pi_i)\right)^{1-r_i} - \left(WTA_i^A(25{,}5, \pi_i)\right)^{1-r_i} + \alpha_i^k\ [25^{1-r_i} - 5^{1-r_i}]$$

$$\Leftrightarrow \alpha_i^A = \frac{A'}{B'}, \tag{6}$$

with

$$A' = \left(WTA_i^R(20{,}15, \pi_i)\right)^{1-r_i} - \left(WTA_i^R(25{,}5, \pi_i)\right)^{1-r_i} + \left(WTA_i^A(25{,}5, \pi_i)\right)^{1-r_i} - \left(WTA_i^A(20{,}15, \pi_i)\right)^{1-r_i}$$

and

$$B' = 25^{1-r_i} - 20^{1-r_i} + 15^{1-r_i} - 5^{1-r_i} > 0.$$

Plugging the result of Equation (6) into one of the Equations (3) also yields δ_i^A.

For subjects with $r_i = 1$, $A' = \ln WTA_i^R(20,15,\pi_i) - \ln WTA_i^R(25,5,\pi_i) + \ln WTA_i^A(25,5,\pi_i) - \ln WTA_i^A(20,15,\pi_i)$, $B' = ln25 - ln20 + ln15 - ln\,5_2$, and $\delta_i^k = \ln(WTA_i^R(x_1, x_2, p = \pi_i)) - \ln(WTA_i^k(x_1, x_2, \pi_i)) + \alpha_i^k[\ln(x_1) - \ln(x_2)]$.

These calculations show that both parameters are identified through comparing WTAs between treatments. By calculating our parameters from differences between WTAs, we avoid the possibility that any systematic bias stemming from the BDM mechanism affects our parameter estimates.

4.2. Hypotheses

Our goal is to find out whether the source of uncertainty affects uncertainty attitudes. Based on the theoretical model, our numerical predictions for the model parameters are given by Bayesian behavior:

Hypothesis 1: There are no systematic attitudes towards or against ambiguity or strategic uncertainty. Parameters α_i^k and δ_i^k are distributed around 0.

Here, we test for each condition $k \in \{A, S, E\}$ whether the parameters α_i^k and δ_i^k from different subjects *i* are distributed around zero. As the literature generally found average subjects to be ambiguity averse, we expect that Hypothesis 1 will be rejected.

Subjects are likely to differ in their uncertainty attitudes and our experiment is designed to capture how individual attitudes are affected by the source of uncertainty being another human's action and by the nature of strategic interaction. Here, we exploit the within-subject design and use as null hypothesis:

Hypothesis 2: Subjects do not make any distinction between the sources of uncertainty and between the considered strategic situation (strategic complementarity versus substitutability): $\alpha_i^A = \alpha_i^S = \alpha_i^E$ and $\delta_i^A = \delta_i^S = \delta_i^E$.

A positive (negative) δ_i^k is interpreted as a general aversion against (preference for) ambiguity or strategic uncertainty. A positive (negative) α_i^k is interpreted as optimism (pessimism) for receiving the higher payoff under ambiguity or strategic uncertainty.

5. Results

This section outlines the main empirical results based on the pre-registered procedures of sample selection and data analysis. They can be summarized as follows. Subjects react to the presence of uncertainty (notwithstanding Hypothesis 1), but also make a systematic distinction between the different sources of uncertainty (notwithstanding Hypothesis 2). Importantly, the magnitude of that last effect depends on the strategic context. Regarding the two parameters of our structural model, we find that the majority of subjects exhibits pessimism [optimism] in the stag-hunt [entry] game while the median subject has neither a preference for nor an aversion against strategic uncertainty.

5.1. Data selection

We begin by applying the data selection criteria to the initial sample of 228 subjects. The elicitation of both WTAs, for the preferred and the non-preferred action, provides us with a consistency measure since it should be that $WTA_{\text{preferred}} \geq WTA_{\text{not preferred}}$. If a participant violates this criterion such that her WTA for participating with her preferred action is lower than the WTA for the not preferred action in at least one of the games, we exclude this participant from our main data analysis. The reason is that such a reversal indicates a systematic misunderstanding of the BDM procedure that could affect all stated WTAs and data from these subjects might just introduce noise. For the same reason, we exclude subjects whose stated WTA for a lottery that pays the higher payoff with probability 1 is lower than the stated WTA for an otherwise equal lottery that pays the higher payoff with probability 0. These criteria were pre-specified. We also pre-specified a robustness check using the full sample.

In 45 [63] cases we observe a violation of choice consistency in the stag-hunt [entry] game: the stated WTA for the preferred action is lower than the WTA for the not preferred one.[12] 19 subjects violate our rationality criterion in the lotteries: the stated WTA for a lottery that surely pays a high payoff is lower than the stated WTA for an otherwise equal lottery that never pays a high payoff. Jointly put, these criteria turn out to be stringent.[13] In total, there are 102 subjects to whom at least one of these exclusion criteria applies. We call the remaining 126 subjects the restricted sample.

Ex post, after conducting the experiments, we detected that certain combinations of choices lead to extreme values of estimated relative risk aversion (beyond +/-100) and thereby also to estimated values for α and δ in astronomical dimensions. In total, there are 15 subjects with an estimated RRA outside $[-100, +100]$, 7 in the restricted sample. We exclude them from the parametric analysis. 5 other subjects (1 from the restricted sample) have an estimated RRA $>$ 1, but stated a WTA of 0 for at least one of the games or lotteries needed to calculate uncertainty parameters. For these subjects, some or all pairs (α_i^k, δ_i^k), *k=A,S,E,* cannot be calculated. So, we exclude these subjects from all analyses of uncertainty parameters.

5.2. Comparison of certainty equivalents

In the experiment, we elicit the WTAs for two lotteries with outcomes depending on the strategy of another player or on ambiguity simultaneously with subjective probabilities for the possible outcomes. As an initial descriptive step of our analyses, we can directly compare the WTA of a lottery in a game (where the outcome is determined by another player's action) with the WTA of a lottery that yields the same payoffs with exogenously given probabilities that match the subjective probabilities in the game. Similarly, the WTA for an ambiguous lottery with unknown probabilities can be compared to the WTA of a lottery yielding the same payoffs with given probabilities that match the subject's stated probabilities for the ambiguous lottery.

Note that in theory, the WTA for a game is the higher of the two WTAs for the two possible actions. As a first step in analyzing uncertainty attitudes, we count the number of subjects whose WTA for a game or for an ambiguous situation is higher than, equal to or lower than the WTA for the analogous lottery played under risk. This informs us about the average preference for, or aversion against, a given source of uncertainty. Note that the size of these deviations may depend on payoffs associated with the chosen strategy, but also on the subjective probabilities.

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[12] For 5 subjects, the selected action in one of the games was not recorded due to a minor software glitch. One of them failed to comply with the inclusion criterion for lottery choices, the remaining 4 are included in the restricted sample.

[13] While lack of understanding of the BDM mechanism may partially account for deviations from expected utility, we also note that the BDM performs not worse than the alternative elicitation methods for certainty equivalents in terms of bias and noise (Hey et al., 2009).

Table 4 presents the results of this comparison separately for the two lotteries under ambiguity, for the lottery implied by the actually chosen action in each game, but also for the counterfactual lottery implied by "replacing" the subject's actual choice with the alternative action.

Table 4. Comparison of certainty equivalents

	Ambiguity: k=A		Stag hunt: k = S		Entry: k = E	
(x_1, x_2)	(20,15)	(25,5)	chosen	replaced	chosen	replaced
$WTA_i^k(x_1, x_2, \pi_i) > WTA_i^R(x_1, x_2, \pi_i)$	43	49	45	60	80	30
$WTA_i^k(x_1, x_2, \pi_i) = WTA_i^R(x_1, x_2, \pi_i)$	26	29	29	23	12	23
$WTA_i^k(x_1, x_2, \pi_i) < WTA_i^R(x_1, x_2, \pi_i)$	57	48	52	43	34	73

Note. In the stag-hunt [entry] game, 81 [101] out of 126 subjects choose the action R.

The WTAs under ambiguity and for the stag-hunt game are not significantly different from the WTAs under risk. A Wilcoxon signed rank test yields p-values above 0.2. For the entry game, however, we find that subjects have a higher WTA for the lottery implied by their own choice in the game than for the respective lottery with exogenously given probability (p-value < 0.001). The opposite effect occurs once we look at the WTA for the lottery implied by replacing the actual choice with the opposite action: it is lower than the WTA for the respective lottery under risk (p-value < 0.001). This indicates that the median subject tends to be optimistic about the behavior of her partner in the entry game. The weight a player puts on the payoff corresponding to her partner choosing a different action than her own exceeds her stated probability of that outcome.

Direct comparisons between WTAs of different games or between a strategic game and an ambiguous situation could only be possible if a subject stated the same probability for getting the higher payoff in both contexts. Unfortunately, restricting analysis to these observations would leave us with just a few matched pairs and possibly introduce a selection bias. Thus, for further econometric analysis, we use strategic-uncertainty attitudes as characterized by the parameters α_i^k and δ_i^k of our structural model. In order to identify these parameters, we need to estimate a utility function for each subject.

5.3. Main results

Our identification strategy relies on a two-step procedure. As a first step, we use the individual certainty equivalents (WTA) elicited in 22 lotteries to estimate individual parameter r_i of the CRRA utility function. We adopt a parametric procedure from Hey et al. (2009). For a given lottery (x_1, x_2, π_i), the observed $WTA_i(x_1, x_2, \pi_i)$ corresponds to the latent expected value $Eu_i(x_1, x_2, \pi_i)$, but is also subject to an *i.i.d.* error $e_i \sim N(0, s_i^2)$: $WTA_i(x_1, x_2, \pi_i) = u_i{}^{-1}(Eu_i(x_1, x_2, \pi_i)) + e_i$. For each individual i, the pair of parameters (r_i, s_i) is estimated through standard maximum likelihood (ML) estimation.[14] As a second step, the estimated

[14] For 14 subjects (among which 6 appear in the restricted sample) the ML procedure cannot converge since their parameter r is unbounded and takes extreme values: it either tends to plus infinity or to minus infinity. For the sake of nonparametric tests, these subjects are assigned extreme realizations of r going beyond values observed in the remainder of the sample: either 200 or -200, respectively. In parametric analyses, we only consider cases where the estimated $r \in$[-100; 100], which requires removing all the subjects mentioned above as well as another one

coefficient $\hat{r}_i$ is used to compute two individual parameters (α_i^k, δ_i^k) for each context of uncertainty $k = A, S, E$ following Equations (3), (5), and (6).

Accordingly, the top part of Table 5 summarizes the first-step risk attitudes and the second-step uncertainty attitude parameters, as estimated in the restricted sample. Most subjects are found to be either risk seeking or risk averse, both types of preferences emerging in similar proportions. Moving to the domain of uncertainty, we find that, in our benchmark AMBIGUITY condition, most subjects are either pessimistic ($\alpha^A < 0$) or optimistic ($\alpha^A > 0$), both of which again happen in equal proportions. In a similar vein, most subjects are found to exhibit either aversion against ($\delta^A > 0$) or preference for ($\delta^A < 0$) ambiguity. In purely descriptive terms, the parameter of uncertainty aversion is not significantly different from zero in any of the conditions. However, we observe that the median subject is pessimistic about the behavior of the other player in the stag-hunt game ($\alpha^S < 0$) and optimistic in the entry game ($\alpha^E > 0$).[15]

Table 5. Summary of estimated uncertainty attitudes

Parameters	Median	#N>0	#N=0	#N<0	Sign test
Restricted sample					
$\hat{r}$	0	60	11	54	-
$\hat{\sigma}$	2.356	108	11	-	-
α^A	0	53	14	58	0.704
α^S	-0.065	41	11	73	0.003
α^E	0.214	92	7	26	<0.001
δ^A	0	58	14	53	0.704
δ^S	0	51	12	62	0.347
δ^E	-0.073	51	4	70	0.101
Unrestricted sample					
$\hat{r}$	-0.191	88	16	119	-
$\hat{\sigma}$	2.535	193	16	-	-
α^A	-0.005	89	20	114	0.092
α^S	-0.133	72	11	140	<0.001
α^E	0.104	131	10	82	0.001
δ^A	0	103	21	99	0.833
δ^S	0	92	16	115	0.126
δ^E	-0.018	96	6	121	0.103

Note. Columns 3-5 summarize the absolute frequencies of estimated parameter values (as listed in column 1) being positive, negative, or null, respectively. The last column provides *p*-values from a sign test of nullity of the median value of the respective parameter. Top (bottom) part of the table: *N*=125, restricted sample (*N*=223, unrestricted sample).

Statistical evidence provided in the last column in Table 5 does not corroborate Hypothesis 1 stating that across all conditions, both parameters are located at zero. The nonparametric sign test strongly rejects the nullity of the median of α in both games; the nullity of the median cannot be rejected at the 5% level for any other parameter.

with the estimated *r* of -112; this subject appears in both the restricted and the unrestricted sample. The resulting range of estimated values of *r* is (-33, 4) in a sample of 207 observations.

[15] Wilcoxon signed rank tests also reject $\alpha^S = 0$ and $\alpha^E = 0$ at the 1% level and across samples. Since the distribution of these parameters is asymmetric, we prefer to report the outcomes of a more conservative sign test which does not require the symmetry assumption.

Next, we provide a complementary parametric analysis using a Seemingly Unrelated Regression (SUR) estimation. For the ith subject, parameters α_i^k and δ_i^k are assumed to depend on the experimental condition $k \in \{A, S, E\}$ in the following way:

$$\alpha_i^k = a_0 + a_S \times 1[k = S] + a_E \times 1[k = E] + u_i^k, \quad (7)$$

$$\delta_i^k = d_0 + d_S \times 1[k = \mathrm{S}] + d_{\mathrm{E}} \times 1[k = E] + v_i^k, \quad (8)$$

where $1[k = X] = 1$ if a decision is made in condition X, and $1[k = X] = 0$ otherwise. The AMBIGUITY condition A is set as the reference condition. Hence, $\mathrm{E}(\alpha_i^A) = a_0$, $E(\alpha_i^S) = a_0 + a_S$, $E(\alpha_i^E) = a_0 + a_E$, and $E(\delta_i^A) = d_0$, $E(\delta_i^S) = d_0 + d_S$, $E(\delta_i^E) = d_0 + d_E$. In each of the two equations, errors are clustered at the individual level due to the within-subject implementation of the experimental conditions.

The main virtue (and relative advantage with respect to the nonparametric methods) of this approach is that it provides a one-size-fits-all framework for fitting our experimental data that fully accounts for the within-subject treatment variation and the presence of two distinct preference parameters, α_i^k and δ_i^k, that simultaneously arise as dependent variables. Furthermore, it allows us to go beyond single-parameter tests, and instead test for the joint hypothesis that a group of parameters has zero mean through a standard Wald test. It also allows us to test for order effects.[16] However, the challenge here is to account for the presence of outliers arising for two reasons. First, extreme risk preferences can drive the estimated uncertainty parameters to astronomical values. Second, due to the cardinality of the value function in Equation (1), the parameter δ_i^k is expressed in units of subjective utility. For both reasons, δ_i^k can take extreme values, whether positive or negative. We tackle this issue in two ways. First, as explained above, parametric analyses consider only subjects whose estimated RRA lies in $[-100, 100]$. For this sample, we apply the negative logarithm transformation to δ_i^k, i.e. we replace δ_i^k in Equation (8) by $sign(\delta_i^k)\log(1 + |\delta_i^k|)$ in order to de-emphasize extreme realizations. Second, we estimate the SUR without logarithmic transformation, by only looking at individuals whose estimated RRA lies in [-3; +3], a range that should be considered reasonable in the light of existing literature (see Charness et al., 2020). Applied to the restricted and unrestricted samples in turn, this procedure delivers four regression specifications that are reported in Table 6. Table 7 further summarizes additional parametric mean tests based on the estimated coefficients.

[16] Order effects may arise since the order of *S* and *E* treatments is random, yet balanced across sessions. To check for the possible order effects, regression models (7) and (8) can be extended by including an indicator variable for the order of the experimental conditions along with its interactions with both independent treatment indicator variables. This specification allows us to compare outcomes across treatments for a given order (in analogy to comparisons made in models (7) and (8)). It also allows for a formal statistical test of order effects in the data through Chow test that we run simultaneously for both extended regressions to check whether the order-related coefficients are jointly insignificant. This exercise points to the lack of order effects at the conventional 5% significance level, and hence does not raise any indication of order effects. See Table A1 in Online Appendix A3 for details.

Table 6. Uncertainty attitudes across treatments: parametric estimates from seemingly unrelated regressions

Dep. variable:	α_i^k	δ_i^k	α_i^k	δ_i^k	α_i^k	δ_i^k	α_i^k	δ_i^k
Specification	(1)		(2)		(3)		(4)	
Indep. Variable	$\hat{a}$	$\hat{d}$	$\hat{a}$	$\hat{d}$	$\hat{a}$	$\hat{d}$	$\hat{a}$	$\hat{d}$
$1[k=S]$	-0.038	-1.194	-0.123*	946.12**	0.027	-1.957	-0.090	214.61
	(0.078)	(1.429)	(0.065)	(413.71)	(0.125)	(2.048)	(0.101)	(216.37)
$1[k=E]$	0.347**	-1.557	0.232**	672.49*	0.575**	-2.353	0.385**	154.93
	(0.154)	(1.434)	(0.108)	(345.11)	(0.259)	(2.114)	(0.173)	(123.52)
Constant	-0.120***	0.364	-0.107***	-819.18*	-0.103**	0.789	-0.093*	-162.32
	(0.040)	(0.853)	(0.041)	(435.00)	(0.047)	(1.251)	(0.048)	(106.58)
Observations (clusters)	624 (208)		561 (187)		354 (118)		321 (107)	

Note. Standard errors are clustered at the subject level and reported in parentheses. $1[k=T]$ is a binary variable set to 1 for condition T, and to 0 otherwise. In all models, we exclude cases with indefinite δ_i^k as well as those with estimated r_i outside the range [-100,100]. Specifications (1) and (3) use neglog transformation of δ_i^k. In specifications (2) and (4), we consider only subjects with an estimated r_i in the range [-3,3]. Specifications (1) and (2) use the unrestricted sample, (3) and (4) the restricted sample. Significance levels: * p<0.1 ** p<0.05 *** p<0.01.

Table 7. Results of mean testing across specifications

Tests	(1)	(2)	(3)	(4)
$E(\alpha_i^A)=0$	0.003	0.009	0.030	0.053
$E(\alpha_i^S)=0$	0.031	<0.001	0.536	0.067
$E(\alpha_i^E)=0$	0.111	0.204	0.054	0.077
$E(\delta_i^A)=0$	0.670	0.060	0.528	0.128
$E(\delta_i^S)=0$	0.345	0.551	0.366	0.763
$E(\delta_i^E)=0$	0.176	0.389	0.242	0.949
$E(\alpha_i^A)=E(\alpha_i^E)=E(\alpha_i^S)$	0.016	<0.001	0.055	0.001
$E(\delta_i^A)=E(\delta_i^E)=E(\delta_i^S)$	0.283	0.075	0.404	0.443
$E(\alpha_i^A)=E(\alpha_i^E)=E(\alpha_i^S)=0$	0.001	<0.001	0.045	0.001
$E(\delta_i^A)=E(\delta_i^E)=E(\delta_i^S)=0$	0.401	0.151	0.580	0.375
Nullity of all parameters	0.001	<0.001	0.026	0.003

Note. p-values corresponding to the stated mean test in column 1 are based on the coefficient estimates from the four specifications reported in Table 6. Respective samples contain 208, 187, 118 and 107 subjects for specifications (1), (2), (3) and (4).

Overall, results reported in Tables 5 (nonparametric median tests) and 7 (parametric mean tests) lead us to reject Hypothesis 1 on the absence of attitudes towards uncertainty.[17] These attitudes

[17] Strictly speaking, joint tests reported at the bottom of Table 7 constitute the target testbed for Hypothesis 1, although it should also be noted that they remain mute on the precise reasons (i.e., which parameters are non-null)

strongly vary across contexts. The nonparametric tests (Table 5) indicate that the median of α_i^S is negative while the median of α_i^E is positive. The parametric tests (Table 7) indicate that the mean of α_i^A differs from zero, while we cannot reject (at p=5%) that the means of α_i^E and α_i^S are zero. Note, however, that the estimated values of α_i^k and δ_i^k are not normally distributed. The p-values from the Shapiro-Wilk W test are all below 0.001. Thus, the main empirical rationale for rejecting Hypothesis 1 comes from the rejection of the joint nullity of all parameters, from pessimism by the median subject in the stag-hunt game and optimism by the median subject in the entry game. The estimates for the AMBIGUITY condition alone would not be sufficient for rejecting Hypothesis 1, because the median of α_i^A equals zero (Table 5). The nullity of parameter δ_i^k, in turn, comes as a persistent empirical finding across all tests and all treatments.

Result 1 – We document systematic attitudes toward uncertainty. Parameters α_i^k are not distributed around 0 under strategic uncertainty pointing to pessimism regarding the behavior of the other player under strategic complementarity, and to optimism under strategic substitutability. Beside this, we do not find a systematic preference for or aversion against strategic uncertainty.

Building on this result, we now turn to the formal comparisons of α and δ between the three experimental conditions of uncertainty (ambiguity, stag-hunt, and entry game) and test Hypothesis 2. Table 8 summarizes pairwise median comparisons based on the Wilcoxon signed rank test, as estimated on either the restricted or the unrestricted sample. Once again, the general finding goes against our initial hypothesis: we observe more optimism in the entry game than in the stag-hunt game or in the benchmark AMBIGUITY condition.[18] Figure 1 provides additional visual support of this result: the cumulative distribution function of α in the entry game first-order stochastically dominates the remaining ones, while not such differences arise for δ.

Table 8. Nonparametric comparisons of uncertainty attitudes across treatments

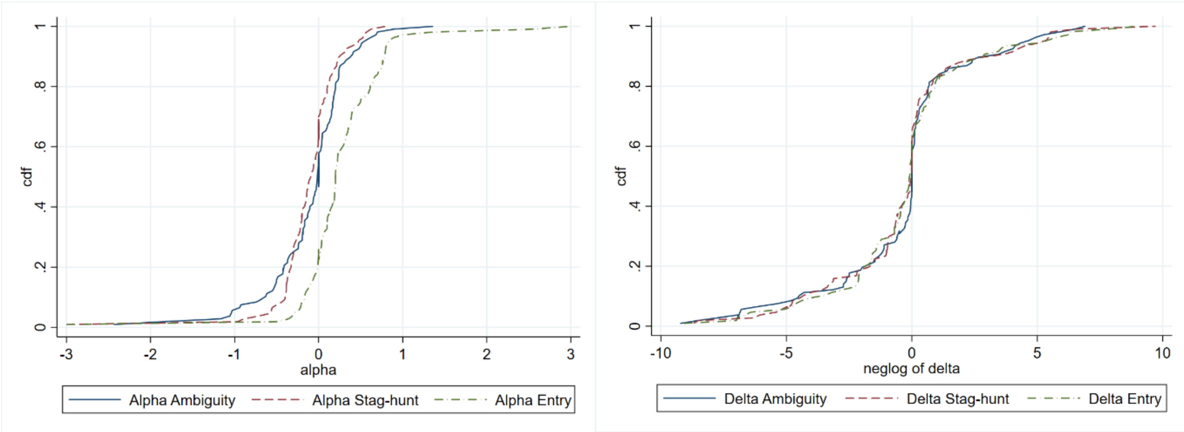
Sample:	Restricted (N=125)		Unrestricted (N=223)	
Comparison/Parameter	α_i^k	δ_i^k	α_i^k	δ_i^k
Ambiguity - Stag hunt	0.226	0.478	0.021	0.571
Ambiguity – Entry	<0.001	0.407	<0.001	0.893
Stag hunt – Entry	<0.001	0.671	<0.001	0.410

Note. Columns 2-5 provide p-values from two-sided Wilcoxon signed rank tests.

for the potential rejection. From this perspective, single-parameter tests reported in Table 5 and the first six lines of Table 7 provide complementary information.

[18] Echoing Footnote 14, one caveat here is that the symmetry assumption required by Wilcoxon signed rank test may not hold in our data. An alternative nonparametric sign test yields the same results with one exception: α_i^k is significantly different between the stag-hunt game and the AMBIGUITY condition (see Online Appendix A.3 for details).

Figure 1. Cumulative density functions of uncertainty attitude parameters across conditions



Note. Data from the restricted sample trimmed to $\hat{r} \in [-3,3]$ (*N*=107). The *x* axis in second graph contains neglog transformation of δ_i^k: $sign(\delta_i^k)\log(1+|\delta_i^k|)$ to account for a wide range of values taken by this variable.

Parametric estimates presented in Table 6 point to similar conclusions: the entry game induces significantly stronger optimism as compared to both AMBIGUITY and the stag-hunt game ($p < 0.05$ in all comparisons).[19] A parametric comparison of δ across treatments does not yield significant results at the 5% level.

Result 2 – Subjects distinguish between the different sources of uncertainty. Uncertainty coming from interaction under strategic substitutability gives rise to more optimism as compared to both ambiguity and interaction under strategic complementarity. Strategic complementarity does not induce significant changes in attitudes towards uncertainty as compared to ambiguity. We do not find significant and systematic differences across the three treatments in terms of preferences towards the source of uncertainty.

In Online Appendix A4, we provide additional analyses on the individual underpinnings of attitudes towards uncertainty based on the individual characteristics described in our pre-results reviewed report. We do not find any systematic association of individual characteristics with the six parameters of interest.

6. Conclusion

We have developed a method for measuring strategic-uncertainty attitudes and distinguishing them from risk and ambiguity attitudes. We elicit certainty equivalents of participating in two strategic 2x2 games (stag-hunt and market-entry games) as well as certainty equivalents of related lotteries that yield the same possible payoffs with exogenously given probabilities (risk) and lotteries with unknown probabilities (ambiguity). We use this information to identify for each game and for the ambiguous environment two parameters of a structural model of uncertainty attitudes. The parameters of this model capture subject-specific uncertainty aversion and optimism regarding the subject's subjective probability for the desired outcome. We then test whether there are significant differences in the distribution of uncertainty attitudes

[19] These comparisons require testing for the equality of $E(\alpha_i^E)$ with $E(\alpha_i^A)$ and $E(\alpha_i^S)$.

between games with strategic complements, games with strategic substitutes, and ambiguous lotteries.

We find systematic attitudes towards uncertainty that vary across contexts. While there is no evidence for a preference for, nor for an aversion against, ambiguity or strategic uncertainty (in the sense of a fixed effect of the source of uncertainty on utility), the median subject seems to be pessimistic about the behavior of the other player in the stag-hunt game, and optimistic in the entry game, where optimism/pessimism are proportional to the difference between the utility expressed by stated WTAs in a given game and the subjective expected utility derived from the stated probability for the other player's choice.

In the entry game, optimism means that the median subject's evaluation of the game is shifted from her expected utility in direction of the higher payoff that arises if the other player chooses the action opposing her own. In the stag-hunt game, the median subject's evaluation is shifted from her expected utility towards the lower payoff. In stag hunt, the lower payoff arises if both players choose opposing actions. Thus, the median subject evaluates both games with an extra weight on the other player choosing the action opposed to her own.

Our results also show that the entry game stands out, because the distribution of optimism in the entry game stochastically dominates the distribution of optimism in stag-hunt and ambiguity treatments. This reflects the results by Nagel et al. (2018) that indicate a higher degree of strategic uncertainty and higher levels of reasoning in entry games than in stag-hunt games and lotteries.

Stag-hunt and entry games differ in the reasoning process leading to a decision. If a player has an initial preference for one action, say L, and considers what she should do had the other player also chosen L, then her initial preference is confirmed in the stag-hunt game. If her partner reasons in the same way, it is optimal for both to choose L. In the entry game, however, if the other player thinks like her and chooses L, then she should choose action R instead; however, if the other player follows the same reasoning as her, then she should switch back to L. This inconclusive reasoning process may be the underlying reason for higher brain activity in Nagel et al. (2018) and for the deviation between the stated value (WTA) of a game and its subjective expected utility. Eventually, the extra weight associated with an opposing action expressed by optimism in entry and pessimism in stag-hunt games is a precaution against the other player applying a different reasoning process leading to a different action.

Our findings further complement the literature on the choice/preference relationship in games. For instance, Clark and Chew (2015) compare choices in a coordination game with strategic complementarities when the opponent is another human or a die in presence of a safe opt-out option. Their findings indicate that the source of uncertainty does not significantly alter choices in this game.[20] In another related experiment, Calford (2020) finds that uncertainty aversion measured with a game can account for choices in another game. Our results are consistent with the literature finding source-dependence in uncertainty attitudes (e.g., Abdellaoui et al., 2011; Clark and Chew, 2015). We add to this literature by developing a general method for identifying and comparing attitudes towards strategic uncertainty. We focus on attitude measurement in two prototypical games, but the method can be easily applied to other settings.

[20] However, they find indicative evidence for the role of source of uncertainty in another game (i.e., matching pennies) relative to coordination game. Their accompanying evidence from neuroimaging data favor ambiguity attitudes over social preferences in explaining these results.

Finally, our empirical evidence highlights the general importance of individual probability distortion (rather than a domain-specific utility function) for understanding decision-making under uncertainty. This finding corroborates some of the previous research on modelling uncertainty in individual (i.e., non-strategic) choices (see, e.g., Abdellaoui et al., 2011; Attema et al. 2013) and further extends it by showing that the relative importance of probability weighting also applies to strategic contexts.

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ONLINE APPENDIX: SUPPLEMENTARY MATERIAL

A1. Instructions

Whether Game 1 or 2 is played first is randomly chosen by the computer. Here we only present instructions where Game 1 is played first.

Welcome!

You are about to take part in an economic experiment. You are not allowed to talk to other participants during the experiment. If you have a cell phone, please switch it off. If you have a question at any time, please raise your hand and someone will come to help you. Please do not ask your question aloud. If the question is relevant for all participants, we will repeat it and answer it aloud. If you violate these rules, we must exclude you from the experiment and from payment.

All the information you provide, the decisions you make, as well as the amount of your gains from this experiment will remain strictly confidential and anonymous.

Participation in this experiment will earn you money. Your earnings will depend on your decisions and may also be affected by the decisions made by others.

The experiment consists of five parts. You will receive specific instructions for each part as the experiment goes on. At the end of the experiment, only one part out of Parts 1 to 4 will be chosen at random to determine your final payoff for the experiment, where each of these four parts has the same chance to be randomly drawn. Within each part, you make several decisions. If a part is randomly chosen for payment, one of those decisions will be drawn for payment by another random mechanism of the computer, where each decision has the same chance to be randomly drawn. Hence, only one of your decisions will affect your final payoff, but it could be *any*one of your decisions. For showing up in time, you additionally obtain 5 Euros.

The fifth part does not offer you the chance to earn money.

Specific Instructions for Part 1

In this part of the experiment, you will face **22 lotteries**. 11 of them pay either 15 or 20 Euros. The others pay either 5 or 25 Euros. For both payoff types, the probability to get the higher of the two possible payoffs varies from 0 to 100% in steps of 10%.

For each of the 22 lotteries, we ask you the following **question**:

- Which amount (in Euro) would you prefer to receive with certainty instead of letting the lottery determine your payoff?

You need to enter your answers for these questions in the columns “Opt-out value for lottery that pays either 15 or 20 Euros” and “Opt-out value for lottery that pays either 5 or 25 Euros”, respectively. You can state any value **from 0 to 30 Euros**, with up to two decimals. Your answers to these questions will determine your candidate payoff for this part of the experiment with **the following two-step procedure**:

If this part is selected for payoff, the computer will randomly select one of the 22 lotteries. Second, the computer will randomly draw an amount from 0.00 to 30.00 Euros with two decimals (each value in the interval is equally likely).

- If the randomly drawn amount is larger than or equal to your stated “Opt-out value” for the selected lottery, your payoff is the amount drawn by the computer.
- If the amount drawn by the computer is smaller than your stated “Opt-out value” for the selected lottery, your payoff will be determined by the rules of this lottery. This means, you will get the higher of the two possible payoffs with the probability p stated in the left column. You will get the lower of the two possible payoffs with the remaining probability $1 - p$.

Example:

- Suppose that the computer selects the lottery that pays either 15 or 20 Euros with a probability of receiving the higher payoff $p = 90\%$. Suppose that your stated “Opt-out value” for this lottery is equal to 17.50.

  If the amount drawn by the computer is at least 17.50, you will receive this amount. So, if the drawn amount is 26.09, you receive 26.09 Euros.

  If the number drawn by the computer is smaller than your opt-out-value, say 9.79, your payoff for this part is determined by the selected lottery. Here, you will receive 20 Euros with probability $p = 90\%$. With probability $1 - p = 10\%$, you will receive 15 Euros.

You will see those 22 lotteries listed on your screen as described in the Table below. Once you state both of your “Opt-out values” for each of the 22 lotteries given in the Table below, you need to confirm these answers by clicking on the “CONFIRM” button. You can change these “Opt-out values” as long as you have not confirmed them.

22 lotteries in Part 1

Probability with which the computer selects the higher payoff	Opt-out values for lottery that pays either 15 or 20 Euros	Opt-out values for lottery that pays either 5 or 25 Euros
0%		
10%		
20%		
30%		
40%		
50%		
60%		
70%		
80%		
90%		
100%		

Before beginning the actual Part 1, you will perform the same task with five different lotteries. This phase is for practice purposes and will not influence your payoff. You will also receive feedback about the random selections of the computer in this practice round and about the consequence of the two-step procedure using your stated opt-out values. Note that in the real experiment, you will not be informed about these outcomes before the end of the experiment.

Specific Instructions for Part 2

In this part of the experiment, you will face **2 lotteries**. One of them pays either 15 or 20 Euros. The other pays either 5 or 25 Euros. Note that these are the same payoffs offered by the lotteries as in the previous part. But now, you will not be informed about the probability with which the computer chooses the higher payoff.

The computer is programmed in such a way, that the probability with which the higher payoff is paid is one of the probabilities stated in Part 1, i.e.: 0, 10%, 20%, …, 100%. The computer selects this probability before you submit your decision for this part. Each of these 11 probabilities might be the one applied to the lotteries in this part, but they are not equally likely. This means, some probabilities are more likely to be drawn than others. However, you will not receive any further information about the precise random mechanism.

For each of the two lotteries, we ask you the following **question**.

- Which amount (in Euro) would you prefer to receive with certainty instead of letting the lottery determine your payoff?

You need to enter your answers for these questions in the boxes “Opt-out value for lottery that pays either 15 or 20 Euros” and “Opt-out value for lottery that pays either 5 or 25 Euros”, respectively. You can state any value **from 0.00 to 30.00 Euros**, with up to two decimals. Your answers to these questions will determine your payoff for this part of the experiment with **the following two-step procedure**:

If this part is selected for payoffs, the computer will randomly select one of the two lotteries. Second, the computer will randomly draw an amount from 0.00 to 30.00 (each amount in the interval is equally likely).

- If the randomly drawn amount is larger than or equal to your stated “Opt-out value” for the selected lottery, your payoff is the amount drawn by the computer.
- If the amount drawn by the computer is smaller than your stated “Opt-out value” for the selected lottery, your payoff will be determined by the rules of the chosen lottery. This means, you will get either of the two possible payoffs 15 or 20 Euros if the lottery that pays either 15 or 20 is selected and 5 or 25 Euros if the lottery that pays either 5 or 25 is selected.

Once you stated the two “Opt-out values”, we will ask you about your guess how likely it is that the computer selects the higher payoff. We are asking your guess for the following question:

- **Out of 10 draws, how many times does the computer select the higher payoff?**

If your guess exactly matches the true number of draws that the computer selects the higher payoff, your payoff from this decision will be 20 Euros. If your guess is not exactly accurate, then you may receive 20 or 10 Euros. The likelihood to receive the high payoff (20 €) is higher, the closer your guess is to the expected number of draws. This means the more accurate your guess is, the higher your payoff from this decision will be. You can look up the precise mechanism rewarding your stated beliefs by clicking on the button “more information.” The mechanism makes sure that it is in your best interest to state your true belief about the expected number of draws.[21]

[21] The computer interface contains a button opening a pop-up window with specific description of this procedure: *If this decision is selected for final payment, your gain will be determined according to the following procedure. First, the computer calculates DIFF: the difference between your answer and the correct answer, and then computes its square value: DIFF2=DIFF*DIFF. Second, the computer randomly draws an integer number between 0 and 100 (each realization being equally likely).*

If the value of DIFF2 is below that random integer, your payoff equals 20 euros; otherwise, your payoff equals 10 euros.

Summary and Payoff Procedure for Part 2:
In this part of the experiment, you will first state your "Opt-out values" for the two lotteries. Second, you will state your guess about the likelihood that the computer selects the higher payoff.
A random mechanism will decide how your candidate payoff for this part of the experiment will be determined. **2 out of 3 times**, it will be determined based on the two-step procedure which uses your stated "Opt-out values" as described in Part 1. **1 out of 3 times**, it will be determined based on the accuracy of your stated guess.

A1.3. STRATEGICUNCERTAINTY treatment

Specific Instructions for Part 3

In this part, you are randomly matched with another participant in this session. We will never inform you about the identity of this other participant. You and this other participant will each choose between two Actions L and R.

The payoffs (in Euro) for you and the other participant are presented in the Table below: in each cell, the first amount is your payoff, and the second amount is the other participant's payoff. These payoffs can be summarized as follows:

– If you and the participant you are matched with both choose L, you both receive **20 Euros**;

– If you choose L and the participant you are matched with chooses R, then you receive **15 Euros** and the other participant receives **5 Euros**;

– If you and the participant you are matched with both choose R, you both receive **25 Euros**;

– If you choose R and the participant you are matched with chooses L, then you receive **5 Euros** and the other participant receives **15 Euros**.

Decision situation in Part 3 and associated payoffs in Euro.

		The other participant's decision	
		L	R
Your decision	L	20 €, 20 €	15 €, 5 €
	R	5 €, 15 €	25 €, 25 €

First, you and the other participant will **decide between Actions L and R.** We call this "**Decision 1**".

If this part is selected for payoffs, with 1/3 probability, your payoff as well as the other participant's payoff are determined by your and the other participant's Decision 1 as described above.

Once you made your Decision 1 (and before payoffs are determined), we ask you to state two "Opt-out values" similar to the ones in Parts 1 and 2. The precise questions are the following:

- **If the computer replaces your decision with Action L**, which amount (in Euro) would you prefer to receive with certainty instead of continuing with Action L?
- **If the computer replaces your decision with Action R**, which amount (in Euro) would you prefer to receive with certainty instead of continuing with Action R?

Just as in Parts 1 and 2, you need to **state an amount from 0.00 to 30.00 Euros** for both questions above. You need to enter your answers for these questions in the columns "Opt-out value for Action L" and "Opt-out value for Action R", respectively. You can state any value **from 0.00 to 30.00 Euros**, up to two decimals. Your answers to these questions will determine your payoff for this part of the experiment with **the following two-step procedure**: If Part 3 is selected for payoffs, with 1/3 probability, your payoff will be determined based on the two-step procedure which uses your stated "Opt-out values". In this case, the computer will randomly select one of the two actions L or R for you. Second, the computer will randomly draw an amount from 0.00 to 30.00 Euros (each amount in the interval is equally likely).

- If the randomly drawn amount is larger than or equal to your stated "Opt-out value" for the action selected by the computer, your payoff is the amount drawn by the computer.
- If the amount drawn by the computer is smaller than your stated "Opt-out value" for the action selected by the computer, your payoff will be determined by this action and the action chosen in "Decision 1" by the participant you are matched with.

Example: Suppose the computer replaces your action by R and draws the amount 21.24. If your opt-out value for Action R is smaller than 21.24, you receive 21.24 Euros. If your opt-out value is larger, your payoff depends on the other participant's Decision 1. If the other participant has chosen L, you receive 5 Euros. If the other participant has chosen R, you receive 25 Euros.

Once you stated the two "Opt-out values", we will ask you about your guess how likely it is that the other participants in this room choose Action R. We are asking your guess for the following question:

- **How many of the other 10 participants in this session choose Action R?**

The payoff for your guess will be determined in the same way as in Part 2.
If your guess exactly matches the true number of choices for Action R, your payoff from this decision will be 20 Euros. If your guess is not exactly accurate, then you may receive 20 or 10 Euros. The likelihood to receive the high payoff (20 €) is higher, the closer your guess is to the expected number of draws. This means the more accurate your guess is, the higher your payoff from this decision will be. You can look up the precise mechanism rewarding your stated beliefs

by clicking on the button “more information.” The mechanism makes sure that it is in your interest to state your true belief about the expected number of draws.

Finally, you need to confirm your decisions by clicking on the “CONFIRM” button. You can change your decisions as long as you have not confirmed them.

Summary and Payoff Procedure for Part 3:
In this part of the experiment, you will answer **four questions**. First, you will state your preferred action (either L or R) for Decision 1. Second, you will state the two “Opt-out values” in case the computer replaces your decision by L or R. Third, you will state your guess on how many out of 10 randomly drawn other participants would choose Action R as their preferred action.

Another random mechanism will decide how your candidate payoff for this part of the experiment will be determined. **1 out of 3 times**, it will be determined based on yours and the other participant’s preferred action. **1 out of 3 times**, it will be determined based on the two-step procedure that uses your stated “Opt-out values”. **1 out of 3 times**, it will be determined based on the accuracy of your stated guess.

Specific Instructions for Part 4

In Part 4, you will make exactly the same decisions as in Part 3. You are matched with another participant (possibly different from Part 3). The only difference compared to Part 3 is in the payoffs that you and the other participant receive depending on your choices between Action L and Action R.

The payoffs (in Euro) for you and the other participant are presented in the table below: in each cell, the first amount is your payoff, and the second amount is the other participant’s payoff. These payoffs can be summarized as follows:

- If you and the participant you are matched with both choose L, you both receive **5 Euros**;
- If you choose L and the participant you are matched with chooses R, then you receive **25 Euros** and the other participant receives **20 Euros**;
- If you and the participant you are matched with both choose R, you both receive **15 Euros**;
- If you choose R and the participant you are matched with chooses L, then you receive **20 Euros** and the other participant receives **25 Euros**.

Decision situation in Part 4 and associated payoffs.

		The other participant's decision	
		L	R
Your decision	L	5 €, 5 €	25 €, 20 €
	R	20 €, 25 €	15 €, 15 €

Summary and Payoff Procedure:

You will answer the same four questions as in Part 3 and your candidate payoff for this part of the experiment will be determined based on the same mechanism.

A1.4. Completion and Questionnaires

You have completed the first four parts of the experiment. In each part, the payoff resulting from one of your decisions is chosen as the candidate payoff for that part of the experiment. One of these four candidate payoffs will be selected as your final payoff by a random mechanism (each candidate payoff is equally likely to be your final payoff).

Before announcing your final payoff, we ask you to answer a series of questions (Part 5). You will answer these questions using the interface on your computer screen. Please follow the specific instructions on your screen to answer these questions.

A2. Example of Comprehension quiz for the STRATEGICUNCERTAINTY treatment

(inserted on screens before Parts 3 and 4; information will be adapted to the games used in the respective parts)

Before making your decisions for Part 3, please answer the following questions:

1. You will interact with another, randomly matched, participant;
   - True
   - False

Answer: True

2. In the decision situation of Part 3, if you choose L and the other participant chooses R, your associated payoff is
   - 5 €
   - 15 €
   - 20 €
   - 25 €

Answer (Game 1): 15 €

Answer (Game 2): 25 €

3. In the decision situation of Part 3, if you choose R and the other participant chooses L, your associated payoff is
   - 5 €
   - 15 €
   - 20 €
   - 25 €

Answer (Game 1): 5 €

Answer (Game 2): 20 €

A3. Additional tables and figures

Table A1. Seemingly unrelated regressions with treatment order effects

Dep. variable:	α_i^k	δ_i^k	α_i^k	δ_i^k	α_i^k	δ_i^k	α_i^k	δ_i^k
Sample:	(1)		(2)		(3)		(4)	
Indep. Variable	$\hat{a}$	$\hat{d}$	$\hat{a}$	$\hat{d}$	$\hat{a}$	$\hat{d}$	$\hat{a}$	$\hat{d}$
$1[k = S]$	.031	-.661	-.087	880.34*	.113	-2.089	-.048	88.012
	(.099)	(1.190)	(.057)	(531.73)	(.146)	(1.681)	(.067)	(79.483)
$1[k = E]$	.363**	-.623	.349**	742.04	.539**	-1.850	.541**	22.871
	(.151)	(1.190)	(.147)	(533.36)	(.228)	(1.707)	(.218)	(27.070)
$StagFirst$	-.014	.730	-.020	663.03	-.093	-.429	-.097	11.172
	(.079)	(1.861)	(.082)	(766.11)	(.099)	(2.892)	(.100)	(198.11)
$StagFirst * 1[k = S]$	-.158	-1.216	-.086	147.57	-.211	.324	-.110	330.39
	(.159)	(3.120)	(.148)	(845.60)	(.266)	(4.707)	(.250)	(554.20)
$StagFirst * 1[k = E]$	-.037	-2.136	-.284	-168.900	.089	-1.236	-.406	344.64
	(.329)	(3.129)	(.215)	(637.31)	(.591)	(4.871)	(.354)	(317.72)
Constant	-.114**	.045	-.099*	-1092.19	-.064	.964	-.056	-166.60
	(.055)	(.718)	(.056)	(710.73)	(.057)	(.984)	(.059)	(154.77)
Observations (clusters)	624 (208)		561 (187)		354 (118)		321 (107)	
Chow test	0.702	0.448	0.466	0.232	0.552	0.483	0.317	0.493
Joint Chow test	0.627		0.269		0.483		0.299	

Note. $StagFirst$ is a binary variable set to 1 if the stag-hunt game is played before the entry game, and to 0 otherwise. $1[k = T]$ is a binary variable set to 1 for condition T, and to 0 otherwise. Standard errors are clustered at the subject level and reported in parentheses. In all models, we exclude cases with indefinite δ_i^k as well as those with estimated r_i outside the range (-100,100). Specifications (1) and (3) use neglog transformation of δ_i^k. In specifications (2) and (4), estimated r_i is trimmed to the range [-3,3]. Specifications (1) and (2)/(3) and (4) use unrestricted/restricted sample. The last two rows provide the resulting p-values from Chow tests that is the joint insignificance of all the coefficients in front of the dummy $StagFirst$ for the specific parameter and for the entire SUR model. Significance levels: * p<0.1 ** p<0.05 *** p<0.01.

Table A2. Nonparametric comparisons of strategic uncertainty attitudes across treatments

Sample:	Restricted (*N*=125)		Unrestricted (*N*=223)	
Comparison/Parameter	α_i^k	δ_i^k	α_i^k	δ_i^k
Ambiguity - Stag hunt	0.005	0.275	<0.001	0.734
Ambiguity – Entry	<0.001	0.203	0.007	0.497
Stag hunt – Entry	<0.001	0.779	<0.001	0.441

Note. Columns 2-5 provide p-values from two-sided sign tests.

A4. Individual underpinnings of attitudes towards uncertainty

In this online appendix, we explore individual underpinnings of attitudes towards uncertainty. We use a seemingly unrelated regression model to estimate six simultaneous equations. Each of the six individual preference parameters $y_i \in \{\alpha_i^A, \alpha_i^S, \alpha_i^E, \delta_i^A, \delta_i^S, \delta_i^E\}$ is regressed on a set of individual characteristics:

$$y_i = b_{y,0} + b_{y,1}\widehat{s_i} + b_{y,2}Raven\_Score_i + b_{y,3}RMET\_Score_i + b_{y,4}SSS\_Score_i + \\ + \sum k \, c_{y,k}SocDemInf_i^k + w_i,$$

where:

- $\widehat{s_i}$ is the individual noise parameter estimated by ML from the RISK treatment data;

- $Raven\_Score_i$ is the Raven test score;

- $RMET\_Score_i$ is the Reading the Mind in the Eyes Test score;

- SSS_Score_i is the total score on the Sensation Seeking Scale (SSS);

- $SocDemInf_i^k$ is a set of k basic socio-demographic variables: age, gender (*Female* is an indicator variable that takes the value one for female subjects) and major (*Econ_Buss* and *Engineer* are also indicator variables that take the value one when subjects' major is economics or business and engineering, respectively);

- and w_i is the residual.

Table A3 reports the estimated results. Although there is no systematic association between any of the explanatory variables and the six parameters of interest, we do reject a joint hypothesis of coefficient nullity across the three α regressions with $p < 0.001$; we do not so, however, for the three δ regressions. This suggests that the heterogeneity in pessimism (α) observed in our (restricted) experimental sample is partially transmitted by individual differences which, however, cannot account for the heterogeneity in the general preferences towards uncertainty (δ). However, we also note that this result should be handled with care, since it is not entirely confirmed in unrestricted sample estimations. Estimates provided in Table A4 point to a weak statistical link between our set of explanatory variables and the six parameters of interest.

Table A3. Seemingly unrelated regressions with individual characteristics: restricted sample

	α_i^A	α_i^S	α_i^E	δ_i^A	δ_i^S	δ_i^E
$\widehat{\sigma}_i$	-.031	-.147	-.068	.630	-.028	-.202
	(.029)	(.127)	(.168)	(.589)	(.640)	(.669)
Raven_Score	-.019	-.123	-.068	-.332	.214	.219
	(.015)	(.086)	(.063)	(.744)	(.739)	(.762)
RMET_Score	.005	-.003	-.020	-.453	.724	.820
	(.016)	(.016)	(.023)	(.517)	(.513)	(.546)
SSS_total	.015	.035	-.010	.505*	-.292	-.324
	(.010)	(.031)	(.059)	(.277)	(.284)	(.286)
Female	-.163*	.418	.704*	-.202	-2.595	-2.604
	(.098)	(.314)	(.419)	(2.283)	(2.322)	(2.362)
Age	.002	-.006	-.015	.001	-.062	-.081
	(.005)	(.014)	(.018)	(.192)	(.191)	(.199)
Econ_Buss	-.030	-.032	.757	-.636	-3.485	-4.612
	(.146)	(.172)	(1.174)	(4.264)	(4.568)	(4.478)
Engineer	.097	.202	-.323	1.726	-4.353**	-4.614**
	(.090)	(.274)	(.406)	(2.181)	(2.215)	(2.286)
Constant	-.284	1.037	2.307*	1.668	-8.631	-9.287
	(.294)	(.941)	(1.339)	(7.534)	(7.870)	(8.216)
Joint insignificance (*p*-value):	0.336	0.716	0.005	0.359	0.690	0.672

Note. Standard errors are clustered at the subject level and reported in parentheses. Data correspond to specification (3) in Table 6 (*N*=118). Parameter δ_i^k is neglog-transformed. Significance levels: * p<0.1, ** p<0.05, *** p<0.01. Joint insignificance of coefficients for the three α (δ) regressions: *p*<0.001 (*p*=0.707). Joint insignificance of coefficients across the six models: *p*<0.001.

Table A4. Seemingly unrelated regressions with individual characteristics: unrestricted sample

	α_i^A	α_i^S	α_i^E	δ_i^A	δ_i^S	δ_i^E
$\widehat{\sigma}_i$	-.035*	-.057	-.049	-.078	-.178	-.229
	(.021)	(.065)	(.083)	(.465)	(.477)	(.476)
Raven_Score	-.021	-.051	-.016	-.160	-.109	-.080
	(.013)	(.049)	(.037)	(.477)	(.477)	(.474)
RMET_Score	.010	-.008	-.025*	-.174	.456	.543
	(.013)	(.012)	(.015)	(.346)	(.334)	(.351)
SSS_total	.014*	.023	-.019	.138	.044	.008
	(.007)	(.020)	(.036)	(.217)	(.225)	(.214)
Female	-.091	.257	.454*	-1.250	-1.668	-1.663
	(.082)	(.194)	(.266)	(1.824)	(1.867)	(1.822)
Age	.000	.002	-.009	.022	-.099	-.127
	(.005)	(.010)	(.013)	(.166)	(.163)	(.170)
Econ_Buss	.070	.014	.386	-1.533	-2.293	-3.399
	(.110)	(.137)	(.679)	(2.790)	(2.875)	(2.861)
Engineer	.112	.039	-.297	-.438	-1.100	-2.335
	(.083)	(.177)	(.249)	(1.622)	(1.639)	(1.636)
Constant	-.350	.088	1.667*	3.591	-6.278	-6.582
	(.298)	(.590)	(.901)	(6.233)	(6.369)	(6.248)
Joint insignificance (*p*-value):	0.087	0.001	0.023	0.729	0.870	0.839

Note. Standard errors are clustered at the subject level and reported in parentheses. Data correspond to specification (1) in Table 6 (*N*=208). Parameter δ_i^k is neglog-transformed. Significance levels: * p<0.1, ** p<0.05, *** p<0.01. Joint insignificance of coefficients for the three α (δ) regressions: *p*<0.001 (*p*=0.606). Joint insignificance of coefficients across the six models: *p*<0.001.

A5. Screenshots

Figure A4. Screen used in RISK treatment

Figure A5. Screen used in STRATEGICUNCERTAINTY treatment (stag-hunt game)