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Maria Erazo Diaz

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THÈSE DE DOCTORAT EN SCIENCES ECONOMIQUES

Présentée en vue de l'obtention du grade de docteur de l'Université de Lyon,
délivré par l'Université Lumière Lyon 2

Essays on Decision-making Under Uncertainty

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Résumé de la thèse

Cette thèse vise à mettre en lumière le rôle des croyances, des préférences pour l'ambiguïté et de la dynamique de l'attention dans les décisions économiques. En s'appuyant sur la combinaison d'expériences de laboratoire et de modèles issus de la théorie économique, elle apporte deux principales contributions au domaine en constante expansion de l'économie comportementale. La première est méthodologique, participant d'une part d'une contribution dans le champ méthodologique de l'expérimentation par le développement d'une nouvelle méthode pour identifier les croyances et les paramètres des modèles de prise de décision en avenir incertain, et d'autre part d'un élargissement des outils de l'économie expérimentale par l'exploration de l'utilisation de l'eye-tracking comme un outil alternatif d'évaluation des modèles de comportement. La seconde est empirique : par la collecte de nouvelles données expérimentales, les résultats des différents chapitres mettent à l'épreuve et éclairent différents modèles issus de la théorie économique.

Le chapitre 1 propose une nouvelle méthode pour mesurer les croyances, les décisions impliquant la confiance et les attitudes face à l'ambiguïté lorsque les sujets sont confrontés à différentes sources d'incertitude. Pour mieux comprendre les attitudes face à l'ambiguïté, le chapitre 2 compare expérimentalement les paramètres de préférence face à l'ambiguïté d'ordre supérieur lorsque l'ambiguïté est introduite sur le bon ou le mauvais état de la nature. Il vise à fournir des

réponses concernant les théories économiques existantes qui sont plus en phase avec des situations ambiguës spécifiques. Enfin, le chapitre 3 étudie le lien entre échantillonnage de l'information et décisions de trading en utilisant l'outil d'eye-tracking dans une expérience sur le marché des actifs.

Présentation des chapitres

Chapitre 1 : Mesure des croyances et des attitudes face à l'ambiguïté envers des sources discrètes d'incertitude

La théorie standard en matière d'ambiguïté – l'utilité espérée subjective (UES) – considère que les sujets *i*) forment des probabilités subjectives (des croyances) sur les événements, *ii*) ont la même fonction d'utilité en cas d'ambiguïté qu'en cas de risque, et *iii*) évaluent les loteries selon l'espérance mathématique de l'utilité qu'elles rapportent, selon la distribution induite par les croyances. Cependant, des preuves antérieures comme le paradoxe de [Ellsberg \(1961\)](#) ont montré que les sujets présentent des attitudes spécifiques face à l'ambiguïté (aversion ou même recherche), ce qui est une preuve du fait que les sujets s'écartent de l'UES en transformant leurs croyances. Cette transformation des croyances se fait par le biais de la fonction de pondération (e.g. [Gilboa, 1987](#); [Klibanoff et al., 2005](#)). La fonction de pondération opère à travers deux composantes : *i*) composante motivationnelle (i.e., optimisme/pessimisme) et *ii*) composante cognitive (i.e., insensibilité à la vraisemblance) ([Gonzalez and Wu, 1999](#)).

Traditionnellement, l'estimation des fonctions d'utilité et de pondération – en tant que mesure des attitudes face à l'ambiguïté – s'est concentrée sur les sources continues d'incertitude, ce qui signifie que l'événement universel est un intervalle de nombres réels (e.g. [Van De Kuilen and Wakker, 2011](#); [Abdellaoui et al., 2021b](#)). Au contraire, une source d'incertitude discrète désigne toute

source d'incertitude qui prend ses valeurs dans un ensemble discret d'événements, qui ne sont pas nécessairement de probabilité égale. L'objectif de ce chapitre est de développer une méthode pour estimer complètement les croyances, la fonction de pondération et la fonction d'utilité pour les sources d'incertitude discrètes.

Nous mettons en œuvre notre méthode de manière expérimentale pour des sources d'incertitude égales et différentes dans deux contextes : les jeux de confiance et les jeux de coordination. Nous avons choisi ces jeux parce qu'ils représentent deux contextes différents et que les structures des deux jeux permettent d'introduire ensemble et séparément les trois sources d'incertitude suivantes : premièrement, l'incertitude stratégique, où l'incertitude porte sur les actions des autres dans les interactions stratégiques ; deuxièmement, l'ambiguïté sociale, qui apparaît lorsque l'incertitude provient des décisions non stratégiques des autres individus ; enfin, l'aversion pour la trahison, qui représente un contexte dans lequel les actions des autres pourraient conduire à la trahison.

Ce chapitre aboutit à deux résultats principaux. Premièrement, à sources d'incertitude égales, les sujets ont des croyances sur les événements indépendantes du contexte, mais des fonctions d'utilité et de pondération qui elles dépendent du contexte. Cela signifie que la transformation des croyances par la fonction de pondération varie d'un contexte à l'autre. Ce résultat implique que la comparaison de différentes sources d'incertitude nécessite une mesure complète des fonctions d'utilité et de pondération. Deuxièmement, différentes sources d'incertitude où les événements ne sont pas également probables conduisent à une augmentation de l'insensibilité à la vraisemblance, ce qui indique que le processus de formation de croyances sur des événements inconnus est cognitivement exigeant.

Chapitre 2 : Sur la communication des attitudes d’ambiguïté d’ordre supérieur

L’aversion au risque et à l’ambiguïté détermine les choix dans de nombreux contextes économiques. Cependant, l’aversion pour le risque et l’ambiguïté ne suffisent pas à expliquer toutes les décisions prises dans des situations risquées ou ambiguës. Pour comprendre en profondeur le comportement humain dans ces contextes, nous devons explorer les préférences d’ordre supérieur en matière de risque et d’ambiguïté (c’est-à-dire la prudence et la tempérance). Entre autres, l’étude des préférences d’ordre supérieur en matière de risque et d’ambiguïté permet notamment de mieux comprendre le comportement de prévention (e.g. [Treich, 2010](#); [Bleichrodt et al., 2019](#)), les décisions d’épargne (e.g. [Alary et al., 2013](#); [Berger, 2014](#)), et les décisions d’assurance (e.g. [Fei and Schlesinger, 2008](#)).

Les modèles théoriques d’un contexte de dommages purs impliquent deux états de la nature : un bon état (pas de dommages) et un mauvais état (dommages). Ces modèles prédisent les préférences d’ordre supérieur des agents par rapport à deux situations ambiguës. Les préférences des agents peuvent être reliées au concept de dominance stochastique défini par [Ekern \(1980\)](#), qui établit un ordre partiel des distributions de probabilité. La définition des changements d’ambiguïté sur les probabilités à travers le concept spécifique de dominance stochastique au sens d’Ekern, permet de définir un lien statistique entre les distributions de probabilité capturant le niveau d’ambiguïté sur la probabilité de perte ([Courbage and Rey, 2016a](#)).

Sous ambiguïté, lorsque l’ambiguïté est associée au bon état de la nature, un agent ayant une aversion pour l’ambiguïté préférera une certaine situation à une situation ambiguë (avec une variable aléatoire de moyenne nulle) qui est dominée stochastiquement au sens d’Ekern par la première. De même aux ordres supérieurs, un agent prudent (ou tempéré) préfère un premier aléa à un second

quand il le domine stochastiquement à l'ordre 3 (ou 4) au sens d'Ekern. Dans un article théorique, [Courbage and Rey \(2016a\)](#) montrent que lorsque le hasard induisant l'ambiguïté est introduit sur le mauvais état de la nature, ces résultats sont inversés pour les ordres impairs. Alors, un agent prudent sur l'ambiguïté préfère l'option qui est stochastiquement dominée à l'ordre 3. C'est une question empirique ouverte que de savoir si à l'ordre 3 les gens sont prudents face à l'ambiguïté quel que soit le contexte, bon ou mauvais, auquel est associée la probabilité de capturer l'ambiguïté.

Ce chapitre confronte donc ces résultats théoriques à des données expérimentales. Dans ce but, nous menons une expérience en laboratoire dans laquelle nous testons des attitudes d'ambiguïté d'ordre supérieur : l'aversion à l'ambiguïté (ordre 2), la prudence face à l'ambiguïté (ordre 3) et la tempérance face à l'ambiguïté (ordre 4), en utilisant un modèle avec deux états de la nature (un bon et un mauvais). Nous comparons ensuite les attitudes d'ambiguïté lorsque l'ambiguïté est introduite sur la probabilité associée au bon et au mauvais état de la nature. Nous pouvons interpréter un mal, qui est soit une variable aléatoire de moyenne nulle, soit une certaine diminution (augmentation) sur la probabilité du bon (mauvais) état de la nature, comme une mauvaise nouvelle ; et une faveur, qui est une certaine diminution sur la probabilité du mauvais état, comme une bonne nouvelle. Ensuite, dans le but d'évaluer l'effet de la communication des nouvelles sur les attitudes d'ambiguïté, dans le cas de l'ordre 3, nous comparons également les attitudes d'ambiguïté lorsque la variable aléatoire capturant l'ambiguïté est présentée comme deux maux versus un maux et une faveur.

Nous constatons que les résultats empiriques sont plus conformes aux résultats théoriques lorsque la variable aléatoire capturant l'ambiguïté est introduite sur la probabilité associée au mauvais état de la nature que lorsqu'elle porte sur le bon. De plus, dans le cas de l'ordre 3, la prudence n'est observée que lorsque

les sujets font face à un mal et une faveur. Ensuite, nos résultats ont des implications en termes de communication des nouvelles. Le fait que la prudence soit prépondérante lorsque l'histoire est présentée avec l'ambiguïté introduite sur le mauvais état, et sous la forme d'une bonne et d'une mauvaise nouvelle, montre que la manière dont les nouvelles sont communiquées influence le degré de réceptivité des personnes à ces nouvelles.

Chapitre 3 : Trading et cognition sur les marchés d'actifs : une expérience d'eye-tracking

Les décisions d'achat et de vente sur les marchés d'actifs sont déterminantes dans la réalisation effective des variables économiques qui incluent, sans s'y limiter, le commerce international ([Berman and Héricourt, 2010](#)) et les choix de politique gouvernementale ([Mosley, 2000](#)). Sur les marchés, nous observons différents modèles d'échanges, ce qui semble indiquer l'existence de plusieurs types d'acteurs. Dans ce chapitre, nous nous appuyons sur la typologie proposée par [De Long et al. \(1990\)](#) et affinée par [Haruvy and Noussair \(2006\)](#), qui repose sur une classification en trois types de traders : les feedback, les passive et les speculator.

Ces trois types d'acteurs se caractérisent par leurs différents modèles de décision d'achat et de vente d'actifs en fonction de l'état du marché et de leurs anticipations. En général, les traders de type feedback suivent la tendance précédente du marché : ils demandent plus d'actifs lorsque la tendance des prix réalisés durant les périodes précédentes est à la hausse, et moins lorsqu'elle est à la baisse. Les traders de type passive basent quand à eux leurs décisions sur la valeur fondamentale de l'actif. Ainsi, ils achètent d'avantage lorsque le prix de l'actif est supérieur à sa valeur fondamentale, et vendent d'avantage lorsque le prix est au dessus de la valeur fondamentale. Enfin, les acteurs de type

speculator construisent des prédictions sur les prix futurs de l'actif, et basent leurs décisions sur leurs prédictions : ils demandent d'autant plus d'actifs qu'ils s'attendent à ce que les prix augmentent.

Dans ce chapitre, nous souhaitons tester la cohérence entre la classification basée sur le comportement des agents et leur mode d'échantillonnage de l'information. En particulier, les traders de type feedback devraient prêter relativement plus attention aux prix passés, et les traders de type passive à la valeur fondamentale et aux prix. Les traders de type speculator devraient quant à eux utiliser toute l'information à leur disposition, et en particulier les prédictions faites par les autres acteurs du marché, qui n'entrent pas dans le modèle comportemental des autres types.

Pour tester ces hypothèses, nous menons une expérience sur le marché des actifs en laboratoire, à partir de laquelle nous analysons les décisions des sujets en matière de négociation et de prévision afin de les classer, sur la base de leurs comportements, dans l'une des trois catégories définies ci-dessus. Pour étudier les mécanismes cognitifs sous-jacents associés aux différents types de traders, nous analysons les schémas d'attention et d'échantillonnage de l'information des sujets grâce à des données d'eye-tracking. Grâce à l'analyse combinée des données comportementales et d'eye-tracking, nous sommes en mesure d'évaluer la cohérence de chaque type de trader avec son modèle sous-jacent d'échantillonnage de l'information. Nos résultats sont hétérogène : alors que nous trouvons bien la relation attendue pour les traders de type speculator, nos résultats ne corroborent que partiellement nos hypothèses pour les traders de type passive, et rejettent celle des traders de type feedback.

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General introduction

Beliefs shape the way we understand and navigate the world, driving many of our decisions. One can see beliefs as an internal voice that whispers behind many of our actions. Then, it turns relevant to wonder how our beliefs change according to different situations. For instance, how do beliefs affect choices like how much or how little are we willing to take risks?

The influence of beliefs on our behavior translates into an effect of beliefs in economic outputs. For instance, system-wide bank runs, which occur when depositors rush to withdraw their funds from all banks in the economy simultaneously because they believe that other depositors will withdraw their funds as well. Such bank runs were common in the United States in the late nineteenth and early twentieth centuries and have also occurred in more recent times in other countries including Brazil in 1990, Ecuador in 1999, and Argentina in 2001 ([Ennis and Keister, 2009](#)).

Beliefs are usually formed under uncertainty, which characterizes most of our decision situations. Uncertainty is a rich domain. It includes risk, ambiguity, higher order risk and ambiguity attitudes (prudence and temperance), strategic uncertainty, social ambiguity, among others. Subjects make decisions under risk when the objective probabilities of the possible events are known. In contrast, subjects face ambiguous situations when the objective probabilities are unknown ([Knight, 1921](#)). [Gigerenzer \(2015\)](#) states the following.

“The world of uncertainty is huge compared to that of risk. Whom to trust? What to do with the rest of one’s life? In an uncertain world, it is impossible to determine the optimal course of action by calculating the exact risks. We have to deal with “unknown unknowns”. Surprises happen. Even when calculation does not provide a clear answer, however, we have to make decisions” (p. 30),

Our own attitudes towards uncertainty then guide many of our actions and decisions. In his book, [Bernstein \(1996\)](#) states the following. “The ability to define what may happen in the future and to choose among alternatives lies at the heart of societies. Uncertainty management guides us over a vast range of decisions-making, from allocating wealth to safeguarding public health, from waging war to planning a family, from paying insurance to wearing a seat-belt, from planting corn to marketing cornflakes” (p. 2).

Decisions under ambiguity vary from simple daily choices to major investment decisions. For instance, one of the most urgent matters currently in our societies is to address climate change by improving energy efficiency. Transitioning to a low-carbon economy will require an expanding share of firms to allocate their capital investments to carbon-free technologies ([IPCC, 2022](#)). Firms’ investment decisions involve ambiguity regarding future carbon prices. Hence, both ambiguity attitudes and beliefs regarding the future price of carbon are fundamental for firms’ decisions ([Campiglio et al., 2022](#)).

Higher order risk and ambiguity attitudes refer to prudence and temperance. This plays a key role on decisions that have an impact on individuals’ potential welfare such as precautionary savings ([Eeckhoudt and Schlesinger, 2008](#)). For example, someone who is prudent is more likely to save more money in the present if the risk (or ambiguity) of future income increases.

Decisions of others represent another source of uncertainty called strategic uncertainty. This is present in almost every social interaction and refers to

the fact that subjects are confronted with the delicate task of forming beliefs about other subjects' decisions (Renou and Schlag, 2010). An example of this are negotiations, where subjects must form beliefs about the choices of others as well as how others will react towards the choices of their counterpart in the negotiation. Also, decisions under strategic uncertainty can involve the element of trust. Rousseau et al. (1998) define trust as “a psychological state comprising the intention to accept vulnerability based upon positive expectations of the intentions of behavior of another” (p. 395). Subjects might abstain from situations that involve trust because they are “betrayal averse”, meaning that they are averse to the cost generated from a violation of their trust (Bohnet et al., 2008). Clearly, decisions involving trust mirror our beliefs and attitudes towards uncertainty, and imply social and economic consequences. As Arrow (1972) wrote “virtually every commercial transaction had within itself an element of trust”.

Finally, uncertainty can take the form of social ambiguity, which involves the uncertainty of the actions of others, but when these actions are not part of a strategic interaction. More precisely, social ambiguity refers to the fact that people treat acts by humans, even in the absence of strategic interactions, differently from acts of nature (Li et al., 2020).

An experimental approach to study beliefs and ambiguity attitudes

This section presents some of the experimental approaches to analyze beliefs and ambiguity attitudes and their appropriateness as a tool to investigate the effects of beliefs and ambiguity attitudes on human behavior. Experimental and behavioral economics have repeatedly study subjects' beliefs and ambiguity attitudes through experiments. In fact, experiments are almost the only way to

observe ambiguity attitudes because they allow to directly monitor choices under a controlled environment, meaning that the source of uncertainty in question is isolated from other elements that might have an impact on decisions. Therefore, experiments permit to clearly recover ambiguity attitudes that are related only to a specific source of uncertainty. Typically, decisions in experiments are incentivized, which allows *i*) to model a situation that resembles real-life decisions, and *ii*) to generate real uncertainty regarding the monetary compensation. The following are some of the most common applied experimental settings and their potential to answer multiple research questions.

An extensively implemented game in experiments is the Trust Game. Generally, two players participate in this game. The first player called the “trustor” is endowed with an amount of money and, she can decide to send part of this money to the second player called the “trustee”. Then, the amount sent by the trustor is tripled and given to the trustee. Finally, the trustee chooses how much to send back to the trustor from the amount she received. The following are some of the type of questions that have been studied using this game. Trusts levels and their relationship with risk preferences (e.g. [Chetty et al., 2021](#)), betrayed aversion (e.g. [Bohnet et al., 2008](#)), and the connection between trust decisions and personality characteristics (e.g. [Müller and Schwieren, 2020](#)).

One of the most common methods to elicit risk and ambiguity attitudes in experimental economics is a lottery-choice task. Conventionally, subjects are asked to choose between two different lotteries, where one is always more risky (or ambiguous) than the other one. The ten paired lottery-choice task developed by [Holt and Laury \(2002\)](#) is one of the most widely-used in experiments. Based on this type of games, it is even possible to analyze higher order ambiguity attitudes. For instance, [Baillon et al. \(2018\)](#) reported ambiguity aversion,

ambiguity prudence and, to a lesser extent, ambiguity temperance, based on the results from an experiment in which a lottery-choice task was implemented.

Beliefs, uncertainty, and cognition

A key element in the process of beliefs' formation under uncertain situations is the way we sample the available information in our environment. Then, understanding how people gather and process information allows to open a window towards the analysis of the cognitive mechanisms underlying the basis of beliefs formation and consequently decisions.

An example of some of the real life choices that determine actual economic variables are trading decisions in asset markets. Naturally, traders choices are influenced by their beliefs. However, traders' final decisions provide limited information regarding the underlying cognitive mechanisms to reach such decisions. To fill this gap, it is then appropriate to go beyond the observable behavior. For instance, by studying patterns of acquisition and processing of information. One valuable research tool to explore this dimension is eye-tracking, which has been broadly implemented to analyze different cognitive and affective mechanisms both in economics and psychology ([Rahal and Fiedler, 2019](#)).

Eye-tracking systems allow to record in a non-invasive way eye-position, pupil dilatation, and eye-movements. Hence, it is possible to study data such as how long subjects fixate in different visual information sets on the screen, subjects sequences of information acquisition (i.e., in which order they look at the information sets on the screen), and the type of information acquired . Then, the analysis of this data translates into patterns and dynamics of attention.

The use of the eye-tracking methodology to study sampling information and patterns of attention has been growing fast during the last years in economics. The numerous successful answers to a broad variety of questions in experimental

economics has proven its adequacy to investigate different cognitive aspects in decision-making processes. Below we present some examples of different research questions that have supported their answers on the implementation of eye-tracking in experiments.

Patterns of attention recorded with eye-tracking have been used to investigate topics from choices in moral dilemmas (e.g. [Pärnamets et al., 2015](#)) to food regarding choices (e.g. [Krajbich et al., 2010](#); [Towal et al., 2013](#)). The focus of the studies goes from strategic decision-making, like two-people games (e.g. [Knoepfle et al., 2009](#); [Polonio and Coricelli, 2019](#); [Marchiori et al., 2021](#)) to individual decision-making, which includes individual financial decisions (e.g. [Bose et al., 2022](#)). Also, the relationship of risk preferences with different dynamics of attention (e.g. [Engelmann et al., 2021](#)). Additionally, it has been shown that differences in social value orientation are consistent with different patterns of sampling information (e.g. [Fiedler et al., 2013](#)). Lastly, [Krajbich et al. \(2012\)](#)'s results show that when subjects pay more attention to the characteristics of a product than to its price, they are more likely to purchase this product.

Objectives

This thesis aims to shed light on the causes and consequences of beliefs, ambiguity preferences, and dynamics of attention in economic decisions. By relying on the combination of laboratory experiments with models from economic theory, it leads to the following two main contributions to the constantly growing field of behavioral economics. First, it extends and provides insights into the current methodological experimental approaches. This is accomplished both by the development of a new method to elicit beliefs and ambiguity attitudes under uncertainty and the implementation of eye-tracking as an alternative tool in the laboratory to evaluate models of trading behavior. Second, it brings

further empirical evidence that confronts existing models of economic theory with behavioral data collected in the laboratory. This is accomplished thanks to the behavioral results obtained from each of the experiments comprised in this thesis.

Chapter 1 proposes a new method that sheds light on the most appropriate way to measure beliefs, decisions involving trust, and ambiguity attitudes when subjects face different sources of uncertainty. To further understand ambiguity attitudes, Chapter 2 compares higher order ambiguity attitudes experimentally when ambiguity is introduced on the good versus the bad state of nature. It aims to provide answers regarding which existing economic theories are more in line with specific ambiguous situations. Finally, Chapter 3 studies cognitive mechanisms underlying sampling information behind trading decisions using the eye-tracking tool in an asset market experiment.

Overview of the chapters

Chapter 1: Measuring Beliefs and Ambiguity Attitudes Towards Discrete Sources of Uncertainty

The standard theory under ambiguity – Subjective Expected Utility (SEU) – considers that subjects *i*) form subjective probabilities or beliefs on events, *ii*) have the same utility function under ambiguity as under risk, and *iii*) value lotteries as expected utility over outcomes in which the weights are the beliefs. However, previous evidence like [Ellsberg \(1961\)](#)'s paradox showed that subjects exhibit ambiguity attitudes (aversion or even seeking), which is evidence of the fact that subjects deviate from SEU by transforming their beliefs. Such transformation of beliefs is done through the weighing function (e.g. [Gilboa, 1987](#); [Klibanoff et al., 2005](#)). The weighing function operates throughout

two components *i*) motivational component (i.e., optimism/pessimism) and *ii*) cognitive component (i.e., likelihood insensitivity) (Gonzalez and Wu, 1999).

Traditionally, the estimation of the utility and weighting functions – as a measure of ambiguity attitudes – has been focused on continuous sources of uncertainty, meaning that the universal event is an interval of real numbers (e.g. Van De Kuilen and Wakker, 2011; Abdellaoui et al., 2021). Contrary, a discrete source of uncertainty refers to any source of uncertainty that takes their values in a discrete set of events, which are not necessarily equally likely. The objective of this chapter is to develop a method to completely estimate beliefs, weighing function, and utility function for discrete sources of uncertainty.

We implement our method experimentally to both equal and different sources of uncertainty in two contexts: trust and coordination games. We chose these games because they represent two different contexts and the two games' structures allow to introduce both together and separately the following sources of uncertainty. First, strategic uncertainty, which represents situations in which the actions of others are uncertain in strategic interactions. Second, social ambiguity, which appears when the uncertainty is derived from the non-strategic decisions of other individuals. Finally, betrayal aversion, being a context in which the actions of others could lead to betray.

This chapter reaches two main results. First, for equal sources of uncertainty subjects have context-independent beliefs on events, but context-dependent utility and weighting functions. This means that the transformation of beliefs through the weighing function varies from one context to another. This result implies that comparing different sources of uncertainty requires a complete measurement of the utility and weighting functions. Second, different sources of uncertainty where the events are not equally likely lead to an increase in the

likelihood insensitivity, which indicates that the process of forming beliefs about unknown events is cognitively demanding.

Chapter 2: On the Communication of Higher Order Ambiguity Attitudes

Risk and ambiguity aversion drive choices in many economic contexts. However, risk and ambiguity aversion alone are not sufficient to explain all the decisions done under risky or ambiguous situations. To deeply understand human behavior in these contexts, we need to explore higher order risk and ambiguity preferences (i.e., prudence and temperance). For instance, the investigation of higher order risk and ambiguity preferences sheds light on the understanding of prevention behavior (e.g. [Treich, 2010](#); [Bleichrodt et al., 2019](#)), saving decisions (e.g. [Alary et al., 2013](#); [Berger, 2014](#)), and insurance decisions (e.g. [Fei and Schlesinger, 2008](#)).

Theoretical models of a pure damage context involve two states of nature: a good state (no damage) and a bad state (damage). These models predict the agents' higher order preferences with respect to two ambiguous situations. Agents preferences can be compared with the concept of stochastic dominance defined by [Ekern \(1980\)](#), which establishes a partial ordering of probability distributions. The definition of changes in ambiguity over probabilities through the specific concept of stochastic dominance in the sense of Ekern, makes it possible to define a statistical link between the probability distributions capturing the level of ambiguity over the loss probability ([Courbage and Rey, 2016](#)).

Under ambiguity, when the probability is associated with the good state of nature, a prudent (temperate) agent prefers a first hazard that stochastically dominates in the sense of Ekern at order 3 (4) a second hazard. The same holds for order 2. An ambiguity averse agent prefers a certain situation to a

an ambiguous situation (with zero-mean random variable) that is stochastically dominated in the sense of Ekern. In a theoretical paper, [Courbage and Rey \(2016\)](#) show that when the hazard capturing ambiguity is introduced on the bad state of nature, these results are reversed for odd orders. Then, an ambiguity prudent agent prefers the random variable that is stochastically dominated in the sense of Ekern at order 3. It is an open empirical question whether at order 3 people are ambiguity prudent whatever the context, good or bad, to which the probability capturing ambiguity is associated.

This chapter therefore confronts these theoretical results with experimental data. To this aim, we conduct a laboratory experiment in which we test higher order ambiguity attitudes: ambiguity aversion (order 2), ambiguity prudence (order 3), and ambiguity temperance (order 4), using a model with two states of nature (a good one and a bad one). We then compare ambiguity attitudes when ambiguity is introduced on the probability associated with the good versus the bad state of nature. We can interpret a harm, which is either a zero-mean random variable or a certain decrease (increase) on the probability of the good (bad) state of nature, as bad news; and a favor, which is a certain decrease on the probability of the bad state, as good news. Then, with the aim of evaluating the effect of news communication on ambiguity attitudes, in the case of order 3, we also compare ambiguity attitudes when the random variable capturing ambiguity is presented as two harms versus one harm and one favor.

We find that empirical results are more in line with the theoretical results when the random variable capturing ambiguity is introduced on the probability associated with the bad state of nature. In addition, in the case of order 3, prudence is only observed when subjects face one harm and one favor. Then, our results have implications in terms of news communication. The fact that prudence is preponderant when the story is presented with the ambiguity introduced on

the bad state and in the form of good news and a bad news, shows that the way the news are communicated influences the extent to which people are receptive of these news.

Chapter 3: Trading and Cognition in Asset Markets: an Eye-tracking Experiment

Trading decisions in asset markets are determinant in actual realization of economic variables which include, but are not limited to, international trade (Berman and Héricourt, 2010) and government policy choices (Mosley, 2000). In markets we observe different patterns of trading, which is evidence of the existence of several types of traders. The work of De Long et al. (1990) and Haruvy and Noussair (2006) is based on the classification of three types of traders: feedback, passive, and speculators.

The main trading characteristics of feedback, passive, and speculator traders types are the following. First, feedback traders follow the previous trend of the market. Then, they demand more assets when prices have been rising. Second, passive traders trade based on the value of the fundamentals. Hence, they buy more when prices are below fundamentals and sell more when prices are above fundamentals. Finally, speculator traders trade based on the estimated prices in the near future. Specifically, they purchase more when there is an expected increase in prices.

Knowledge regarding models of traders' types and their respective underlying cognitive mechanisms is limited. Therefore, this chapter aims to provide contributions to fill this gap in the literature. To this aim, we conduct an asset market experiment in the laboratory, from which we analyze trading and forecast subjects' decisions to classify their performance into feedback, passive, or speculator traders. To study the underlying cognitive mechanisms associated

with different traders' types, we analyze subjects' patterns of attention and information sampling through eye-tracking data. By the combined analysis of the behavioral and eye-tracking data, we are able to assess the consistency of each trader type with its expected underlying pattern of information sampling.

Our results show that the consistency between traders' types and their expected patterns of information sampling does not hold equally for all the types of traders. First, we do not find evidence to corroborate the expected relationship between feedback traders and their patterns of attention. Second, we partially support the expected dominant source of information proper of passive traders. Finally, we find evidence that corroborates a coherent relationship between speculator traders and their underlying patterns of information sampling.

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Chapter 1

Measuring Beliefs and Ambiguity Attitudes Towards Discrete Sources of Uncertainty

This chapter is based on a paper co-authored with Yao Thibaut Kpegli.

Abstract

This chapter proposes a new method to measure beliefs and ambiguity attitudes towards events that are not necessarily equally likely and belong to a discrete set (i.e., discrete sources of uncertainty). Our method increases robustness to misspecification and allows flexibility in parametric choices compared to previous methods. We implement our method experimentally to both equal and different sources of uncertainty in two contexts: trust and coordination games. We find two main results. First, for equal sources of uncertainty, our method successfully reveals that subjects have context-independent beliefs on events, but context-dependent utility and weighting functions. This result indicates that comparing different sources of uncertainty requires a complete measurement of the utility and weighting functions. Second, different sources of uncertainty where the events are not equally likely lead to an increase in likelihood insensitivity, which indicates that the beliefs formation process of unknown events is cognitively demanding.

Keywords: Subjective beliefs, ambiguity attitudes, sources of uncertainty, trust game, coordination game.

1.1 Introduction

Ambiguous situations are pervasive in human decisions. These decisions vary from choosing a place to work to important investment decisions. Subjects decide under ambiguous situations when the objective probabilities of the possible events are unknown (Knight, 1921). In contrast, subjects make decisions under risk when the objective probabilities are known.

The standard theory under ambiguity – Subjective Expected Utility (SEU) – considers that subjects (i) form subjective probabilities or beliefs on events, (ii) have the same utility function under ambiguity as under risk, and (iii) value lotteries as expected utility over outcomes in which the weights are the beliefs. Ellsberg (1961)’s paradox showed that people deviate from SEU by exhibiting *ambiguity attitudes* (aversion or even seeking). Consequently, several models (e.g. Gilboa, 1987; Schmeidler, 1989; Tversky and Kahneman, 1992; Klibanoff et al., 2005) have been proposed to account for ambiguity attitudes by allowing events weighting function and a difference in utility between risk and ambiguity.

The estimation of the utility and weighting functions – as a measure of ambiguity attitudes – has been focused on *continuous-valued sources of uncertainty*, meaning that the universal event is an interval of real numbers (Abdellaoui et al., 2021b; Van De Kuilen and Wakker, 2011). The main advantage of *continuous-valued sources of uncertainty* is that the concept of *exchangeability of events*, introduced by Baillon (2008), can be used to build elicitation methods (see subsection 1.2.2). Two events are exchangeable for a decision maker when she is indifferent towards permutations of their outcomes. Exchangeability allows to iteratively partition the universal event in equally likely events. Then, with a set of exchangeable events for which the subjective probabilities are known, elicitation methods can provide a measurement of the utility and weighting functions.

In our daily life, situations of *continuous-valued sources of uncertainty* are not common compared to situations that involve *discrete sources of uncertainty*. A *Discrete source of uncertainty* refers to any source of uncertainty that takes their values in a discrete set of events, which are not necessarily equally likely. The universal event is no longer an interval of real numbers. As such, it excludes the possibility of building *exchangeable events*. [Baillon et al. \(2018a,b\)](#) shed light on this regard by proposing two methods that do not require exchangeable events; therefore, the two methods can be used for discrete sources of uncertainty. However, these methods rely on restricted parametric assumptions (source independent utility function and the neo-additive weighting function of [Chateauneuf et al. \(2007\)](#)), which makes them prone to misspecification issues.

The objective of this chapter is to develop a method to completely estimate utility function, weighting function and beliefs for discrete sources of uncertainty. Examples of discrete sources of uncertainty are present in almost all fields of economics. Some of the experimental from game theory include trust, ultimatum, and public good games. In the trust game (e.g. [Bohnet et al., 2008](#)), for instance, the universal event of the Trustor is often the union of two unequally likely events; either the Trustee reciprocates or betrays. Also, in the ultimatum game (e.g. [Slonim and Roth, 1998](#)), the universal event for the first mover is the union of two unequally likely events; either the second mover accepts or rejects the money sent by the first mover. Similarly, in a public good game with two players (e.g. [Kosfeld et al., 2009](#)), the universal event of each player is the union of two unequally likely events; either the other player contributes or the other player does not contribute.

Further examples of discrete sources of uncertainty can be found in health economics. For instance, the universal event of someone that consumes harmful products (e.g., tobacco, alcohol, unhealthy diets) can be represented as the union

of two unequally likely events: either the development of a non-communicable disease or stay healthy (e.g. Bloom et al., 2020; Mane et al., 2019). This example can also be extended to communicable diseases like AIDS or COVID-19, where people do not know the exact probability of getting sick and they decide whether or not to wear condoms or masks (e.g. Cuddington, 1993; Rieger et al., 2020). Additionally, transport economics (e.g. Guarda et al., 2016) and taxation economics (e.g. Dhami and Al-Nowaihi, 2007; Dhami and Hajimoladarvish, 2020) exemplified these situations. For instance, subjects who do not pay for the transport tickets face the union of two unequally likely events; being checked or not by controllers. Similarly, subjects who avoid taxes can be caught or not.

To measure these types of discrete sources of uncertainty, we propose a two-stage method in which the parametric assumptions of the utility function and the weighting function are made sequentially. The method allows for source-dependent utility function and any two-parameter weighting function (e.g. Goldstein and Einhorn, 1987; Prelec, 1998; Chateauneuf et al., 2007). Using simulations, we show that the two-stage structure of the method favors robustness to misspecification issues (see subsection 1.D).

We combine our method and the empirical data from an experiment conducted based on the trust and coordination game, in which subjects make decisions under different sources of uncertainty. Our data allows us to confront the method with two validity tests on (i) symmetric events and (ii) stability of beliefs for unequally likely events of the same sources of uncertainty involved in different decision contexts. Our method successfully passes validity tests, which supports the reliability of the results derived from it.

We provide three main results. First, we identify which sources of uncertainty are captured by likelihood insensitivity or pessimism. We find that several forms of uncertainty attitudes operate through variations in the likelihood insensitivity

component, the main driver of the inverse S-shaped weighting function in the literature (e.g. Wakker, 2010; Åstebro et al., 2015; Abdellaoui et al., 2011a). Subjects exhibit more likelihood insensitivity towards sources of uncertainty involving not symmetric events, which indicates that the beliefs formation process of unknown events is cognitively demanding. Second, empirical evidence supports theories that model ambiguity attitudes with the weighting function rather than with the utility function. Finally, our method reveals that subjects exhibit two additional behaviors which are not related to attitudes toward the source of uncertainty: *payoff dependence aversion* and *variety of payoffs seeking*. *Payoff dependence aversion* refers to the fact that subjects dislike that their own payoffs depend on the preferences of others, this behavior is captured by a more concave utility function. *Variety of payoffs seeking* means that subjects prefer a greater number of possible payoffs, when such possible payoffs depend on the preference of others, this is captured by a decrease in pessimism.

The remainder of this chapter proceeds as follows. Section 1.2 presents different theoretical approaches to model ambiguity attitudes and existing measurement methods. Section 1.3 presents our elicitation method. Section 1.4 provides a review of related literature about attitudes towards sources of uncertainty in the coordination and trust game. Section 1.5 presents the experimental design. Section 1.6 provides the results. We discuss the results in section 1.7 and, conclude in section 1.8.

1.2 Theoretical background

This section presents a general theoretical framework of ambiguity attitudes. Also, we present existing methods of measuring ambiguity attitudes and beliefs and, the explanation of their limits.

1.2.1 Biseparable preferences model

Denote by $L = (x, y; E, E^c)$ a binary lottery that gives the outcome x if the event E occurs and y otherwise. E denotes an event of the state space Ω and E^c denotes the complement of E in Ω . Outcomes are real numbers. For notational convenience, we assume that $x > y \geq 0$. We denote \succsim as the preference relation of the decision-maker over prospects. The relations \succ and \sim denote strict preference and indifference, respectively. The preference relation of the decision-maker is represented by the following model that values the prospect $L = (x, y; E, E^c)$ as

$$V(L) = W(P(E))(U(x) - U(y)) + U(y) \quad (1.1)$$

where $W(\cdot)$ is the weighting function or source function for uncertainty ([Abdellaoui et al., 2011a](#)), $P(E)$ is the subjective probability or beliefs of E occurring, and $U(\cdot)$ the utility function that captures the attitude toward outcomes. Both $W(\cdot)$ and $U(\cdot)$ are strictly increasing functions.

Model (2.1) corresponds to the biseparable preferences model of [Ghirardato and Marinacci \(2001\)](#), with the assumption that the decision maker can assign subjective probabilities to events, even when she does not maximize SEU (e.g. [Ellsberg, 1961](#), p. 659). The biseparable preference model is a very general ambiguity model (e.g., [Attema et al., 2018](#); [Abdellaoui et al., 2021a](#)) because it contains many of the ambiguity models (e.g. [Gilboa, 1987](#); [Schmeidler, 1989](#); [Gilboa and Schmeidler, 1989](#); [Tversky and Kahneman, 1992](#)) that have been proposed to explain Ellsberg's paradox as special cases.

For decisions under risk, the objective probabilities of events are known. Denote by $L = (x, y; p, 1 - p)$ a binary lottery that gives outcome x with probability p and y otherwise. The preference relation of the decision-maker is

represented by the following model that values the prospect $L = (x, y; p, 1 - p)$ as

$$V(L) = w(p)(u(x) - u(y)) + u(y) \quad (1.2)$$

with $w(\cdot)$ as the weighting function or source function for risk and $u(\cdot)$ the utility function that captures the attitude toward the outcomes. Both $w(\cdot)$ and $u(\cdot)$ are strictly increasing functions.

Source-dependent Utility (SDU) models assume identical weighting functions between risk and uncertainty, *i.e.* $W(\cdot) = w(\cdot)$. Source-dependent weighting (SDW) models assume identical utility functions between risk and uncertainty, *i.e.* $U(\cdot) = u(\cdot)$.

1.2.2 Existing methods

1.2.2.1 Elicitation methods based on exchangeability of events

The main difficulty for measuring the ambiguity model (2.1) resides in how to disentangle the weighting function $W(\cdot)$ from the beliefs $P(\cdot)$ (e.g. [Li et al., 2020](#)) (LW, hereafter). The solution proposed in the literature is based on the concept of *exchangeability of events* ([Baillon, 2008](#)). Two events are exchangeable for a decision-maker when she is indifferent towards permutations of their outcomes. Formally, two events E_1 and E_2 are exchangeable if $(x, E_1, y) \sim (x, E_2, y)$, which implies that such events are equally likely or symmetric: $P(E_1) = P(E_2)$. If these events are complementary, then the subjective probability associated with each event should be $\frac{1}{2}$, assuming the additivity of $P(\cdot)$.

Based on this concept of exchangeability of events, several methods have been proposed (e.g. [Abdellaoui et al., 2011a](#); [Van De Kuilen and Wakker, 2011](#); [Abdellaoui et al., 2021a](#); [Gutierrez and Kemel, 2021](#)). The common idea underlying these methods is to start by splitting the universal event into two

exchangeable events E_1 and E_2 , such that $P(E_1) = P(E_2) = \frac{1}{2}$. The following steps of these methods consist of splitting E_1 and E_2 into exchangeable events that will result in $\frac{1}{4}$ as the subjective probability. Repeating the procedure allows to construct iteratively a series of exchangeable events that have a subjective probability of $\frac{1}{2^i}$, with $i = 1, 2, \dots, n$. With the set of exchangeable events for which one knows the subjective probability, these methods can provide a measurement for $W(\cdot)$ and $U(\cdot)$.

The construction of these exchangeable events are only possible for *continuous-valued sources of uncertainty*, which means that the universal event is an interval of real numbers (Abdellaoui et al., 2021b; Van De Kuilen and Wakker, 2011). For instance, when the source of uncertainty is the temperature in a town or the stock market index.

1.2.2.2 Elicitation method not based on exchangeable events

Oppositely, a *discrete source of uncertainty* comes from a source of uncertainty that takes their values in a discrete set of events which are not necessarily equally likely. Consequently, the universal event is no longer an interval of real numbers, therefore, it is not longer possible to build *exchangeable events*. In the next subsection, we introduce the indexes of Baillon et al. (2018b) (BW, hereafter), which are applicable to measure ambiguity towards *discrete sources of uncertainty*.

Belief hedges method of BW

For *discrete sources of uncertainty*, BW introduced the *belief hedges method* that consists of evaluating ambiguity attitudes through two indexes. BW assume a minimal degree of richness of the state space Ω , meaning that there should be three nonnull events $E_1 = A$, $E_2 = B$ and $E_3 = C$ that are mutually exclusive

and exhaustive: $E_1 \cup E_2 \cup E_3 = \Omega$ and $E_i \cap E_j = \emptyset$ for $i \neq j$. Denote by E_{ij} the union $E_i \cup E_j$ of two events. We call E_i a single event and E_{ij} a composite event. Denote by $\Omega_1^* = \{E_1, E_2, E_3\} = \{A, B, C\}$ the set of single events and by $\Omega_2^* = \{E_{12}, E_{13}, E_{23}\}$ the set of the composite events.

BW propose their two indexes in the framework of SDW. The difference in the weighting functions under ambiguity and risk is measured by the *ambiguity function* $f(\cdot) = w^{-1}[W(\cdot)]$. The matching probability m_E of an event E is the probability that ensures the following indifference $(x, y; E, E^c) \sim (x, y; m_E, 1 - m_E)$. Under SDW, the *ambiguity function* corresponds to the *matching probability* (Dimmock et al., 2016, Theorem 3.1):

$$m_E = f[P(E)] \quad (1.3)$$

The two indexes of the ambiguity function of BW are given by:

$$\begin{aligned} b &= 1 - (m_1 + m_2) \\ a &= 3 \left[\frac{1}{3} - (m_2 - m_1) \right] \end{aligned}$$

with $m_1 = \frac{1}{3}[m_A + m_B + m_C]$ and $m_2 = \frac{1}{3}[m_{AB} + m_{AC} + m_{BC}]$ being the averages matching probability for the single and composite events.

The quantity b , called *ambiguity aversion index*, approximates the elevation of the decision maker's ambiguity function. Ambiguity neutrality (*i.e.* $w(\cdot) = W(\cdot)$) implies $b = 0$. A higher value of b is associated with more ambiguity aversion from the pessimism component of the weighting function. The quantity a , called *ambiguity-generated insensitivity* (a-insensitivity), approximates the flatness of the ambiguity function in the middle region. Ambiguity-neutrality implies $a = 0$. A higher value of a is associated with more ambiguity aversion from the likelihood insensitivity component of the weighting function.

The main purpose of the two indexes of BW is to compare a risky situation with an ambiguous situation. Although, it can be tempting to use these two indexes to compare two different sources of uncertainty, our main point (formulated in Proposition 1) is to stress the fact that this second use of the two indexes could be misleading.

Proposition 1. Consider two different sources of uncertainty 1 and 2 involving each three mutually exclusive and exhaustive events E_i , $i = 1, 2, 3$. Denote by $W_j(\cdot)$ and $P_j(\cdot)$ the weighting and belief functions for the source of uncertainty j , with $j = 1, 2$. Assume that subjects have:

(A1) the same non-linear weighting functions for the two sources of uncertainty
 : $W_1(\cdot) = W_2(\cdot) \equiv W(\cdot)$

(A2) different beliefs for events : $P_1(\cdot) \neq P_2(\cdot)$.

Assumptions (A1) and (A2) imply that $a_1 \neq a_2$ and $b_1 \neq b_2$

Proof

Under (A1), we have the same ambiguity function $f_1(\cdot) = f_2(\cdot) = w^{-1}[W(\cdot)] \equiv f(\cdot)$, with $w(\cdot)$ being the probability weighting function for risk. So, there is no difference in ambiguity attitudes in the sense of SDW. The two indexes of BW for the two sources of uncertainty are given by

$$\begin{aligned}
 b_i &= 1 - \frac{1}{3} \left(\sum_{E \in \Omega_1^*} f[P_i(E)] + \sum_{E \in \Omega_2^*} f[P_i(E)] \right) & i = 1, 2 \\
 a_i &= 1 - \left(\sum_{E \in \Omega_2^*} f[P_i(E)] - \sum_{E \in \Omega_1^*} f[P_i(E)] \right) & i = 1, 2
 \end{aligned}$$

Since the ambiguity function $f(\cdot)$ is bijective and $P_1(\cdot) \neq P_2(\cdot)$, there is no reason, a priori, to expect that $b_1 = b_2$ and $a_1 = a_2$. To illustrate, let's consider the following numerical example. For the source of uncertainty 1, assume that E_1 , E_2 , and E_3 are symmetric: $P_1(E_1) = P_1(E_2) = P_1(E_3) = \frac{1}{3}$. For the source 2, assume $P_2(E_1) = \frac{1}{10}$, $P_2(E_2) = \frac{1}{10}$ and $P_3(E_3) = \frac{8}{10}$. Also, assume $w(p) = p$ for risk and the non-linear [Prelec \(1998\)](#) compound invariance family $W(z) = (\exp(-(-\ln(z))^\alpha))^\beta$ with $\alpha = 0.65$ and $\beta = 1.05$ ([Wakker, 2010](#), pg. 270) for both treatments 1 and 2. With these values, we have $b_1 = 0.11 \neq 0.06 = b_2$ and $a_1 = 0.31 \neq 0.19 = a_2$. QED.

The Proposition 1 shows that the indexes of BW may be misleading to learn about the differences in ambiguity functions related to different sources of uncertainty when the distributions of beliefs differ markedly between these sources. Note that the only case where the indexes of BW work perfectly, is when the ambiguity function is linear ([Baillon et al., 2021](#), Theorem 16). This happens when the weighting functions $w(\cdot)$ and $W(\cdot)$ are the specification of [Chateauneuf et al. \(2007\)](#).

Our point applies in particular to LW, who compare the indexes of BW between uncertainty generated by nature with uncertainty generated by a second player in the trust game. In this case, events are symmetric for nature (e.g [Abdellaoui et al., 2011a](#)), while they are asymmetric for the trust game. Hence, the results found by LW might be driven by the beliefs. A second drawback is that the indexes are proposed under the framework of SDW and this does not allow for ambiguity attitudes to be captured by the utility function.

Neo-additive method

[Baillon et al. \(2018a\)](#) proposed a method which releases the assumption of identical utility functions across sources or, in particular, between risk and

uncertainty. This method allows to elicit the utility function, the neo-additive weighting function $W(P(E)) = sP(E) + c$ proposed by [Chateauneuf et al. \(2007\)](#), and the beliefs do not require exchangeable events.¹ The method consists of using certainty equivalent data of binary lotteries that involve three mutually exclusive and exhaustive events (E_1, E_2, E_3) and, one composite event (say E_{12}). The neo-additive weighting function and the parametric utility function (e.g. power utility x^α) are specified. The certainty equivalent data can be used in three-stages or one-stage procedure to estimate the utility, the neo-additive weighting function, and the beliefs of each $P(E_i)$, $i = 1, 2, 3$.

In the three-stages procedure, parametric assumptions are made sequentially. In the one-stage, the certainty equivalent data associated to one event (say E_1) is used to estimate the utility function parameter (say α) and the one event weight (say $W(P(E_1))$), according to the method of [Abdellaoui et al. \(2008\)](#). In the second stage, the certainty equivalent data related to the three remaining events (E_2, E_3 and E_{12}) are used to compute, in a deterministic way, the three event weights $W(P(E_2))$, $W(P(E_3))$ and $W(P(E_{12}))$, according to [Abdellaoui et al. \(2011b\)](#). In the third stage, the four event weights from the first and second stage allow to estimate the two-parameter of the neo-additive weighting function and the three beliefs as follows

$$c = W(P(E_1)) + W(P(E_2)) - W(P(E_{12})) \quad (1.4)$$

$$s = \sum_{i=1}^3 W(P(E_i)) - 3(W(P(E_1)) + W(P(E_2)) - W(P(E_{12}))) \quad (1.5)$$

$$P(E_i) = \frac{W(P(E_i)) - c}{s} \quad \text{for} \quad i = 1, 2, 3 \quad (1.6)$$

¹Similar procedure is proposed by [Gutierrez and Kemel \(2021, study C\)](#), but they keep the assumption of same utility for all sources of uncertainty.

In the one-stage procedure, the parametric assumption of the utility and the weighting functions are not made sequentially, but simultaneously. Then, the certainty equivalent data is used in a single step to estimate the utility function parameter (say α), the two-parameters (s and c) of the neo-additive weighting function, and the two beliefs $P(E_1)$ and $P(E_2)$, knowing that $P(E_3) = 1 - P(E_1) - P(E_2)$.

Even though the one-stage and three-stages neo-additive methods allow for source-dependent utility function, they might suffer from two drawbacks. The first drawback applies to both methods. This drawback relies on the fact that the assumption of the neo-additive weighting function may be restrictive to fit the data (e.g. [Li et al., 2018](#)), probably due to misspecification issues ([Kpegli et al., 2022](#)). Second, in the case of the three-stages approach, the certainty equivalents that are used to compute the event weights in a deterministic way during the second stage contain with response errors. These response errors are not controlled and, then they could bias the future estimates of the event weights in the second stage, as well as generate additional bias in the beliefs of the third stage ([Etchart-Vincent, 2004](#), pg. 221).

1.3 Elicitation Method

In this section, we extend the multistage neo-additive method of [Baillon et al. \(2018a\)](#) to any two-parameter weighting function to elicit beliefs $P(\cdot)$, utility function $U(\cdot)$, and weighting function $W(\cdot)$ for discrete sources of uncertainty. In addition, we show that the two-stage method is more robust to misspecification than the one-stage method. We keep the same notations as in section 1.2.

1.3.1 Stage 1: Elicitation of utility function and willingness to bet

This stage is based on the *all at once method* of [Kpegli et al. \(2022\)](#). The researcher starts by considering a set of $m = 3$ mutually exclusive and exhaustive nonnull events $\Omega_1^* = \{E_1, E_2, E_3\}$.² The resulting set of composite events is given by $\Omega_2^* = \{E_{12}, E_{13}, E_{23}\}$. Further, the researcher will pick a composite event in Ω_2^* , say E_{12} (see also [Baillon et al., 2018a](#)). Subsequently, the researcher elicits in an experiment, at least two certainty equivalents for each single event and the chosen composite event $E \in \Omega_1^* \cup E_{12}$

$$ce_k^h \sim (x_E^h, y_E^h; E, E^c), \quad h = 1, 2, \dots, N_E \quad \text{and} \quad N_E \geq 2 \quad (1.7)$$

with N_E being the number of certainty equivalents that involve the event E . x_E^h and y_E^h refer to the outcomes such that $x_E^h > y_E^h$. In total, the number of certainty equivalents elicited is $N = \sum_{E \in \Omega_1^* \cup E_{12}} N_E \geq 2(m + 1) = 8$.

Now, we denote by \mathbf{ce} , \mathbf{x} , and \mathbf{y} the variables that collect the values ce_E^h , x_E^h , and y_E^h , respectively. Also, we denote by \mathbf{I}^E a dummy variable that takes the value 1 if the event E occurs and 0 otherwise. Denote $\delta_E \equiv W(P(E))$ for $E \in \Omega_1^* \cup E_{12}$. We call δ_E the *willingness to bet* on the event E ([Ghirardato and Marinacci, 2001](#); [Abdellaoui et al., 2011a](#)). Also, we assume that the certainty equivalents are observed with additive response error terms \mathbf{e} . Assuming that U is invertible, it turns out

$$\mathbf{ce}_l = U^{-1} \left[(U(\mathbf{x}_l) - U(\mathbf{y}_l)) \left(\sum_{E \in \Omega_1^* \cup E_{12}} \delta_E \mathbf{I}_l^E \right) + U(\mathbf{y}_l) \right] + \mathbf{e}_l \quad (1.8)$$

²We cover the cases of $m \neq 3$ in the subsection 1.3.2.

where l is the l^{th} line in \mathbf{ce} , \mathbf{x} , and \mathbf{y} . Finally, the Eq. (1.8) is estimated by nonlinear least squares, by giving an explicit functional form for U (and thus for U^{-1}). The two-popular utility function are power (eq. 1.16) and exponential (eq. 1.17).

From the estimations results, one gets the parameter(s) of the utility function $U(\cdot)$ and the willingness to bet δ_E on the event $E \in \Omega_1^* \cup E_{12}$. These willingness to bet correspond to the compound function $W(P(\cdot))$ evaluated at each single and composite events in the set $\Omega_1^* \cup E_{12}$.

This stage allows to reject subjective expected utility theory (that is $W(z) = z$), if any of the following two equalities is not satisfied

$$\sum_{E \in \Omega_1^*} \hat{\delta}_E = 1 \quad \text{and} \quad \hat{\delta}_{E_{12}} = \hat{\delta}_{E_1} + \hat{\delta}_{E_2} \quad (1.9)$$

The following stage allows to break down the willingness to bet in terms of weighting function $W(\cdot)$, and beliefs $P(E)$ for $E \in \Omega_1^* \cup E_{12}$.

1.3.2 Stage 2: Elicitation of weighting function and beliefs

Following [Gonzalez and Wu \(1999\)](#), we assume that the weighting function $W(\cdot)$ is characterized by two parameters η and γ , which correspond to the *insensitivity* of the decision-maker to likelihood information, and the decision-maker's *pessimism/optimism*, respectively. To make explicit the dependence of the weighting function on η and γ , we write $W(\cdot) \equiv W_{\eta,\gamma}(\cdot)$.

With $m = 3$ single events, we have the following system of 5 equations:

$$W_{\eta,\gamma}(P(E_i)) = \hat{\delta}_{E_i} \quad , \quad i = 1, 2, \dots, m = 3 \quad (1.10)$$

$$W_{\eta,\gamma}(P(E_1) + P(E_2)) = \hat{\delta}_{E_{12}} \quad (1.11)$$

$$\sum_{i=1}^m P(E_i) = 1 \quad (1.12)$$

The system of equations (1.10)-(1.12) contains exactly 5 unknown elements: $P(E_1)$, $P(E_2)$, $P(E_3)$, η , and γ . The first three equations in (1.10) come from Eq. (1.8). The fourth Eq. in (1.11) comes from Eq. (1.8) and, the fact that the events E_1 and E_2 are mutually exclusive. The last Eq. in (1.12) comes from the fact that the events E_1, E_2 , and E_3 are exhaustive. Any two-parameter weighting functions can be specified (see [Epper and Fehr-Duda, 2020](#), for a review) in the system of equations (1.10)-(1.12). The three popular weighting functions in the ambiguity literature are the specifications³ of GE87 (eq. 1.18), P98 (eq. 1.19) and CEG7 (eq. 1.20).

When the estimated decision weights satisfy strict monotonicity⁴ in the sense that $\delta_{E_{12}} > \delta_{E_1}$ and $\delta_{E_{12}} > \delta_{E_2}$, the system of equations (1.10) - (1.12) could be solved (numerically) to estimate the strictly increasing two-parameter weighting function (*i.e.* η and γ) and the beliefs $P(E_1)$, $P(E_2)$, and $P(E_3)$.

It is noteworthy to talk about our method when the number m of single events is different from 3. When the number of single events is more than 3, the procedure to apply our method remains unchanged. The beliefs of additional single events can be estimated by using the corresponding number m of the single events in equations (1.10) and (1.12). When the number of single events is $m = 2$, the Eq. (1.11) collapses from the method because $W(1) = 1$ by assumption. In this case, our method does not allow to identify two-parameters weighting

³We refer to [Goldstein and Einhorn \(1987\)](#) as GE87.

⁴Monotonicity at the aggregate level (e.g. pooled data, mean data and median data) will naturally hold. But, at the individual level this condition might not be satisfied.

function. Instead, it allows to identify one-parameter weighting function (e.g. [Tversky and Kahneman, 1992](#); [Prelec, 1998](#)).

Despite the fact that we focus on the presentation of our method on discrete source of uncertainty, it can also apply to continuous-valued sources of uncertainty (see [Appendix 1.A](#) for details). In this context, using the subjective probabilities of the three exclusive and exhaustive events $E_1, E_2, E_3 \subset \mathcal{R}$ allows to completely estimate continuous two-parameter distribution like the beta distribution ([Abdellaoui et al., 2021a](#)). Consequently, our method covers all types of sources of uncertainty.

Also, the method accommodates both SDU and SDW since we do not require equality of utility or weighting functions between risk and uncertainty. Then, the data allows to discriminate between SDU and SDW.⁵

1.4 Related literature on uncertainty attitudes in experiments

The reminder of the chapter shows how our method can be used to measure beliefs and disentangle crucial forms of uncertainty in trust and coordination games. In this section, we present some of the related literature.

1.4.1 Crucial forms of uncertainty in trust and coordination games

In economic experiments, subjects playing the traditional trust game, face two sources of uncertainty: *strategic uncertainty* and *social ambiguity*. First, subjects

⁵In [Appendix 1.D](#) we present the parameter recovery and misspecification exercises (e.g. [Gao et al., 2020](#); [Kpegli et al., 2022](#); [Nilsson et al., 2011](#)) with the aim of comparing our multi-stage approach with the one-stage approach.

face *strategic uncertainty* when the actions of others are uncertain in strategic interactions. Strategic uncertainty confronts individuals with the delicate task of forming beliefs about other individuals' decisions (Renou and Schlag, 2010). Second, decision-makers face *social ambiguity*, when the uncertainty comes from the non-strategic decisions of other individuals. Social ambiguity refers to the fact that subjects treat acts by humans, even in the absence of strategic interactions, differently from acts of nature, which do not involve human agency (LW). Hence, behind any strategic uncertainty, there is also social ambiguity, which might play a role in the decision-making process.

Additionally, social preferences play a role in trust games since players are aware that their actions impact not only their payoffs, but also the payoffs of others (Bohnet et al., 2008) (BZ, hereafter). Also, in a modified version of the trust game, Trustors can interact with nature instead of another person, in which case, they face *nature ambiguity*. This means that the ambiguous outcomes are determined by a non-human source.

Besides social ambiguity, strategic uncertainty, and social preferences (all present in strategic interactions), a key component that differentiates the trust game from other games that comprise strategic interactions in game theory (e.g., beauty contest, and coordination games) is *betrayal aversion*. Betrayal aversion represents a cost for the Trustor when trust is violated (BZ). This cost is viewed by BZ as a dis-utility that enters into the utility function alongside the utility towards one's own payoffs and social preferences. It becomes clear that strategic uncertainty, social ambiguity and betrayal aversion can play a major role in strategic interactions and trust decisions.

1.4.2 Social ambiguity, strategic uncertainty and betrayal aversion

Under SDU, *strategic uncertainty*, *social ambiguity* and *betrayal aversion* would be captured by the utility function. Contrary, under SDW, they would be captured by the weighting function. The weighting function captures such ambiguous attitudes into two components: optimism/pessimism and likelihood insensitivity (Gonzalez and Wu, 1999). Optimism/pessimism reflects the extent to which subjects overweight/underweight the beliefs regarding whether the resulting outcome will be beneficial for them. On the other hand, likelihood insensitivity refers to subjects' cognitive ability to distinguish between several levels of subjective probabilities or beliefs (e.g. Choi et al., 2022). Wakker (2010) refers to optimism/pessimism as a motivational component and, to likelihood insensitivity as a cognitive component in the decision-making process.

BZ develop an experiment, using a version of the trust game, to identify betrayal aversion through the Minimum Acceptable Probability (MAP) related to the utility function. The MAP is the probability for which the Trustor is indifferent between trust and distrust. BZ identify betrayal aversion as the difference in MAP between two treatments: the trust game and the risky dictator game (RDG). In the trust game treatment, if the Trustor decides to trust, the final payoffs for both Trustor and Trustee are determined by the Trustee. Contrary, in the RDG, if the Trustor trusts, the payoffs for both players are determined by nature. The possible payoffs under both treatments are the same. Their results show that subjects state higher MAPs in the trust game compared to the RDG, which means that subjects are betrayal averse. Quercia (2016) provides an improvement of MAP design and confirm betrayal aversion.

LW show that the MAP design of BZ does not hold under SDW. The difference in MAP across treatments can be explained by the weighting function

and beliefs instead of the utility. The authors use the two indexes of pessimism and likelihood insensitivity provided by BW to disentangle social ambiguity and strategic uncertainty in the trust game. They find that pessimism is lower when subjects face social ambiguity than when they face nature ambiguity. Also, they find that strategic uncertainty and betrayal attitudes only have cognitive implications by making subjects more likelihood insensitive in the trust game compared to nature ambiguity. The fact that social ambiguity is captured by the pessimism component of the weighting function in the trust game, suggests that social ambiguity plays a major role in strategic uncertain situations. Therefore, it is important to control for social ambiguity when studying strategic uncertainty. Nevertheless, a vast majority of previous studies (e.g., [Heinemann et al., 2009](#); [Ivanov, 2011](#); [Bruttel et al., 2022](#)), do not control for social ambiguity when they investigate strategic uncertainty. In this chapter, we also aim to identify which components of the utility function and the weighting function (pessimism and likelihood insensitivity) capture the effect of social ambiguity, strategic uncertainty, and betrayal aversion.

1.5 Experimental Design

We recruit 174 students to participate in a computerized experiment, which is conducted online. Subjects are invited through the subjects pool of GATE-Lab. Subjects are told that the experiment could last up to 45 minutes, that they would receive €1.5 as a participation fee and, they could additionally earn a variable amount up to €20. Such additional payment corresponds to a randomly selected outcome of one of the decisions made during the experiment. The mean age of subjects is 21 years and 56.9% are female. Our experiment follows a within-subjects design.

The experiment consists of 5 experimental conditions. Four out of these conditions have two stages, the remaining condition consists only of the second stage. In the first stage, we implement experimental treatments based on the coordination game and the trust game. In the second stage, we apply a binary decisions task between a safe option and a lottery to elicit beliefs, ambiguity attitudes, and utility functions.⁶ The order in which subjects play the five experimental conditions is randomized.

We refer to the blocks containing one or two stages as experimental conditions and to the task implemented in each of the stages as experimental treatments. The goal of the conditions and treatments is to implement our method experimentally and combine it with empirical data. Each of the experimental conditions allows to elicit ambiguity attitudes linked to different crucial forms of uncertainty.

1.5.1 First stage

We use a within-subjects design along the experiment. In four out of the five conditions of the experiment, the first stage contains the following experimental treatments: *social ambiguity – coordination game (social ambiguity - cg)*, *strategic uncertainty - coordination game (strategic uncertainty - cg)*, *social ambiguity – trust game (social ambiguity - tg)*, and *betrayal ambiguity*. In these conditions, 89 subjects play the role of Player 1 and, 85 subjects take the role of Player 2. Subjects keep their role along the whole experiment. For each condition, new couples formed by Player 1 and Player 2 are randomly re-matched. Subjects are informed that they do not play against the same partner more than once and, they do not receive feedback about the decisions of their counterparts until the end of the experiment.

⁶The complete instructions can be found in the Appendix 1.C

At the beginning of each condition, Player 1s are informed whether the condition contains one or two stages, specific instructions for each stage are given at the beginning of each stage. Our implemented procedure for incentives allows to avoid hedging issues and it is established as follows. Player 1 received the payoff of one randomly selected decision in either one of the two stages of the four conditions, or one of the decisions made in the remaining treatment (*nature*). Also, one out of the four decisions done by Player 2, is randomly selected for payoff.

With the *social ambiguity - cg* treatment, we measure ambiguity attitudes and social ambiguity. Player 1s make a strategic decision between Left (L), Right (R), and Middle (M). On the other hand, Player 2s receive €5 and, their task is to answer where they would prefer to spend this money between an Amazon voucher, a Google Play voucher, and an Apple Store voucher. Player 2s do not know the payoff matrix. As such, Player 2s decide between three possible options that represent their own preferences and are independent of Player 1s' decisions. Therefore, Player 1s should not base their decisions on a strategic interaction. However, decisions of Player 2s directly affect Player 1s' payoff, which is why Player 1s face social ambiguity. The structure of the payments⁷ for this treatment is displayed in Table 1.1.

Table 1.1: Social ambiguity - coordination game treatment.

		Player 2		
		Amazon	Google Play	Apple Store
Player 1	Left	15, 5	10, 5	8, 5
	Right	8, 5	15, 5	10, 5
	Middle	10, 5	8, 5	15, 5

To measure strategic uncertainty, we implement the *strategic uncertainty - cg* treatment. The matrix of the game, which follows a traditional coordination

⁷The exchange rate is such that 1 ECU = 1 euro.

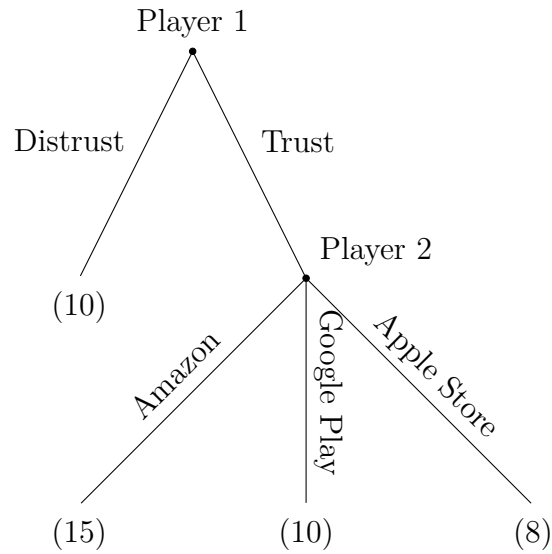
game, and is known by both Player 1 and Player 2, is shown in Table 1.2. Both Players 1 and 2 make a strategic decision between alternatives L , R , or M . Hence, subjects make their decisions under ambiguity attitudes, strategic uncertainty, and social ambiguity. Contrary to the choice alternatives presented to Player 2 in the *social ambiguity - cg* treatment, in the *strategic uncertainty - cg* treatment, we use the frame L , R , and M in order to keep a neutral language unrelated with preferences.

Table 1.2: Strategic uncertainty - coordination game treatment.

		Player 2		
		Left	Right	Middle
Player 1	Left	15, 15	10, 18	8, 22
	Right	8, 22	15, 15	10, 18
	Middle	10, 18	8, 22	15, 15

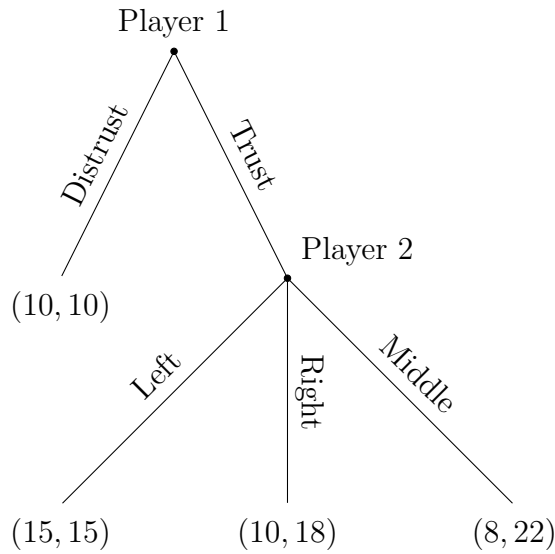
Treatments *social ambiguity - tg* and *betrayal ambiguity* are based on the experimental design of LW. In the *social ambiguity - tg* treatment (see Figure 1.1), Player 1 decides between distrust (D) or trust (T). If Player 1 decides D, she receives a payoff of 10 ECU with certainty. On the other hand, if Player 1 decides T, the payment is determined based on the preferences of Player 2. Player 2s receive €5 and are asked to decide where they would prefer to spend this money between an Amazon voucher, a Google Play voucher, or an Apple Store voucher. In this treatment, as in the *social ambiguity - cg*, Player 1s make their decisions facing ambiguity attitudes and social ambiguity.

Figure 1.1: Social ambiguity - trust game treatment



Finally, we study ambiguity attitudes, social ambiguity, strategic uncertainty, betrayal aversion, and social preferences in the *betrayal aversion* treatment. Player 1 decides between the safe option D and the ambiguous option T. In case Player 1 chooses D, both Players 1 and 2 receive 10 ECU and no further decisions are made. Differently, if Player 1 decides T, Player 2's decision between L, R, or M, determines the final payoffs for both players. Player 2's decisions L, R, and M represent reciprocation, no hurt, and betrayal, respectively. The structure of the game and payments are shown in Figure 1.2. In this treatment, Player 1 faces ambiguity regarding the strategic decision made by Player 2, which also leads to the possibility for Player 1 to be betrayed by Player 2.

Figure 1.2: Betrayal aversion treatment



1.5.2 Second stage: elicitation of beliefs, ambiguity attitudes, and utility function

Only Player 1s perform the second stage of each condition and the remaining condition. The first stage in every condition is followed by the second stage. Therefore, Player 1 perform the second stage of each condition immediately after each of the treatments and, only when the task of the second stage is completed, Player 1 moves to the next condition. We elicit Player 1s' certainty equivalents through the switching outcome technique (Gonzalez and Wu, 1999; Tversky and Kahneman, 1992) for a list of 12 binary lotteries $L = (x, y; E, E^c)$ that involved Player 2s' decisions as events. Such events can be either L, R, and M, or Amazon, Google Play, and Apple Store vouchers, depending on the immediately latest treatment performed by the participant. To infer the certainty equivalent of each lottery $L = (x, y; E, E^c)$, Player 1s are asked to make a series of binary

decisions between a lottery and a list of equally spaced safe payoffs, ranged from the maximum value x to the minimum value y of the lottery.

Table 1.3 displays an example of the lotteries corresponding to the second stage of the conditions containing the treatments *strategic uncertainty - cg* and *betrayal aversion*, where the decisions done by Player 2s correspond to the options L , R , or M . Consider for example, lottery number 1 in the first set of lotteries in Table 1.3. In this case, Player 1 is asked to make eight decisions between a safe outcome and a lottery. Payoffs for the safe option vary from 15 ECU to 8 ECU, while the lottery remains constant.

Table 1.3: Binary lotteries

No. of lottery	x	y	E	E^c	Midpoint of outcome lotteries
First set of lotteries					
1	15 ECU	8 ECU	$E_1 = L$	$E_1^c = R \cup M$	11.5 ECU
2	15 ECU	8 ECU	$E_1 = R$	$E_1^c = L \cup M$	11.5 ECU
3	15 ECU	8 ECU	$E_1 = M$	$E_1^c = L \cup R$	11.5 ECU
4	15 ECU	8 ECU	$E_1 = L \cup R$	$E_1^c = M$	11.5 ECU
Second set of lotteries					
5	10 ECU	0 ECU	$E_1 = L$	$E_1^c = R \cup M$	5 ECU
6	10 ECU	0 ECU	$E_1 = R$	$E_1^c = L \cup M$	5 ECU
7	10 ECU	0 ECU	$E_1 = M$	$E_1^c = L \cup R$	5 ECU
8	10 ECU	0 ECU	$E_1 = L \cup R$	$E_1^c = M$	5 ECU
Third set of lotteries					
9	15 ECU	0 ECU	$E_1 = L$	$E_1^c = R \cup M$	7.5 ECU
10	15 ECU	0 ECU	$E_1 = R$	$E_1^c = L \cup M$	7.5 ECU
11	15 ECU	0 ECU	$E_1 = M$	$E_1^c = L \cup R$	7.5 ECU
12	15 ECU	0 ECU	$E_1 = L \cup R$	$E_1^c = M$	7.5 ECU

Finally, Player 1s complete another set of binary decisions which are not linked with any treatment performed before by the participant. Such an additional set of binary decisions is the experimental condition called *nature ambiguity*. In this task, Player 1s also decide between a safe outcome or a lottery. However, in this case, the outcome of the lottery is determined by nature, which is a randomly equally likely selection between L, R, or M made by the computer. Therefore, this condition allows us to measure only ambiguity attitudes. Figure 1.3 shows

a screen shot of some of the binary decisions contained in the *nature ambiguity* task.⁸

Figure 1.3: Nature ambiguity.

Safe payments for alternative A:	Alternative A	Alternative B	Variable payments for alternative B:
15 ECU	A1	B1	You get 15 ECU if the computer randomly chooses Left or 8 ECU if the computer randomly chooses Right or Middle.
14 ECU	A2	B2	
13 ECU	A3	B3	
12 ECU	A4	B4	
11 ECU	A5	B5	
10 ECU	A6	B6	
9 ECU	A7	B7	
8 ECU	A8	B8	

Example of one of the screens of the task in the nature ambiguity treatment.

Our experimental design allows us to disregard social preferences in this part of the experiment. Therefore, at the stage of elicitation of certainty equivalents, social preferences collapse for Player 1s' decision-making process. We use the data of certainty equivalents as input to elicit the utility function, weighting function, and beliefs with our method presented in Section 1.3.

1.5.2.1 Comparison between treatments and hypotheses

We perform a series of comparisons based on the decisions done by Player 1 in the second stage of the conditions previously presented. The aim of these comparisons between the five treatments is to isolate and capture the effect of social ambiguity, strategic uncertainty, and betrayal aversion. The following are our conjectures.

1. Comparison between *social ambiguity - cg* and *strategic uncertainty - cg*: the condition *social ambiguity - cg* measures ambiguity attitudes and social ambiguity. The *strategic uncertainty - cg* condition,

⁸The image is presented in English for illustration purposes. However, the experiment was conducted in French.

measures ambiguity attitudes, social ambiguity, and strategic uncertainty.⁹ Hence, with the comparison between these two conditions, we are able to capture the effect of strategic uncertainty.

2. **Comparison between *nature ambiguity* and *social ambiguity - cg*:** the *nature ambiguity* condition captures only ambiguity attitudes and, the *social ambiguity - cg* condition captures both ambiguity attitudes and social ambiguity. Consequently, the comparison of these two conditions, allows us to capture the effect of social ambiguity under the context of the coordination game.
3. **Comparison between *nature ambiguity* and *social ambiguity - tg*:** *nature ambiguity* condition measures ambiguity attitudes and, *social ambiguity - tg* measures both ambiguity attitudes and social ambiguity. Hence, through the comparison of these conditions, we are able to capture the effect of social ambiguity in the context of the trust game.
4. **Comparison between *social ambiguity - tg* and *betrayal aversion*:** the condition *social ambiguity - tg* measures ambiguity attitudes and social ambiguity. The *betrayal aversion* condition, captures ambiguity attitudes, social ambiguity, strategic uncertainty, and betrayal aversion. Through the comparison of these two treatments we can capture the combined effect of strategic uncertainty and betrayal aversion. In addition, we are able to disentangle the effect of strategic uncertainty and betrayal aversion by controlling for the isolated effect of strategic uncertainty obtained from

⁹Following Li et al. (2020), social preferences collapse in the second stage of the conditions. Therefore, social preferences are not considered in these comparisons.

comparison 1.¹⁰ Consequently, comparing *social ambiguity - tg* and *betrayal aversion*, allows to measure the effect of betrayal aversion.

5. **Comparison between *social ambiguity - cg* and *social ambiguity - tg*:** these two conditions have the same source of uncertainty, but differ in two aspects. First, in the *social ambiguity - cg* treatment, Player 1 does not have the possibility to make her payoffs independent from the preferences of Player 2. Contrary, the *social ambiguity - tg* offers this possibility. We call such difference *dependence payoff attitudes*. Second, in the *social ambiguity - cg*, Player 1 has multiple options of payoffs (8, 10, and 15) associated to each preference (*i.e.* Amazon, Google Play and Apple Store) of Player 2. Opposite, the *social ambiguity - tg* treatment does not offer such variety of payoff to Player 1 associated to each preference of Player 2. We call this second difference *variety of payoff attitudes*.

Based on the previous comparisons, we aim to test the following predictions.¹¹

Hypothesis 1: social ambiguity is captured by pessimism.

Hypothesis 2: strategic uncertainty is captured by likelihood insensitivity.

Hypothesis 3: betrayal aversion is captured by the utility function.

1.6 Results

All statistical tests are two-sided z -test computed from median regressions, unless otherwise stated. Inline with the simulation results (see Appendix 1.D), we perform our multi-stage method by assuming sequentially power utility function (Eq. 1.16) in the first stage and the weighting function of GE87 (Eq. 1.18) in

¹⁰Comparison 1 refers to the difference found between the treatments *social ambiguity - cg* and *strategic uncertainty - cg*.

¹¹This design and behavioral conjectures have been pre-register at AsPredicted (#71020).

the second stage. First, we estimate the utility and willingness to bet on the events. Second, we estimate beliefs, likelihood insensitivity, and pessimism. The details of individual estimates are provided in Appendix 1.B.

1.6.1 First stage: utility and event weights

In the first stage, we estimate at the individual level, the utility and willingness to bet on the events.

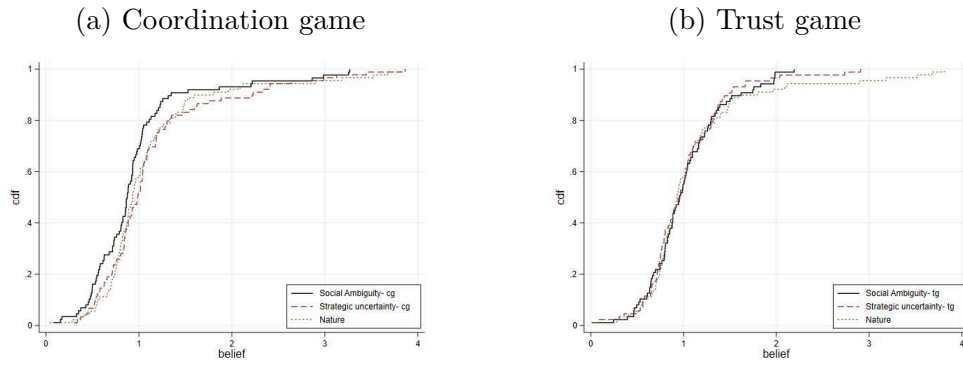
Utility curvature: Figure 1.4 displays the cumulative distributions of the utility curvature and Table 1.4 provides the summary of the estimated values. The median utility curvatures are 0.930, 0.876, 0.988, 0.968 and 0.968 for *nature ambiguity*, *social ambiguity - cg*, *strategic uncertainty - cg*, *social ambiguity - tg*, and *betrayal aversion*, respectively. These values are less than 1, the utility functions are concave in all treatments. Also, the utility curvature in the *social ambiguity -cg* is significantly different from linear ($p - values < 0.0001$). Contrary, for the other treatments, we cannot reject null hypothesis of linear utility (all $p - values > 0.0733$).

Table 1.4: Utility function

	Nature	Social ambiguity- cg	Strategic uncertainty	Social ambiguity- tg	Betrayal aversion
Median (α)	0.930	0.876	0.988	0.968	0.968
IQR	[0.771, 1.196]	[0.625, 1.042]	[0.760, 1.194]	[0.790,1.259]	[0.750 ,1.248]

IQR: interquartile range

Figure 1.4: Cumulative distribution of utility curvature



Events weights: Figure 1.5 provides the cumulative distribution of the event weights and Table 1.5 provides the summary of the estimated values. SEU is true if we cannot reject both that (i) the weights of three mutually exclusive events sum 1 and, (ii) the weight of the composite event is equal to the sum of the weights of the two single events involved in the composition (Eq. 1.9). Condition (i) cannot be rejected for *social ambiguity -cg* ($p - value = 0.7642$) and it is rejected in all the other treatments (all $p - values < 0.0002$). Condition (ii) is systematically rejected in all the treatments ($p - values < 0.0045$). Also, a joint test of conditions (i) and (ii) leads to a strong rejection in all treatment (all $p - values < 0.0001$). Then, subjects violate SEU.

Figure 1.5: Cumulative distribution of event weights

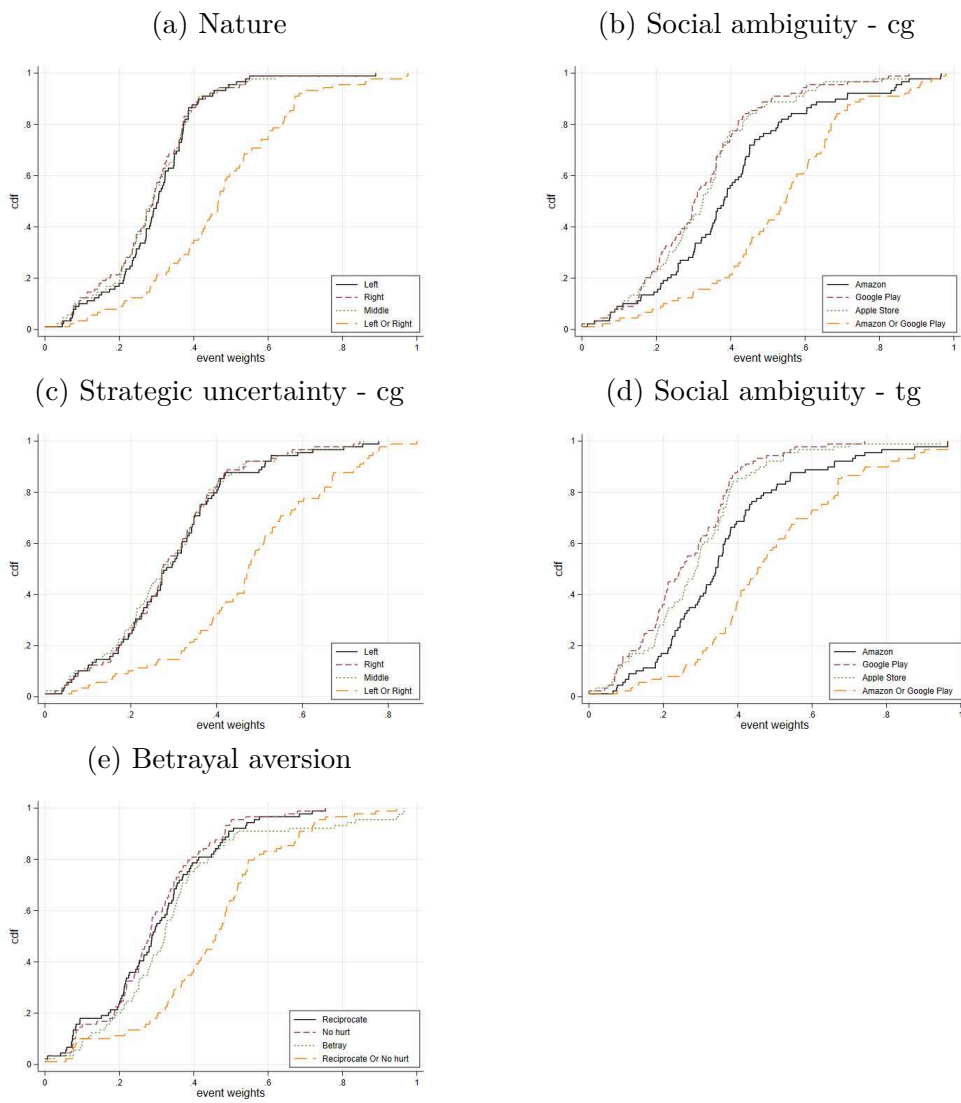


Table 1.5: Median of event weights or willingness to bet

	Nature	Social ambiguity- cg	Strategic uncertainty- cg	Social ambiguity- tg	Betrayal aversion
$W(P(L))$	0.305 [0.235 , 0.369]	0.382 [0.258, 0.478]	0.284 [0.203, 0.364]	0.341 [0.231, 0.432]	0.288 [0.204, 0.383]
$W(P(R))$	0.292 [0.212, 0.292]	0.303 [0.206, 0.399]	0.274 [0.202, 0.361]	0.247 [0.158, 0.354]	0.282 [0.211, 0.361]
$W(P(M))$	0.291 [0.212 , 0.364]	0.325 [0.219 , 0.392]	0.273 [0.187 , 0.369]	0.289 [0.185 , 0.370]	0.323 [0.235 , 0.390]
$W(P(L \cup R))$	0.467 [0.337 , 0.600]	0.549 [0.421 , 0.660]	0.474 [0.363 , 0.586]	0.454 [0.367 , 0.625]	0.459 [0.335 , 0.540]

Interquartile ranges are in [.]

L , R and M mean Amazon, Google Play and Apple Store in social ambiguity- cg and social ambiguity- tg

L , R and M mean Reciprocate, No hurt strategy and Betray in Betrayal aversion

L , R and M mean Left, Right and Middle in nature and strategic uncertainty- cg

1.6.2 Second stage: beliefs and weighting function

In the second stage, we used the weights of single and composite events from the first stage (see Figure 1.5) to estimate the beliefs ($P(\cdot)$), likelihood sensitivity (γ), and the pessimism (η) at the individual level.

Beliefs

Figure 1.6 displays the cumulative distributions of beliefs and Figure 1.7 plots the mean of the estimated values.

The null hypothesis of equally likely events cannot be rejected for the *nature* ($p - value = 0.6656$) and *strategic uncertainty - cg* treatments ($p - value = 0.2974$). A priori, symmetry of events is expected for the treatment *nature*. Similarly, symmetry of events for the *strategic uncertainty - cg* treatment can be expected, since the coordination game does not have any dominated strategy. These results provide a first successful validity test of our method.

On the other hand, symmetry of events is rejected for the *social ambiguity - cg* ($p - value = 0.0061$) and *social ambiguity - tg* ($p - value = 0.0001$). In these two conditions, the cumulative distribution function of the beliefs of Player 1

about Player 2 choosing an Amazon voucher first order stochastically dominates the Player 1's beliefs about Player 2 choosing a Google Play and an Apple Store voucher. In the *social ambiguity - cg* treatment, Player 1 thinks that Player 2 chooses to spend money in Amazon, Google Play and Apple Store vouchers with probability 40.6%, 28.1% and 31.3%, respectively. In the treatment *social ambiguity - tg*, Player 1 believes that Player 2 chooses to spend money in Amazon, Google Play and Apple Store vouchers with probability 43.4%, 25.7% and 30.9%, respectively. Joint test leads to the conclusion that the distribution of beliefs are the same in these two social ambiguity treatments ($p - value = 0.7106$). This result provides a second successful validity test of our method. In fact, these two social ambiguity treatments involve the same events. Therefore, the beliefs in these two different ambiguity situations should remain the same.

Symmetry of events is also rejected for *betrayal aversion* (p-value =0.0051). The cumulative distribution function of the beliefs about the fact that the Trustee will follow the "betray" strategy first order stochastically dominates the strategies of "no hurt" and "reciprocate". We find that Player 1 (Trustor) thinks that Player 2 (Trustee) reciprocates, adopts a no hurt strategy, and betrays with probability 29.3%, 29.7% and 41.0%, respectively.

Figure 1.6: Cumulative distribution of subjective probability (beliefs)

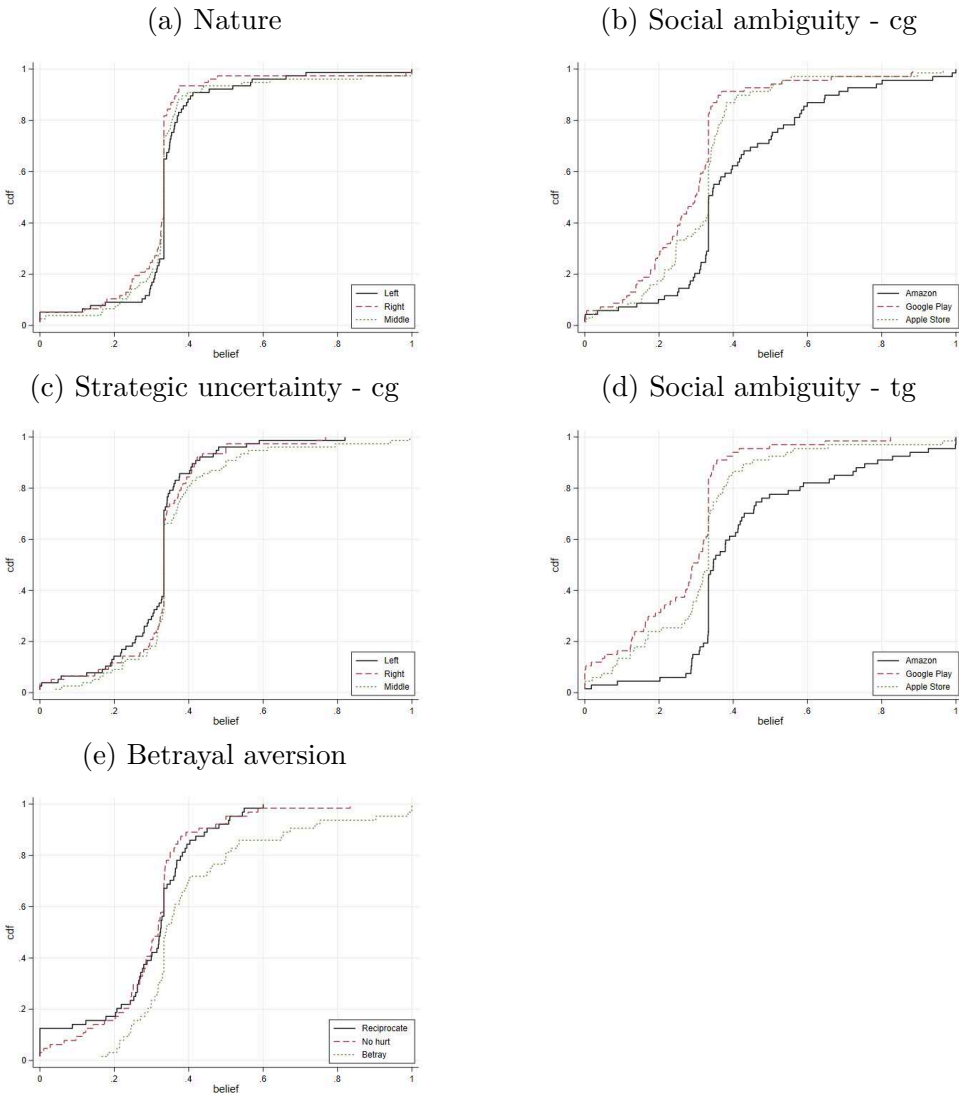
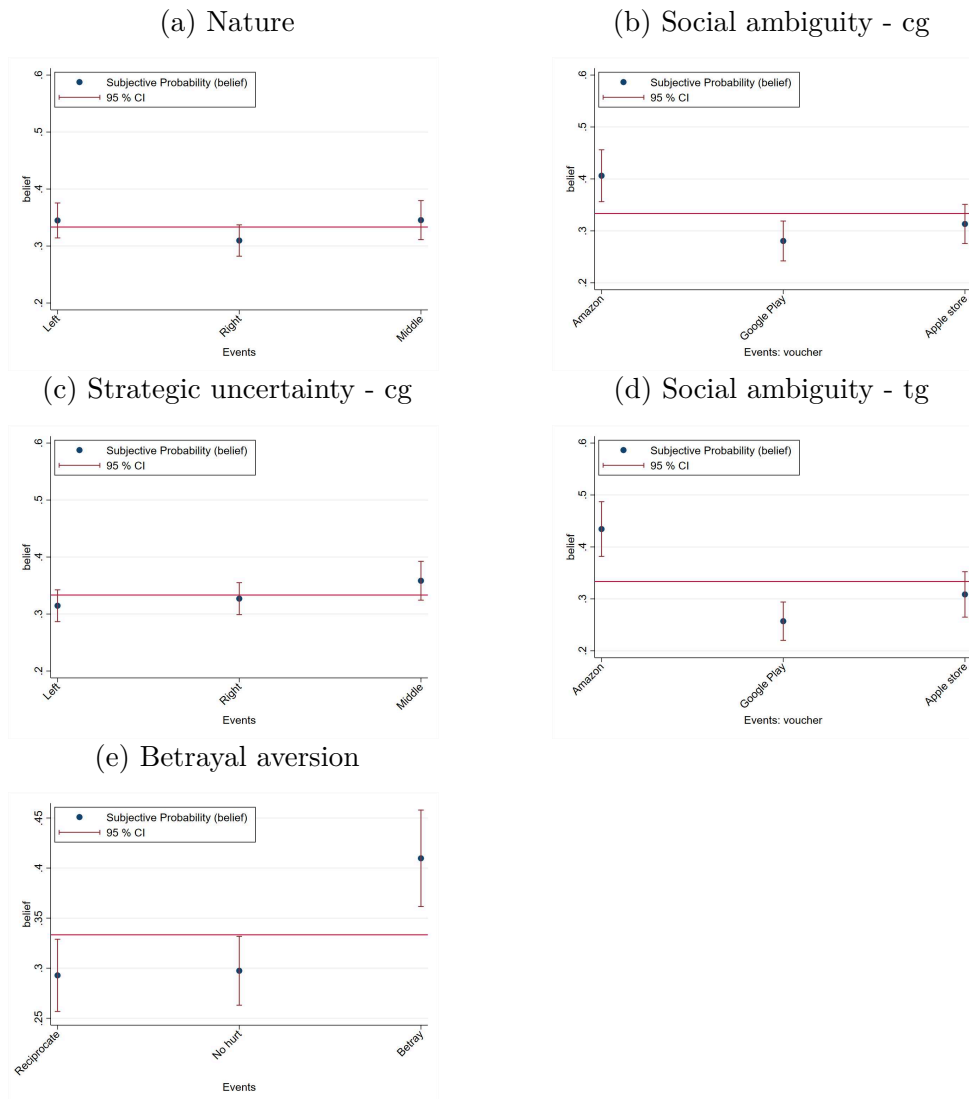


Figure 1.7: Mean of subjective probability (beliefs)



Weighting function

Figures 1.8 and 1.9 provide the cumulative distributions of pessimism (η) and likelihood insensitivity (γ).¹² Figure 1.10 displays the plots of the weighting functions based on the median estimates of η and γ . Table 1.6 summarizes the

¹²The smaller η is, the higher is the level of pessimism. The smaller γ is, the higher is the level of likelihood insensitivity.

results of the weighting function: pessimism (η) and likelihood insensitivity (γ). The usual pattern of over-weighting of small likelihoods and under-weighting intermediate and high likelihoods is reproduced. The cross-over points are 0.210, 0.345, 0.193, 0.266, and 0.264 in the treatments *nature*, *social ambiguity - cg*, *strategic uncertainty - cg*, *social ambiguity - tg*, and *betrayal aversion*, respectively.

Table 1.6: Median weighting function by treatment

	Nature	Social ambiguity- cg	Strategic uncertainty- cg	Social ambiguity- tg	Betrayal aversion
Median (η)	0.615	0.736	0.570	0.611	0.613
IQR	[0.450, 0.973]	[0.472, 1.071]	[0.408, 0.802]	[0.438, 1.018]	[0.508, 0.888]
Median (γ)	0.633	0.534	0.607	0.513	0.524
IQR	[0.425, 0.837]	[0.361, 0.797]	[0.327, 0.922]	[0.272, 0.861]	[0.291, 0.931]

Pessimism and insensitivity correspond to small values of η and γ respectively

IQR: Interquartile ranges are presented in [.]

Figure 1.8: Cumulative distribution of pessimism (η)

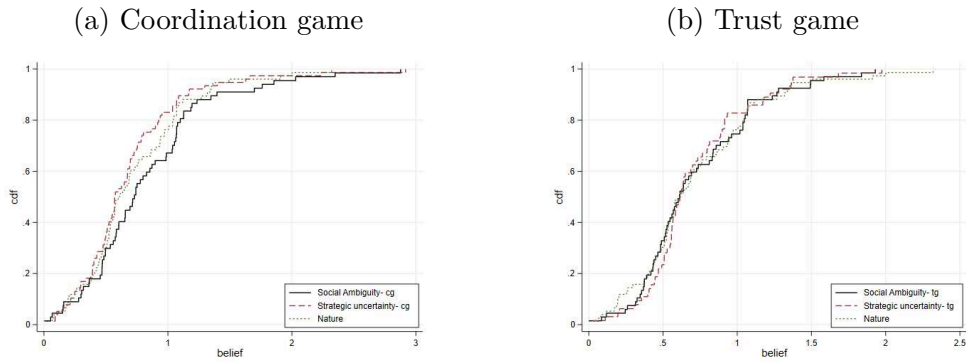


Figure 1.9: Cumulative distribution of likelihood insensitivity (γ)

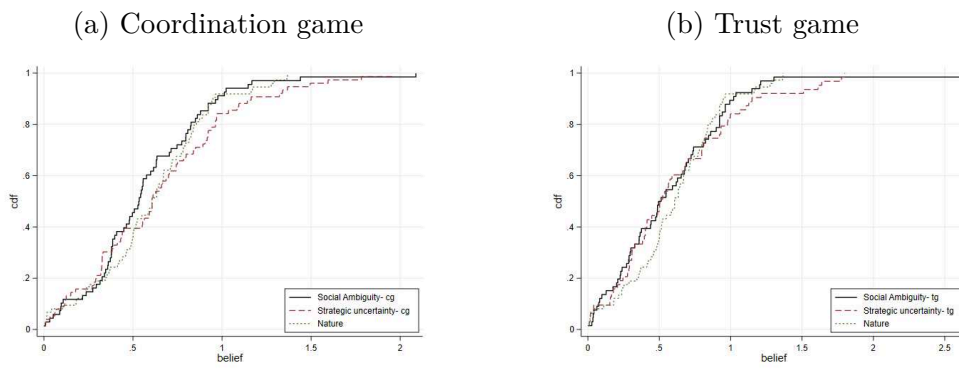
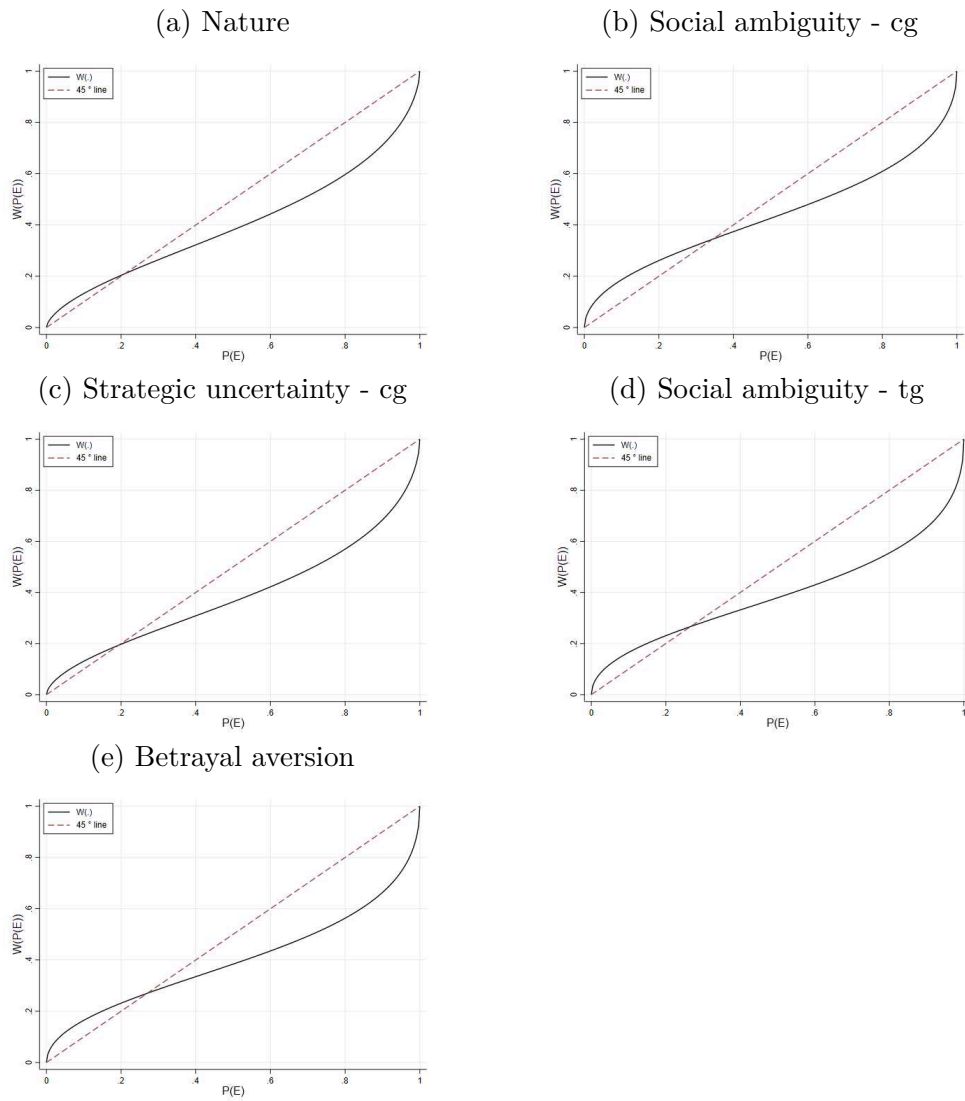


Figure 1.10: weighting function based median of individual estimates



1.6.2.1 Social ambiguity, strategic uncertainty, and betrayal aversion

Now we turn into the main purpose of the application of this chapter: the identification of social ambiguity, strategic uncertainty and betrayal aversion through pessimism, likelihood insensitivity and utility curvature. Table 1.7

presents the results of the estimation of the utility curvature (α), pessimism (η) and likelihood insensitivity (γ).

Table 1.7: Ambiguity attitudes by treatments

	Nature	Social ambiguity - cg	Strategic uncertainty- cg	Social ambiguity - tg	Betrayal aversion
Utility function					
curvature (α)	0.930 [0.771, 1.196]	0.876 [0.625, 1.042]	0.988 [0.760, 1.194]	0.968 [0.790, 1.259]	0.968 [0.750, 1.248]
Weighting function					
Pessimism (η)	0.615 [0.450, 0.973]	0.736 [0.472, 1.071]	0.570 [0.408, 0.802]	0.611 [0.438, 1.018]	0.613 [0.508, 0.888]
Insensitivity (γ)	0.633 [0.425, 0.837]	0.534 [0.361, 0.797]	0.607 [0.327, 0.922]	0.513 [0.272, 0.861]	0.524 [0.291, 0.931]

Pessimism and insensitivity correspond to small values of η and γ respectively

Interquartile ranges are presented in [.]

1. Social ambiguity

The difference between treatments 0 (*nature*) and 1 (*social ambiguity - cg*), as well as the difference between the treatments 0 (*nature*) and 3 (*social ambiguity - tg*) corresponds to what [Li et al. \(2020\)](#) called social ambiguity.

Utility curvature (α): the estimates of the CRRA parameter for treatments 0, 1 and 3 are 0.93, 0.876, and 0.968, respectively. The difference in the utility parameters between treatments 0 and 1 is not significant ($p - value=0.332$, two sided sign test). This is also the case for the difference between the treatments 0 and 3 ($p - value= 1$, two sided sign test).

Pessimism (η): the estimates of pessimism for treatments 0, 1, and 3 are 0.615, 0.736, and 0.611, respectively. Pessimism is lower in treatment 1 in treatment 0 ($p - value= 0.0030$). Pessimism is the same in treatment 3 and in treatment 0 ($p - value= 0.9245$).

Likelihood insensitivity (γ): the estimates of the likelihood insensitivity for treatments 0, 1 and 3 are 0.633, 0.534, and 0.513, respectively. Likelihood insensitivity is lower in treatment 0 than 1 (p -value= 0.0001). Also, the likelihood insensitivity is lower in treatment 0 than in 3 (p -value = 0.0037).

Consequently, we conclude that social ambiguity is captured by an increase in likelihood insensitivity. Also, social ambiguity can operate through a decrease in pessimism (treatments 0 vs 1). This partially confirms our Hypothesis 1: social ambiguity is capture by pessimism.

2. Strategic uncertainty

The difference between treatments 1 (*social ambiguity - cg*) and 2 (*strategic uncertainty - cg*) corresponds to strategic uncertainty.

Utility curvature (α): the estimate of CRRA parameter for treatments 1 and 2 are 0.876 and 0.988, respectively. The difference in the utility parameters between treatment 1 and 2 is not significant (p -value= 0.5900, two sided sign test).

Pessimism (η): the estimate of pessimism for treatments 1 and 2 are 0.736 and 0.570, respectively. Pessimism is lower in treatment 1 than in treatment 2 (p -value < 0.0001).

Likelihood insensitivity (γ): the estimates of likelihood insensitivity for treatments 1 and 2 are 0.534 and 0.607, respectively. The likelihood insensitivity in treatment 1 is larger than in treatment 2 (p -value= 0.0037).

Consequently, we conclude that strategic uncertainty is captured by a decrease in likelihood insensitivity and by an increase in pessimism. This

partially confirms our Hypothesis 2: strategic uncertainty is captured by likelihood insensitivity.

3. **Betrayal aversion**

The difference between treatments 3 (*social ambiguity - tg*) and 4 (*betrayal aversion*) corresponds to the mixture of strategic uncertainty and what BZ called betrayal aversion.

Utility curvature (α): the estimate of CRRA parameter for treatments 3 and 4 are both 0.968. The difference in the utility parameters between treatment 3 and 4 is not significant ($p - value = 0.5203$, two sided sign test).

Pessimism (η): the estimate of pessimism for treatments 3 and 4 are 0.611 and 0.613, respectively. The difference in pessimism between these treatments is not significant ($p - value = 0.9343$).

Likelihood insensitivity (γ): the estimate of likelihood insensitivity for treatments 3 and 4 are 0.513 and 0.524, respectively. The difference in the likelihood insensitivity between treatments 3 and 4 is not significant ($p - value = 0.8122$).

In the previously presented results from strategic uncertainty (treatment 1 versus 2), we show that strategic uncertainty decreases likelihood insensitivity. Additionally, the analysis of betrayal aversion shows a non-significant difference of the likelihood insensitivity between treatments 3 and 4. Nevertheless, given that the comparison between treatments 3 and 4 contains the effect of strategic uncertainty, we should find different likelihood insensitivities. This opposite result is due to the fact that the effect of strategic uncertainty offsets the betrayal aversion effect, leading to a lack of difference in likelihood insensitivity between treatments 3 and 4. In

other words, betrayal aversion and strategic uncertainty are captured by likelihood insensitivity in two opposite directions: strategic uncertainty is captured by a decrease in likelihood insensitivity, while betrayal aversion is captured by an increase in likelihood insensitivity. Consequently, we conclude that betrayal aversion is captured by an increase in likelihood insensitivity. This rejects our Hypothesis 3: betrayal aversion is captured by the utility function.

1.6.3 Dependence payoff aversion and variety of payoff seeking

Besides the previously presented results, we find that subjects exhibit two additional behaviors which are not related to attitudes toward the source of uncertainty. In this section, we present these findings. Treatments 1 (*social ambiguity - cg*) and 3 (*social ambiguity - tg*) have the same source of uncertainty (*i.e.*, preferences of Player 2, which constitutes social ambiguity). Hence, any differences in the utilities and the weighting functions between these two conditions is not due to attitudes toward the underlying source of uncertainty. Instead, the difference between treatments 1 (*social ambiguity - cg*) and 3 (*social ambiguity - tg*) corresponds to the mixture of dependence payoff aversion and the variety of payoff attitudes.

Utility curvature (α): the estimates of CRRA parameter for treatments 1 and 3 are 0.876 and 0.968, respectively. The difference in the utility parameters between treatments 1 and 3 is significant ($p - value = 0.0165$, two sided sign test). Hence, utility is more concave in treatment 1 than in treatment 3.

Pessimism (η): the estimate of pessimism for treatments 1 and 3 are 0.736 and 0.611. The difference between these treatments is significant ($p - value = 0.0001$). Therefore, pessimism is lower in treatment 1 than in treatment 3.

Likelihood insensitivity (γ): the estimates of the likelihood insensitivity for treatments 1 and 3 are 0.534 and 0.513. The difference in the insensitivity between treatments 3 and 4 is not significant ($p - value = 0.5884$).

We conclude that the greater concavity of the utility function in treatment 1 compared to treatment 3, represents a payoff dependence aversion. Also, the higher pessimism in treatment 1 compared to treatment 3 constitutes variety of payoff seeking.

1.7 Discussion

1.7.1 Experimental discussion

Our method allows to replicate some well known results. First, we confirm that the weighting function, in the case of uncertainty, is not an identity function. Consequently, subjects distort beliefs and then violate the traditional SEU theory (e.g. Abdellaoui et al., 2005, 2011a, 2016, 2021a; Attema et al., 2018; Li et al., 2019, 2020; Tversky and Fox, 1995; Camerer and Karjalainen, 1994; Bruttel et al., 2022; Bleichrodt et al., 2018; Fehr-Duda and Epper, 2012; l'Haridon and Vieider, 2019). Typically, subjects overweight small subjective probability and underweight intermediate and high subjective probability. Also, we find that only the weighting function differs across different sources of ambiguity, but not the utility function. This provides support for ambiguity theories based on the weighting function (e.g. Schmeidler, 1989), but not for ambiguity theories based on the utility function (e.g. Klibanoff et al., 2005). These results are consistent with previous studies (e.g. Abdellaoui et al., 2016; Attema et al., 2018; Abdellaoui et al., 2022; Bruttel et al., 2022).

We make two internal validity tests for our method. First, the treatments *social ambiguity - cg* and *social ambiguity - tg* involve the same events. Therefore,

the distributions of beliefs in these two conditions should be the same. Our method successfully produces this results. Second, the events in the *nature* treatment are a priori symmetric; as well as the beliefs in the *strategic uncertainty* - *cg* treatment, which does not have any dominated strategy. Our method also successfully satisfies the symmetry test for both *nature* and *strategic uncertainty* - *cg* treatments. Replicating well known results and successfully passing validity tests provide support for our method (Abdellaoui et al., 2008).

We apply our method to measure beliefs towards different discrete sources of uncertainty. One of the remarkable findings in this regard concerns the beliefs about trustworthiness. When subjects trust, they put themselves in a vulnerable situation based upon the belief the other will respond in a positive way (Özer and Zheng, 2017). As Arrow (1972) wrote "virtually every commercial transaction has within itself an element of trust". Because decisions of trust play a major role in social and economic interactions, it becomes important to be able to measure beliefs about trustworthiness, considering that the trustor distorts her own formation of beliefs (weighting functions). We find that the cumulative distribution function of the beliefs about trustworthiness is first order stochastically dominated by being betrayed. Most subjects believe that trust is not reciprocated with a mean of subjective beliefs of people being trustworthy equal to 29%.

Regarding our empirical aim of identifying the role of social ambiguity, strategic uncertainty and betrayal attitudes, our method provides the following contributions.

First, we find that social ambiguity operates mainly through an increase in the likelihood insensitivity. Therefore, subjects prefer social ambiguity over nature ambiguity when there is a small probability of winning, and prefer nature ambiguity over social ambiguity when there is a high probability of winning. The

increase in likelihood insensitivity suggests that subjects find social ambiguity more cognitively demanding compared to nature ambiguity (e.g. Wakker, 2010; Choi et al., 2022). Social ambiguity can also operate through a decrease in pessimism compared to nature ambiguity. The fact that subjects are less pessimistic towards ambiguity caused by other humans than ambiguity coming from nature, was pointed out by other studies (e.g. Li et al., 2020; Bolton et al., 2016; Chark and Chew, 2015). The decrease in pessimism due to social ambiguity could be explained by the competence hypothesis (Li et al., 2020; Heath and Tversky, 1991; Fox and Weber, 2002). Fox and Tversky (1995) propose under the competence hypothesis that, subjects' confidence is undermined when they contrast their limited knowledge about an event with their superior knowledge about another event. They argue that this contrast between states of knowledge is the predominant source of ambiguity aversion. Subjects' perception of their own knowledge about other humans' choices could be higher than their knowledge perception about choices done by nature.

Second, strategic uncertainty also operates, as social ambiguity, through likelihood insensitivity and pessimism, but in opposite directions. Contrary to social ambiguity, strategic uncertainty leads to a decrease in likelihood insensitivity and an increase in pessimism. The difference of likelihood insensitivity supports that subjects prefer social ambiguity over strategic uncertainty for small probabilities of winning and, prefer strategic uncertainty over social ambiguity for high probabilities of winning. These two opposite effects offset. Accordingly, we did not find a difference of likelihood insensitivity between the treatments *nature* and *strategic uncertainty - cg*. This result suggests that subjects tend to exhibit a similar level of likelihood insensitivity towards sources of uncertainty in which events are symmetric (e.g. *strategic uncertainty - cg* and *nature* treatments). In contrast, subjects tend to exhibit a high likelihood insensitivity when events are

asymmetric, like in our two conditions of social ambiguity (*social ambiguity - cg* and *social ambiguity - tg*). This corroborates that beliefs formation process is cognitively demanding.

Third, betrayal aversion also operates through the likelihood insensitivity. Betrayal aversion increases likelihood insensitivity. We find that subjects prefer betrayal and social ambiguities over nature ambiguity for small probabilities of winning and prefer nature ambiguity over betrayal and social ambiguities for a high probabilities of winning. [Li et al. \(2020\)](#) do not make a distinction between betrayal aversion and strategic uncertainty. The authors find that the overall effect of betrayal aversion and strategic uncertainty increases likelihood insensitivity, suggesting that the effect of betrayal aversion is larger than the effect of strategic uncertainty. However, according to our Proposition 1, we should be cautious with the possibility of having a greater effect of betrayal aversion. Indeed, the fact that events are symmetric under nature ambiguity while they are highly asymmetric in the *betrayal aversion* treatment, can mislead to a difference in likelihood insensitivity measured with the method of [Baillon et al. \(2018b\)](#).

Finally, we identify two main behaviors which are not related to attitudes towards sources of uncertainty. First, the behaviour we call *dependence payoff aversion*, which represents the fact that subjects dislike situations in which their possible payoffs depend on the preferences of others. This behaviour operates by increasing the concavity of the utility function. Second, the behavior we call *variety of payoffs seeking*, which proposes that subjects prefer to have more options of possible payoffs, when these payoffs depend on others. The *variety of payoffs seeking* is captured by a decrease in pessimism for situations that contain more possible payoffs (e.g. social ambiguity - cg) compared to situation containing a lower amount of possible payoffs (e.g. social ambiguity -tg).

1.7.2 Methodological discussion

Our method allows to completely measure the utility function, it is more robust to misspecification issues, it is easy, and error-robust. Below we discuss these features.

Complete measurement of utility function. Throughout the combination of our method with experimental data, we show the importance of measuring the utility function, which contrasts with previous methods, in which the utility function is not measured (e.g. [Baillon et al., 2018b](#); [Gutierrez and Kemel, 2021](#); [Abdellaoui et al., 2021a](#)). We show that the utility function can capture additional behaviors (e.g. *payoff dependence aversion*), unrelated to the source of uncertainty. This implies that not measuring the utility function makes more difficult to have a clean empirical measurement of ambiguity attitudes from the existing methods that do not allow the estimation of utility function (e.g. [Baillon et al., 2018b](#); [Gutierrez and Kemel, 2021](#); [Abdellaoui et al., 2021a](#)).

More robust to misspecification. We propose a multistage method instead of one-stage method ([Gutierrez and Kemel, 2021](#)). In the first stage, we only specify utility and estimate events weights non-parametrically. Based on event weights from the first stage, the method allows to estimate the parameters of any weighting function. Our method thus allows for more flexibility in the parametric choices of weighting function in comparison to existing methods (e.g. [Baillon et al., 2018b, 2021, 2018a](#)) that rely on the neo-additive weighting function of ([Chateauneuf et al., 2007](#)).

Easy and error-robust. Our method is based on simple choices that involve the lowest possible number of outcomes (i.e., three). As such, this method is not cognitively demanding - easy - for subjects, compared to methods that are based on *exchangeable events* or *matching probabilities* (e.g. [Baillon et al., 2018b](#); [Gutierrez and Kemel, 2021](#); [Abdellaoui et al., 2021a](#)), in which each choice

involves four outcomes (Kpegli et al., 2022; Abdellaoui et al., 2008). Finally, contrary to previous methods (e.g. Baillon et al., 2018b,a), our method account for response errors that are pervasive in experimental data (Kpegli et al., 2022).

1.8 Conclusion

We proposed a two-stage method that clearly measures beliefs and ambiguity attitudes towards discrete sources of uncertainty. Subjects make decisions under these types of uncertain situations in a daily life basis. The method successfully passes validity tests and provides plausible results for trust and coordination games, showing the reliability of the results derived from it. In this chapter, we implement our method to discrete sources of uncertainty; nevertheless, it also applies to continuous-valued sources of uncertainty. Therefore, this method allows to measure beliefs and ambiguity attitudes related to several fields in Economics.

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1.A Applicability of the method for continuous-valued sources of uncertainty

This appendix aims to show the validity of our method for continuous-valued sources of uncertainty. Consider the case in which an experimenter aims to measure the distribution of beliefs that a subject holds about a source of uncertainty S that takes its values in an interval $\mathcal{I} = [s_0, s_3] \subset \mathcal{R}$. The experimenter can proceed through the following three stages.

First stage: utility and event weights. In this step, the experimenter needs to arbitrarily split the universal event \mathcal{I} in three exclusive and exhaustive events $E_1 = [s_0, s_1]$, $E_2 = (s_1, s_2]$ and $E_3 = (s_2, s_3]$ with $s_0 < s_1 < s_2 < s_3$. Hence, we have the composite event $E_{12} = [s_0, s_2]$. Applying the stage 1 of our method, presented in section 1.3 allows us to estimate the utility function and the four event weights: $\hat{\delta}_E$ for $E = E_1, E_2, E_3, E_{12}$.

Second stage: weighting and beliefs of single events. Applying the second stage presented in section 1.3 allows us to break down the estimated events weights $\hat{\delta}_E$ into the weighting function (*i.e.* $\hat{\delta}, \hat{\gamma}$) and the beliefs of the single events $P(\widehat{[s_0, s_1]})$, $P(\widehat{[s_1, s_2]})$, and $P(\widehat{[s_2, s_3]})$.

Third stage: density and cumulative distribution over the range $[0, 1]$. This stage complements the two stages presented in section 1.3 because S is a continuous-valued sources of uncertainty. The interval \mathcal{I} can be re-scaled to be in the range $\tilde{\mathcal{I}} = [0, 1]$: $\tilde{s} = \frac{s-s_0}{s_3-s_0} \in [0, 1]$ for $s \in \mathcal{I} = [s_0, s_3]$.

At this stage, a two-parameter specification of the distribution is needed. A common and flexible distribution is the beta distribution $\mathcal{B}(a, b)$ with param-

eters a, b . Denote by $F_{a,b}(\cdot)$ the cumulative distribution function of the beta distribution. We then have the following three equations

$$F_{a,b}(\tilde{s}_i) - F_{a,b}(\tilde{s}_{i-1}) = P(\widehat{[\tilde{s}_{i-1}, \tilde{s}_i]}) \ , \quad i = 1, 2, 3 \quad (1.13)$$

with $F_{a,b}(\tilde{s}_0) = 0$ and $F_{a,b}(\tilde{s}_3) = 1$. These three equations in (1.13) are summarized in the following two equations

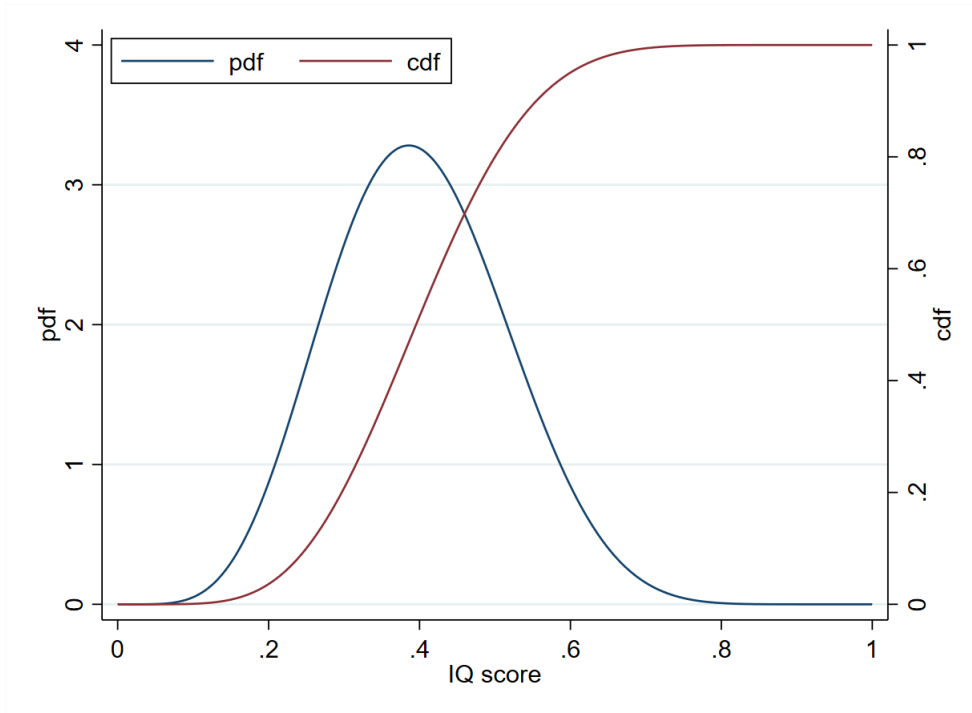
$$F_{a,b}(\tilde{s}_2) = P(\widehat{[\tilde{s}_0, \tilde{s}_1]}) + P(\widehat{[\tilde{s}_1, \tilde{s}_2]}) \quad (1.14)$$

$$1 - F_{a,b}(\tilde{s}_1) = P(\widehat{[\tilde{s}_1, \tilde{s}_2]}) + P(\widehat{[\tilde{s}_2, \tilde{s}_3]}) \quad (1.15)$$

Solving (numerically) the system of the two equations (1.14) and (1.15) provides the estimation of the distribution of beliefs (*i.e.* a, b).

For illustration purposes, lets consider that an experimenter aims to elicit the beliefs of a subject A about the IQ score of a subject B . The IQ score belongs to $[0, 1]$, with high values meaning a high IQ score. After applying stages 1 and 2 with $E_1 = [0, 0.25]$, $E_2 = [0.25, 0.50]$ and $E_3 = [0.5, 1]$, the experimenter finds the following: $P(\widehat{[0, 0.25]}) = 0.1$, $P(\widehat{[0.25, 0.5]}) = 0.7$ and $P(\widehat{[0.5, 1]}) = 0.2$. Then, the equations (1.14) and (1.15) of the third stage corresponds to $F_{a,b}(\frac{2}{3}) = 0.8$ and $1 - F_{a,b}(\frac{1}{3}) = 0.9$. Solving these two equations, provides $\hat{a} = 6.62$ and $\hat{b} = 9.95$. The density and cumulative functions are provided in figure 1.A.1.

Figure 1.A.1: beliefs of subject A about the IQ score of subject B: probability density (pdf) and cumulative density (cdf) functions.



1.B Individual estimates

Tables 1.B.1 - 1.B.9 give results of our first stage (α and $W(P(.))$) and second stage (η , γ and $P(.)$). Dots in tables mean monotonicity violation and then η , γ and $P(.)$ cannot be estimated.

Table 1.B.1: Individual estimate: nature

id	α	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	η	γ	$P(L)$	$P(R)$	$P(M)$
1	0.549	0.494	0.447	0.491	0.643	1.319	0.525	0.361	0.283	0.356
2	0.754	0.386	0.365	0.365	0.672	1.086	0.874	0.348	0.326	0.326
3	1.399	0.235	0.235	0.235	0.337	0.395	0.365	0.333	0.333	0.333
4	0.821	0.385	0.385	0.385	0.601	0.973	0.633	0.333	0.333	0.333
5	3.180	0.113	0.113	0.206	0.113
6	0.554	0.369	0.369	0.415	0.553	0.937	0.584	0.309	0.309	0.382

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Table 1.B.2 – continued from previous page

id	α	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	η	γ	$P(L)$	$P(R)$	$P(M)$
7	2.088	0.153	0.134	0.141	0.153	0.172	0.006	1	0	0
8	0.891	0.229	0.229	0.229	0.483	0.527	0.828	0.333	0.333	0.333
9	0.768	0.243	0.317	0.288	0.358	0.476	0.253	0.176	0.478	0.346
10	1.589	0.174	0.151	0.209	0.197	0.254	0.216	0.294	0.164	0.542
11	0.729	0.305	0.327	0.259	0.327
12	0.580	0.540	0.540	0.540	0.774	2.002	0.772	0.333	0.333	0.333
13	1.392	0.299	0.270	0.309	0.299	0.437	0.013	0.136	0	0.864
14	1.471	0.200	0.220	0.184	0.282	0.297	0.237	0.322	0.441	0.237
15	0.912	0.324	0.308	0.308	0.515	0.687	0.592	0.352	0.324	0.324
16	0.867	0.368	0.368	0.368	0.650	1.038	0.837	0.333	0.333	0.333
17	1.524	0.371	0.467	0.393	0.467	0.753	0.010	0	1	0
18	1.129	0.348	0.295	0.361	0.388	0.599	0.237	0.380	0.180	0.440
19	3.523	0.145	0.098	0.020	0.230
20	0.713	0.410	0.431	0.463	0.683	1.364	0.825	0.306	0.329	0.364
21	3.675	0	0	0.032	0.001	0.006	3.379	0.114	0.267	0.618
22	0.744	0.306	0.374	0.374	0.580	0.907	0.743	0.275	0.363	0.363
23	1.064	0.256	0.296	0.296	0.533	0.692	0.815	0.298	0.351	0.351
24	1.478	0.050	0.067	0.058	0.067	0.067	0.018	0	0.984	0.016
25	0.654	0.291	0.317	0.317	0.613	0.857	0.943	0.314	0.343	0.343
26	1.493	0.323	0.323	0.323	0.458	0.635	0.413	0.333	0.333	0.333
27	1.196	0.284	0.235	0.214	0.289
28	0.772	0.424	0.406	0.406	0.702	1.268	0.857	0.347	0.327	0.327
29	0.695	0.319	0.273	0.273	0.363	0.463	0.182	0.519	0.241	0.241
30	1.108	0.269	0.246	0.246	0.640	0.762	1.164	0.349	0.325	0.325
31	1.490	0.133	0.113	0.094	0.284	0.203	0.671	0.398	0.333	0.269
32	0.532	0.412	0.412	0.442	0.580	1.046	0.517	0.316	0.316	0.368
33	0.858	0.293	0.293	0.293	0.447	0.578	0.483	0.333	0.333	0.333
34	1.269	0.235	0.217	0.261	0.292	0.382	0.288	0.320	0.247	0.433
35	0.809	0.287	0.297	0.269	0.413	0.509	0.355	0.340	0.373	0.286
36	0.783	0.238	0.238	0.238	0.485	0.542	0.797	0.333	0.333	0.333
37	1.228	0.070	0.070	0.070	0.334	0.194	1.364	0.333	0.333	0.333
38	1.122	0.214	0.201	0.201	0.214
39	0.667	0.285	0.236	0.236	0.471	0.525	0.635	0.394	0.303	0.303
40	0.934	0.316	0.300	0.300	0.534	0.701	0.673	0.350	0.325	0.325
41	0.537	0.550	0.550	0.550	0.749	1.911	0.644	0.333	0.333	0.333
42	0.775	0.373	0.373	0.377	0.373
43	0.790	0.076	0.076	0.076	0.076
44	0.884	0.361	0.361	0.361	0.670	1.071	0.922	0.333	0.333	0.333

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Table 1.B.2 – continued from previous page

id	α	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	η	γ	$P(L)$	$P(R)$	$P(M)$
45	0.832	0.354	0.326	0.326	0.644	0.936	0.890	0.354	0.323	0.323
46	1.018	0.273	0.273	0.273	0.465	0.571	0.607	0.333	0.333	0.333
47	0.411	0.455	0.546	0.464	0.861	2.320	1.276	0.310	0.374	0.316
48	1.962	0.307	0.142	0.129	0.482	0.371	0.671	0.566	0.231	0.203
49	0.472	0.369	0.369	0.369	0.634	1.005	0.783	0.333	0.333	0.333
50	0.742	0.254	0.207	0.207	0.391	0.409	0.517	0.411	0.294	0.294
51	1.042	0.348	0.348	0.348	0.669	1.038	0.963	0.333	0.333	0.333
52	1.101	0.272	0.248	0.248	0.419	0.488	0.505	0.370	0.315	0.315
53	1.080	0.322	0.322	0.322	0.443	0.615	0.371	0.333	0.333	0.333
54	0.992	0.246	0.044	0.203	0.878	1.353	3.052	0.385	0.248	0.367
55	1.158	0.313	0.313	0.294	0.600	0.791	0.839	0.341	0.341	0.318
56	0.799	0.386	0.394	0.385	0.394
57	2.902	0.077	0.077	0.077	0.141	0.117	0.489	0.333	0.333	0.333
58	1.334	0.212	0.212	0.212	0.422	0.444	0.719	0.333	0.333	0.333
59	1.334	0.188	0.164	0.164	0.262	0.264	0.343	0.405	0.298	0.298
60	0.884	0.361	0.361	0.361	0.670	1.071	0.922	0.333	0.333	0.333
61	0.871	0.306	0.292	0.163	0.335
62	0.281	0.486	0.524	0.620	0.524	1.338	0.016	0	0	1
63	0.699	0.348	0.205	0.394	0.659	1.120	1.294	0.360	0.243	0.396
64	0.843	0.377	0.444	0.350	0.582	0.864	0.425	0.301	0.453	0.246
65	1.018	0.273	0.273	0.273	0.465	0.571	0.607	0.333	0.333	0.333
66	0.379	0.515	0.414	0.414	0.556	0.941	0.180	0.662	0.169	0.169
67	3.812	0.210	0.146	0.402	0.210	0.423	0.043	0	0	1
68	0.884	0.361	0.361	0.361	0.670	1.071	0.922	0.333	0.333	0.333
69	0.930	0.216	0.258	0.258	0.430	0.512	0.666	0.284	0.358	0.358
70	1.081	0.349	0.349	0.349	0.503	0.735	0.459	0.333	0.333	0.333
71	2.117	0.092	0.092	0.092	0.274	0.195	0.949	0.333	0.333	0.333
72	0.891	0.372	0.372	0.291	0.426
73	1.204	0.218	0.243	0.243	0.386	0.450	0.550	0.296	0.352	0.352
74	1.018	0.273	0.273	0.273	0.465	0.571	0.607	0.333	0.333	0.333
75	0.802	0.074	0.074	0.074	0.965	1.492	4.225	0.333	0.333	0.333
76	1.172	0.451	0.176	0.201	0.533	0.536	0.463	0.715	0.121	0.164
77	0.929	0.281	0.281	0.281	0.536	0.672	0.781	0.333	0.333	0.333
78	0.963	0.373	0.333	0.333	0.400	0.577	0.111	0.571	0.215	0.215
79	0.926	0.346	0.286	0.346	0.471	0.686	0.500	0.373	0.255	0.373
80	1.799	0.083	0.083	0.044	0.437	0.188	1.368	0.369	0.369	0.262
81	0.821	0.385	0.385	0.385	0.601	0.973	0.633	0.333	0.333	0.333
82	0.949	0.323	0.266	0.217	0.497	0.523	0.501	0.455	0.325	0.220

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Table 1.B.2 – continued from previous page

id	α	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	η	γ	$P(L)$	$P(R)$	$P(M)$
83	0.039	0.889	0.889	0.889	0.976	18.021	1.170	0.333	0.333	0.333
84	0.941	0.291	0.291	0.291	0.430	0.556	0.441	0.333	0.333	0.333
85	0.702	0.396	0.368	0.270	0.481
86	0.762	0.246	0.246	0.246	0.468	0.535	0.716	0.333	0.333	0.333
87	1.074	0.300	0.300	0.364	0.300
88	0.952	0.332	0.310	0.310	0.489	0.656	0.496	0.363	0.318	0.318
89	0.967	0.047	0.047	0.047	0.117	0.081	0.710	0.333	0.333	0.333

Table 1.B.3: Individual estimate: social ambiguity- cg

id	α	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	η	γ	$P(L)$	$P(R)$	$P(M)$
1	1.316	0.440	0.168	0.168	0.643	0.604	0.826	0.579	0.210	0.210
2	0.739	0.465	0.379	0.362	0.654	1.035	0.615	0.429	0.298	0.273
3	0.172	0.845	0.807	0.784	0.908	5.999	0.449	0.446	0.308	0.246
4	0.718	0.831	0.350	0.288	0.885	1.761	0.379	0.938	0.042	0.020
5	0.466	0.617	0.594	0.637	0.759	2.349	0.547	0.334	0.296	0.370
6	1.212	0.158	0.509	0.105	0.653	0.470	0.398	0.091	0.879	0.030
7	0.479	0.605	0.605	0.630	0.605
8	0.857	0.303	0.283	0.283	0.456	0.575	0.497	0.363	0.319	0.319
9	1.084	0.211	0.160	0.250	0.211	0.299	0.033	0.034	0	0.966
10	0.966	0.346	0.332	0.273	0.346
11	0.563	0.438	0.409	0.452	0.540	0.984	0.361	0.344	0.275	0.381
12	0.680	0.438	0.295	0.392	0.686	1.186	0.977	0.395	0.256	0.349
13	0.976	0.434	0.346	0.360	0.434
14	0.808	0.391	0.449	0.431	0.501	0.872	0.237	0.215	0.429	0.356
15	0.732	0.333	0.361	0.379	0.498	0.777	0.479	0.284	0.340	0.376
16	0.932	0.605	0.146	0.397	0.747	1.396	1.147	0.520	0.138	0.342
17	0.910	0.631	0.419	0.338	0.631
18	1.194	0.259	0.208	0.225	0.259	0.318	0.010	1	0	0
19	2.219	0.159	0.139	0.159	0.410	0.363	1.013	0.345	0.309	0.345
20	1.017	0.230	0.164	0.374	0.363	0.584	0.774	0.296	0.196	0.507
21	0.376	0.298	0.298	0.108	0.298
22	0.613	0.526	0.311	0.436	0.610	1.100	0.528	0.505	0.156	0.339
23	0.541	0.860	0.484	0.443	0.912	2.877	0.543	0.801	0.113	0.086
24	0.330	0.563	0.563	0.603	0.731	2.031	0.576	0.312	0.312	0.376
25	0.816	0.360	0.360	0.360	0.549	0.828	0.556	0.333	0.333	0.333
26	3.255	0.089	0.089	0.089	0.189	0.151	0.630	0.333	0.333	0.333
27	0.932	0.451	0.267	0.301	0.498	0.653	0.294	0.685	0.120	0.195
28	0.884	0.361	0.361	0.361	0.670	1.071	0.922	0.333	0.333	0.333
29	0.429	0.522	0.485	0.651	0.608	1.698	0.409	0.253	0.191	0.556
30	1.131	0.374	0.224	0.361	0.565	0.855	0.861	0.397	0.221	0.381
31	0.865	0.451	0.297	0.325	0.534	0.742	0.386	0.566	0.189	0.245
32	1.348	0.150	0.209	0.185	0.520	0.496	1.168	0.292	0.369	0.339
33	2.204	0.015	0.055	0.049	0.055	0.055	0.095	0	0.664	0.336
34	0.875	0.304	0.303	0.321	0.530	0.731	0.704	0.326	0.324	0.350
35	0.922	0.219	0.219	0.219	0.219	0.280	0	0.002	0.104	0.894
36	0.533	0.412	0.361	0.353	0.441	0.656	0.108	0.645	0.202	0.152
37	0.352	0.537	0.512	0.598	0.698	1.855	0.599	0.313	0.278	0.409
38	1.529	0.384	0.184	0.151	0.569	0.483	0.631	0.600	0.231	0.169

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Table 1.B.4 – continued from previous page

id	α	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	η	γ	$P(L)$	$P(R)$	$P(M)$
39	0.806	0.259	0.214	0.153	0.553	0.472	0.850	0.412	0.344	0.244
40	0.934	0.357	0.277	0.300	0.442	0.582	0.359	0.466	0.236	0.298
41	0.498	0.966	0.244	0.131	0.979
42	0.890	0.488	0.418	0.359	0.488
43	0.790	0.076	0.076	0.076	0.076
44	0.854	0.391	0.372	0.372	0.662	1.078	0.823	0.348	0.326	0.326
45	0.625	0.254	0.254	0.254	0.478	0.559	0.714	0.333	0.333	0.333
46	3.267	0.880	0.880	0.880	0.880
47	0.455	0.713	0.592	0.497	0.713
48	2.863	0.074	0.151	0.126	0.151	0.160	0.053	0	0.884	0.116
49	0.488	0.529	0.439	0.433	0.625	1.128	0.347	0.496	0.258	0.245
50	0.922	0.320	0.170	0.170	0.517	0.468	0.747	0.502	0.249	0.249
51	1.042	0.348	0.348	0.348	0.669	1.038	0.963	0.333	0.333	0.333
52	0.828	0.478	0.311	0.339	0.555	0.799	0.373	0.590	0.177	0.233
53	1.865	0.265	0.265	0.265	0.406	0.496	0.463	0.333	0.333	0.333
54	0.154	0.714	0.714	0.872	0.714
55	0.876	0.364	0.364	0.364	0.660	1.054	0.879	0.333	0.333	0.333
56	166.3	0.002	0	0	0.002	0	0.390	1	0	0
57	0.547	0.259	0.399	0.472	0.558	1.063	0.797	0.198	0.356	0.446
58	1.256	0.555	0.206	0.169	0.578
59	1.023	0.300	0.242	0.268	0.606	0.752	1.023	0.366	0.302	0.332
60	0.828	0.964	0.069	0.069	0.964
61	0.937	0.404	0.157	0.350	0.404	0.605	0.089	0.786	0	0.214
62	0.079	0.094	0.824	0.576	0.940	4.604	2.088	0.140	0.502	0.358
63	0.865	0.382	0.252	0.231	0.396
64	0.496	0.681	0.355	0.318	0.681
65	0.865	0.451	0.297	0.325	0.534	0.742	0.386	0.566	0.189	0.245
66	0.500	0.432	0.432	0.432	0.563	0.988	0.380	0.333	0.333	0.333
67	2.985	0.381	0.316	0.282	0.381
68	0.884	0.361	0.361	0.361	0.670	1.071	0.922	0.333	0.333	0.333
69	0.985	0.240	0.154	0.326	0.299	0.454	0.508	0.328	0.141	0.531
70	1.173	0.450	0.402	0.491	0.597	1.195	0.552	0.334	0.261	0.404
71	1.227	0.212	0.212	0.212	0.449	0.469	0.797	0.333	0.333	0.333
72	0.568	0.392	0.392	0.392	0.664	1.127	0.808	0.333	0.333	0.333
73	0.762	0.428	0.320	0.320	0.428
74	1.006	0.193	0.193	0.233	0.233	0.304	0.217	0.250	0.250	0.500
75	23.08	0.034	0	0	0.425	0.001	3.733	0.709	0.137	0.154
76	0.935	0.508	0.468	0.468	0.673	1.347	0.535	0.378	0.311	0.311

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Table 1.B.4 – continued from previous page

id	α	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	η	γ	$P(L)$	$P(R)$	$P(M)$
77	0.853	0.305	0.295	0.326	0.471	0.657	0.557	0.326	0.307	0.367
78	1.034	0.350	0.305	0.270	0.350
79	0.584	0.352	0.397	0.397	0.550	0.897	0.533	0.281	0.360	0.360
80	1.112	0.204	0.204	0.204	0.653	0.694	1.440	0.333	0.333	0.333
81	0.949	0.463	0.378	0.378	0.652	1.068	0.635	0.417	0.292	0.292
82	1.235	0.433	0.296	0.276	0.572	0.714	0.482	0.535	0.250	0.215
83	0.627	0.110	0.110	0.110	0.163	0.156	0.327	0.333	0.333	0.333
84	0.717	0.399	0.420	0.379	0.457	0.716	0.097	0.309	0.531	0.159
85	1.050	0.286	0.155	0.234	0.305	0.366	0.275	0.584	0.076	0.340
86	0.578	0.322	0.293	0.258	0.452	0.536	0.378	0.422	0.336	0.242
87	0.729	0.421	0.421	0.576	0.421
88	1.027	0.841	0.188	0.188	0.869	1.235	0.315	0.990	0.005	0.005
89	1.038	0.076	0.038	0.038	0.102	0.067	0.341	0.647	0.176	0.176

Table 1.B.5: Individual estimate: strategic uncertainty

id	α	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	η	γ	$P(L)$	$P(R)$	$P(M)$
1	0.929	0.230	0.230	0.230	0.470	0.515	0.784	0.333	0.333	0.333
2	0.842	0.364	0.350	0.350	0.719	1.174	1.094	0.341	0.329	0.329
3	0.452	0.505	0.462	0.462	0.755	1.629	0.839	0.364	0.318	0.318
4	0.512	0.393	0.393	0.393	0.393	0.649	0	0.005	0	0.995
5	0.369	0.696	0.734	0.697	0.734
6	0.886	0.159	0.159	0.541	0.325	0.754	0.970	0.193	0.193	0.613
7	0.849	0.342	0.328	0.214	0.438
8	0.723	0.261	0.261	0.330	0.510	0.715	0.851	0.304	0.304	0.391
9	1.051	0.194	0.194	0.194	0.260	0.291	0.271	0.333	0.333	0.333
10	0.582	0.514	0.539	0.539	0.539	1.168	0.010	0	0.500	0.500
11	0.542	0.407	0.376	0.376	0.407
12	1.331	0.238	0.263	0.213	0.473	0.493	0.661	0.333	0.380	0.287
13	2.634	0.077	0.077	0.066	0.077
14	0.857	0.262	0.283	0.303	0.474	0.627	0.667	0.300	0.334	0.367
15	0.925	0.320	0.317	0.303	0.511	0.674	0.565	0.345	0.340	0.315
16	2.989	0.178	0.178	0.116	0.316	0.246	0.383	0.419	0.419	0.162
17	0.661	0.512	0.565	0.451	0.672	1.298	0.291	0.326	0.502	0.172
18	0.838	0.318	0.338	0.338	0.338	0.510	0.007	0	0.500	0.500
19	1.351	0.404	0.467	0.369	0.513	0.784	0.106	0.199	0.742	0.059
20	1.301	0.229	0.167	0.316	0.574	0.790	1.368	0.328	0.269	0.403
21	1.597	0.063	0.055	0.055	0.063

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Table 1.B.6 – continued from previous page

id	α	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	η	γ	$P(L)$	$P(R)$	$P(M)$
22	0.798	0.284	0.309	0.351	0.470	0.692	0.593	0.280	0.323	0.397
23	0.868	0.624	0.624	0.434	0.866	2.232	0.750	0.403	0.403	0.194
24	2.340	0.046	0.046	0.046	0.146	0.091	0.905	0.333	0.333	0.333
25	1.184	0.249	0.249	0.249	0.481	0.553	0.743	0.333	0.333	0.333
26	1.187	0.331	0.331	0.331	0.530	0.747	0.592	0.333	0.333	0.333
27	0.841	0.309	0.354	0.334	0.475	0.673	0.434	0.280	0.384	0.336
28	0.884	0.361	0.361	0.361	0.670	1.071	0.922	0.333	0.333	0.333
29	0.991	0.171	0.276	0.171	0.572	0.525	1.036	0.289	0.423	0.289
30	1.108	0.269	0.246	0.246	0.640	0.762	1.164	0.349	0.325	0.325
31	1.018	0.273	0.273	0.273	0.465	0.571	0.607	0.333	0.333	0.333
32	0.804	0.303	0.303	0.303	0.549	0.727	0.742	0.333	0.333	0.333
33	0.522	0.380	0.287	0.374	0.380	0.605	0.034	0.590	0	0.410
34	1.279	0.208	0.202	0.202	0.391	0.403	0.651	0.342	0.329	0.329
35	1.541	0.171	0.171	0.206	0.194	0.250	0.151	0.220	0.220	0.561
36	0.462	0.527	0.375	0.596	0.652	1.662	0.686	0.358	0.185	0.457
37	1.041	0.101	0.184	0.223	0.348	0.391	0.972	0.217	0.362	0.421
38	1.091	0.248	0.274	0.292	0.445	0.576	0.627	0.291	0.338	0.371
39	0.985	0.173	0.181	0.113	0.411	0.298	0.705	0.376	0.394	0.230
40	0.725	0.307	0.417	0.382	0.547	0.864	0.554	0.231	0.415	0.354
41	3.864	0.040	0.040	0.040	0.206	0.103	1.322	0.333	0.333	0.333
42	0.760	0.499	0.468	0.468	0.499
43	0.627	0.110	0.110	0.110	0.163	0.156	0.327	0.333	0.333	0.333
44	0.744	0.417	0.417	0.417	0.530	0.899	0.327	0.333	0.333	0.333
45	0.529	0.203	0.203	0.243	0.603	0.698	1.340	0.320	0.320	0.359
46	1.018	0.273	0.273	0.273	0.465	0.571	0.607	0.333	0.333	0.333
47	0.302	0.741	0.526	0.742	0.747	2.917	0.280	0.480	0.031	0.489
48	3.127	0.119	0.059	0.166	0.119	0.164	0.068	0.057	0	0.943
49	0.641	0.277	0.212	0.172	0.583	0.539	0.941	0.410	0.324	0.267
50	0.903	0.197	0.154	0.154	0.500	0.427	1.084	0.374	0.313	0.313
51	1.042	0.348	0.348	0.348	0.669	1.038	0.963	0.333	0.333	0.333
52	1.086	0.342	0.239	0.252	0.356	0.432	0.121	0.820	0.067	0.113
53	0.848	0.420	0.383	0.420	0.538	0.918	0.412	0.360	0.279	0.360
54	2.404	0.208	0.246	0.002	0.764
55	1.625	0.269	0.269	0.260	0.393	0.476	0.394	0.342	0.342	0.315
56	1.042	0.348	0.348	0.348	0.669	1.038	0.963	0.333	0.333	0.333
57	3.447	0.068	0.068	0.068	0.102	0.091	0.319	0.333	0.333	0.333
58	1.056	0.343	0.343	0.343	0.383	0.570	0.125	0.333	0.333	0.333
59	1.035	0.225	0.265	0.331	0.315	0.477	0.323	0.177	0.295	0.528

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Table 1.B.6 – continued from previous page

id	α	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	η	γ	$P(L)$	$P(R)$	$P(M)$
60	1.189	0.224	0.024	0.139	0.415	0.338	1.495	0.474	0.147	0.379
61	1.886	0.044	0.104	0.058	0.421	0.212	1.595	0.277	0.408	0.316
62	1.746	0.151	0.156	0.134	0.742	0.667	1.955	0.337	0.342	0.321
63	0.708	0.336	0.424	0.093	0.779
64	1.178	0.347	0.347	0.374	0.448	0.697	0.332	0.307	0.307	0.386
65	1.018	0.273	0.273	0.273	0.465	0.571	0.607	0.333	0.333	0.333
66	0.580	0.527	0.576	0.576	0.590	1.399	0.118	0.126	0.437	0.437
67	2.412	0.238	0.238	0.211	0.238
68	0.884	0.361	0.361	0.361	0.670	1.071	0.922	0.333	0.333	0.333
69	1.084	0.211	0.211	0.211	0.488	0.506	0.917	0.333	0.333	0.333
70	2.229	0.099	0.158	0.158	0.318	0.296	0.893	0.249	0.376	0.376
71	1.466	0.051	0.078	0.051	0.464	0.217	1.782	0.315	0.370	0.315
72	0.552	0.401	0.401	0.401	0.638	1.086	0.700	0.333	0.333	0.333
73	1.194	0.183	0.221	0.284	0.264	0.377	0.324	0.168	0.292	0.540
74	1.018	0.273	0.273	0.273	0.465	0.571	0.607	0.333	0.333	0.333
75	1.297	0.071	0.135	0.453	0.157	0.393	0.552	0.049	0.157	0.794
76	0.431	0.778	0.719	0.728	0.778
77	0.832	0.589	0.398	0.187	0.725
78	1.218	0.296	0.215	0.215	0.363	0.394	0.293	0.556	0.222	0.222
79	1.041	0.206	0.259	0.232	0.356	0.409	0.431	0.258	0.409	0.332
80	0.922	0.409	0.320	0.320	0.651	0.938	0.798	0.406	0.297	0.297
81	0.952	0.377	0.377	0.377	0.586	0.926	0.613	0.333	0.333	0.333
82	0.842	0.320	0.292	0.184	0.525	0.499	0.440	0.466	0.393	0.141
83	2.218	0.001	0.001	0.001	0.054	0.007	3.119	0.333	0.333	0.333
84	0.980	0.318	0.318	0.318	0.337	0.487	0.061	0.333	0.333	0.333
85	0.988	0.298	0.405	0.239	0.490	0.550	0.178	0.190	0.768	0.041
86	0.625	0.408	0.318	0.185	0.800	0.953	1.142	0.430	0.349	0.221
87	1.094	0.389	0.239	0.239	0.389
88	0.715	0.362	0.403	0.403	0.488	0.802	0.327	0.256	0.372	0.372
89	0.340	0.331	0.331	0.331	0.480	0.676	0.451	0.333	0.333	0.333

Table 1.B.7: Individual estimate: social ambiguity- tg

id	α	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	η	γ	$P(L)$	$P(R)$	$P(M)$
1	1.757	0.270	0.079	0.018	0.391
2	1.266	0.245	0.203	0.203	0.597	0.615	1.149	0.365	0.318	0.318
3	0.806	0.397	0.302	0.302	0.619	0.838	0.741	0.419	0.291	0.291
4	28.42	0	0	0	0	0	0.506	1	0	0
5	0.745	0.643	0.643	0.701	0.643
6	1.296	0.092	0.092	0.525	0.113	0.375	0.327	0.018	0.018	0.965
7	1.620	0.219	0.203	0.191	0.540	0.527	1.037	0.353	0.331	0.316
8	0.677	0.379	0.379	0.379	0.530	0.831	0.442	0.333	0.333	0.333
9	1.972	0.098	0.052	0.052	0.118	0.085	0.240	0.732	0.134	0.134
10	1.259	0.299	0.386	0.286	0.386
11	0.604	0.367	0.367	0.298	0.367
12	0.909	0.365	0.285	0.332	0.402	0.577	0.226	0.498	0.163	0.339
13	0.394	0.315	0.300	0.300	0.315
14	1.353	0.245	0.263	0.289	0.396	0.516	0.513	0.288	0.327	0.385
15	0.876	0.296	0.321	0.321	0.528	0.726	0.676	0.308	0.346	0.346
16	1.231	0.504	0.212	0.293	0.504	0.649	0.042	1	0	0
17	1.516	0.431	0.247	0.175	0.431
18	0.746	0.376	0.376	0.376	0.376	0.602	0	0.286	0.286	0.428
19	0.986	0.392	0.392	0.384	0.558	0.887	0.474	0.339	0.339	0.323
20	1.832	0.146	0.042	0.378	0.251	0.451	1.211	0.310	0.128	0.561
21	0.644	0.107	0.134	0.107	0.134
22	0.902	0.417	0.239	0.311	0.417	0.569	0.035	0.999	0	0.001
23	0.968	0.661	0.205	0.205	0.810	1.047	0.861	0.673	0.164	0.164
24	0.468	0.541	0.541	0.523	0.670	1.494	0.375	0.347	0.347	0.305
25	1.977	0.108	0.108	0.108	0.333	0.245	1.021	0.333	0.333	0.333
26	1.984	0.179	0.179	0.179	0.367	0.356	0.705	0.333	0.333	0.333
27	0.794	0.328	0.352	0.352	0.454	0.673	0.359	0.289	0.356	0.356
28	0.884	0.361	0.361	0.361	0.670	1.071	0.922	0.333	0.333	0.333
29	0.634	0.491	0.400	0.371	0.734	1.279	0.808	0.414	0.308	0.278
30	1.226	0.717	0.213	0.215	0.902	1.584	1.303	0.589	0.205	0.206
31	0.699	0.420	0.409	0.433	0.478	0.836	0.201	0.331	0.280	0.389
32	0.920	0.308	0.348	0.370	0.557	0.858	0.723	0.287	0.342	0.371
33	0.610	0.380	0.191	0.563	0.409	0.943	0.483	0.291	0.054	0.655
34	1.077	0.239	0.294	0.255	0.406	0.483	0.438	0.272	0.416	0.312
35	1.095	0.660	0.554	0.657	0.660	1.930	0.037	0.548	0	0.452
36	0.800	0.231	0.186	0.186	0.434	0.419	0.736	0.390	0.305	0.305
37	0.954	0.286	0.092	0.209	0.286	0.325	0.083	0.926	0	0.074
38	1.290	0.222	0.139	0.162	0.260	0.260	0.288	0.580	0.158	0.262

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Table 1.B.8 – continued from previous page

id	α	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	η	γ	$P(L)$	$P(R)$	$P(M)$
39	0.464	0.469	0.374	0.374	0.650	1.054	0.619	0.430	0.285	0.285
40	1.005	0.359	0.243	0.337	0.485	0.692	0.592	0.413	0.215	0.372
41	0.828	0.964	0.069	0.069	0.964
42	0.666	0.529	0.523	0.523	0.529
43	0.790	0.076	0.076	0.076	0.076
44	0.884	0.361	0.361	0.361	0.670	1.071	0.922	0.333	0.333	0.333
45	0.946	0.184	0.184	0.184	0.306	0.315	0.487	0.333	0.333	0.333
46	1.340	0.742	0.742	0.944	0.742
47	0.494	0.876	0.442	0.400	0.876
48	1.500	0.186	0.186	0.202	0.321	0.346	0.547	0.320	0.320	0.360
49	0.796	0.224	0.187	0.177	0.472	0.438	0.846	0.380	0.319	0.301
50	0.648	0.417	0.294	0.294	0.454	0.588	0.176	0.754	0.123	0.123
51	1.042	0.348	0.348	0.348	0.669	1.038	0.963	0.333	0.333	0.333
52	0.955	0.432	0.293	0.293	0.494	0.636	0.272	0.659	0.171	0.171
53	1.148	0.258	0.258	0.258	0.463	0.547	0.654	0.333	0.333	0.333
54	0.802	0.074	0.074	0.074	0.965	1.492	4.225	0.333	0.333	0.333
55	0.995	0.349	0.349	0.349	0.680	1.069	0.994	0.333	0.333	0.333
56	44.23	0.194	0	0	0.194
57	0.009	0.506	0.354	0.354	0.506
58	1.163	0.542	0.241	0.267	0.599	0.738	0.359	0.789	0.088	0.123
59	1.027	0.438	0.320	0.280	0.511	0.637	0.209	0.723	0.190	0.087
60	1.042	0.348	0.348	0.348	0.669	1.038	0.963	0.333	0.333	0.333
61	1.174	0.127	0.254	0.457	0.254	0.534	0.077	0	0.003	0.997
62	0.636	0.335	0.174	0.477	0.419	0.811	0.691	0.334	0.124	0.542
63	0.991	0.292	0.140	0.253	0.292	0.374	0.063	0.829	0	0.171
64	1.462	0.709	0.112	0.060	0.738
65	1.163	0.463	0.231	0.231	0.463
66	0.878	0.339	0.377	0.254	0.480	0.560	0.128	0.333	0.648	0.020
67	2.192	0.341	0.341	0.338	0.341
68	0.884	0.361	0.361	0.361	0.670	1.071	0.922	0.333	0.333	0.333
69	0.851	0.214	0.065	0.299	0.305	0.433	0.941	0.378	0.125	0.496
70	1.094	0.247	0.208	0.265	0.398	0.489	0.627	0.347	0.272	0.382
71	1.391	0.212	0.212	0.212	0.409	0.431	0.680	0.333	0.333	0.333
72	0.517	0.421	0.421	0.421	0.588	1.018	0.487	0.333	0.333	0.333
73	1.302	0.381	0.148	0.148	0.381
74	0.531	0.316	0.317	0.300	0.336	0.465	0.028	0.456	0.498	0.046
75	0.828	0.964	0.069	0.069	0.964
76	1.747	0.256	0.181	0.089	0.256

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Table 1.B.8 – continued from previous page

id	α	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	η	γ	$P(L)$	$P(R)$	$P(M)$
77	1.378	0.179	0.159	0.179	0.383	0.368	0.824	0.346	0.308	0.346
78	0.652	0.541	0.478	0.478	0.625	1.236	0.301	0.461	0.269	0.269
79	1.020	0.314	0.296	0.229	0.440	0.483	0.296	0.455	0.383	0.162
80	1.186	0.223	0.148	0.185	0.544	0.520	1.203	0.378	0.287	0.334
81	1.034	0.331	0.265	0.283	0.396	0.509	0.286	0.477	0.230	0.293
82	1.986	0.264	0.072	0.116	0.876	0.962	2.606	0.406	0.276	0.318
83	0.245	0.450	0.091	0.091	0.450
84	0.837	0.348	0.370	0.370	0.389	0.611	0.098	0.203	0.399	0.399
85	1.013	0.232	0.205	0.258	0.303	0.389	0.366	0.332	0.245	0.424
86	0.463	0.581	0.449	0.449	0.805	1.837	0.899	0.423	0.289	0.289
87	1.068	0.341	0.341	0.387	0.341
88	0.767	0.787	0.198	0.244	0.833	1.267	0.547	0.876	0.048	0.076
89	0.852	0.065	0.145	0.065	0.169	0.119	0.230	0.088	0.824	0.088

Table 1.B.9: Individual estimate: betrayal aversion- tg

id	α	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	η	γ	$P(L)$	$P(R)$	$P(M)$
1	1.284	0.287	0.187	0.187	0.407	0.397	0.488	0.507	0.246	0.246
2	1.025	0.286	0.268	0.277	0.673	0.888	1.214	0.342	0.325	0.333
3	0.906	0.353	0.353	0.353	0.544	0.807	0.562	0.333	0.333	0.333
4	0.660	0.332	0.332	0.812	0.474	1.975	0.704	0.124	0.124	0.753
5	1.006	0.485	0.426	0.437	0.519	0.915	0.154	0.544	0.203	0.253
6	0.835	0.248	0.219	0.415	0.304	0.557	0.382	0.203	0.143	0.654
7	1.417	0.171	0.186	0.163	0.367	0.336	0.679	0.328	0.363	0.309
8	0.770	0.309	0.288	0.288	0.465	0.592	0.500	0.364	0.318	0.318
9	2.036	0.056	0.056	0.025	0.056
10	0.968	0.291	0.329	0.345	0.329	0.508	0.016	0	0.097	0.903
11	0.561	0.494	0.395	0.439	0.516	0.914	0.166	0.600	0.117	0.283
12	0.668	0.369	0.439	0.390	0.683	1.173	0.816	0.299	0.378	0.322
13	1.929	0.207	0.140	0.103	0.222
14	0.962	0.274	0.220	0.247	0.544	0.625	0.931	0.368	0.298	0.334
15	1.056	0.219	0.261	0.300	0.419	0.557	0.664	0.262	0.335	0.403
16	1.522	0.152	0.071	0.310	0.174	0.308	0.524	0.262	0.065	0.673
17	1.295	0.383	0.316	0.277	0.517	0.640	0.396	0.481	0.305	0.214
18	0.939	0.341	0.368	0.368	0.368	0.583	0.010	0	0.500	0.500
19	2.736	0.083	0.083	0.099	0.282	0.208	1.109	0.320	0.320	0.361
20	0.561	0.577	0.337	0.285	0.623
21	0.017	0	0	0.096	0.946	1.361	15.938	0.270	0.270	0.460
22	0.706	0.252	0.335	0.517	0.335	0.734	0.039	0	0	1
23	1.366	0.472	0.501	0.147	0.832
24	0.764	0.409	0.409	0.409	0.547	0.915	0.403	0.333	0.333	0.333
25	0.712	0.719	0.385	0.385	0.719
26	1.493	0.323	0.323	0.323	0.458	0.635	0.413	0.333	0.333	0.333
27	1.017	0.355	0.273	0.313	0.481	0.650	0.503	0.419	0.251	0.330
28	0.884	0.361	0.361	0.361	0.670	1.071	0.922	0.333	0.333	0.333
29	0.752	0.215	0.215	0.382	0.215
30	1.365	0.346	0.189	0.366	0.352	0.560	0.245	0.442	0.028	0.531
31	1.076	0.255	0.255	0.354	0.400	0.604	0.575	0.271	0.271	0.458
32	1.035	0.225	0.251	0.328	0.331	0.492	0.414	0.219	0.285	0.496
33	1.054	0.176	0.284	0.124	0.284
34	0.940	0.314	0.298	0.338	0.424	0.613	0.402	0.326	0.285	0.389
35	1.319	0.454	0.483	0.483	0.483	0.933	0.010	0	0.500	0.500
36	0.573	0.331	0.223	0.327	0.518	0.723	0.797	0.383	0.239	0.378
37	1.439	0.072	0.100	0.100	0.256	0.196	0.981	0.279	0.360	0.360
38	1.216	0.266	0.240	0.240	0.342	0.406	0.291	0.403	0.298	0.298

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Table 1.B.10 – continued from previous page

id	α	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	η	γ	$P(L)$	$P(R)$	$P(M)$
39	0.729	0.211	0.211	0.181	0.469	0.442	0.812	0.350	0.350	0.299
40	0.976	0.329	0.286	0.326	0.494	0.688	0.589	0.360	0.285	0.355
41	5.298	0.007	0.007	0.007	0.081	0.025	1.800	0.333	0.333	0.333
42	0.511	0.684	0.679	0.658	0.684
43	0.790	0.076	0.076	0.076	0.076
44	1.094	0.371	0.292	0.292	0.452	0.583	0.309	0.511	0.245	0.245
45	0.307	0.094	0.442	0.389	0.720	1.279	1.639	0.178	0.428	0.395
46	1.103	0.755	0.755	0.953	0.755
47	0.883	0.543	0.645	0.507	0.734	1.682	0.329	0.258	0.559	0.183
48	1.123	0.042	0.347	0.779	0.347	1.366	0.207	0	0.010	0.990
49	0.533	0.448	0.381	0.455	0.577	1.067	0.504	0.368	0.251	0.381
50	0.723	0.201	0.285	0.251	0.488	0.566	0.798	0.266	0.393	0.342
51	0.802	0.074	0.074	0.965	0.074
52	1.371	0.266	0.182	0.218	0.529	0.561	0.978	0.391	0.280	0.329
53	1.665	0.301	0.252	0.252	0.301
54	0.802	0.074	0.074	0.965	0.074
55	0.922	0.347	0.347	0.347	0.724	1.181	1.150	0.333	0.333	0.333
56	1.395	0.244	0.253	0.253	0.545	0.636	0.933	0.326	0.337	0.337
57	1.537	0.477	0.477	0.323	0.477
58	0.799	0.348	0.485	0.453	0.485	0.883	0.040	0	0.835	0.165
59	1.208	0.217	0.217	0.255	0.531	0.623	1.064	0.319	0.319	0.363
60	43.27	0	0	0	0	0	1.002	0.021	0.021	0.958
61	1.317	0.059	0.324	0.368	0.324	0.528	0.157	0	0.350	0.650
62	0.654	0.280	0.259	0.239	0.451	0.508	0.538	0.378	0.332	0.290
63	0.851	0.392	0.288	0.191	0.889	1.376	1.777	0.395	0.334	0.270
64	0.891	0.084	0.084	0.356	0.319	0.509	1.510	0.243	0.243	0.514
65	0.993	0.280	0.280	0.320	0.406	0.568	0.448	0.301	0.301	0.398
66	0.721	0.494	0.485	0.511	0.589	1.222	0.308	0.325	0.301	0.375
67	0.739	0.540	0.540	0.836	0.540
68	1.013	0.298	0.316	0.316	0.636	0.899	0.998	0.320	0.340	0.340
69	0.580	0.204	0.204	0.403	0.484	0.796	1.127	0.268	0.268	0.464
70	1.330	0.213	0.238	0.213	0.395	0.421	0.565	0.315	0.371	0.315
71	1.227	0.212	0.212	0.212	0.449	0.469	0.797	0.333	0.333	0.333
72	0.657	0.345	0.458	0.345	0.526	0.766	0.278	0.207	0.586	0.207
73	0.768	0.459	0.288	0.288	0.459
74	1.669	0.072	0.084	0.118	0.084	0.111	0.017	0	0	1
75	0.075	0.094	0.094	0.945	0.094
76	0.716	0.396	0.361	0.318	0.511	0.699	0.310	0.450	0.336	0.214

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Table 1.B.10 – continued from previous page

id	α	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	η	γ	$P(L)$	$P(R)$	$P(M)$
77	1.039	0.388	0.242	0.166	0.488
78	1.045	0.288	0.275	0.365	0.346	0.552	0.287	0.252	0.212	0.536
79	0.750	0.296	0.346	0.281	0.434	0.547	0.291	0.288	0.472	0.240
80	2.908	0.195	0.174	0.174	0.375	0.356	0.686	0.364	0.318	0.318
81	0.968	0.286	0.372	0.205	0.430
82	1.297	0.198	0.198	0.235	0.683	0.814	1.613	0.323	0.323	0.354
83	0.790	0.076	0.076	0.076	0.076
84	0.753	0.467	0.497	0.471	0.497
85	1.168	0.227	0.253	0.350	0.271	0.447	0.178	0.087	0.173	0.740
86	0.359	0.507	0.484	0.484	0.507
87	1.037	0.413	0.413	0.462	0.413
88	0.861	0.563	0.282	0.323	0.563
89	0.643	0.328	0.262	0.262	0.382	0.468	0.224	0.549	0.225	0.225

1.C Instructions

In this appendix we present the instructions we show to Players 2 in the experiment. The order of the presentation of the instructions of each experimental condition is randomized, accordingly to the randomization of the order of the conditions in the experiment. These instructions are translated from the original French instructions.

Beginning instructions

The experiment consists of five (5) parts and will last approximately 45 minutes. You will receive specific instructions for each part at the beginning of each of them. At the end of the experiment, only one part out of the five will be randomly selected to determine your final payment. Each of these five parts has the same chance of being randomly selected by the computer. In each part, you make several decisions. If a part is randomly selected for payment, one of the decisions in that part will be randomly selected by the computer. Each decision

has the same chance of being drawn at random. Therefore, only one of your decisions will affect your final payment, but it could be any of your decisions. Thus, it is in your best interest to make each decision as if it were the one that will be selected for payment.

Payments for your decisions will be expressed in experimental currency units (ECU). Please note that each ECU is equal to 1 euro. For example, 1 ECU = €1 and 15 ECU = €15.

Social ambiguity - coordination game

You will now read the instructions for Part 1 of the experiment. Part 1 has two sub-parts. You will receive instructions for each sub-part before you make your decisions in each of them.

First stage

Instructions for the first sub-part of Part 1

In this part of the experiment, you are randomly paired with another participant, we call this person, Participant 2. You will never be informed of Participant 2's identity, nor will Participant 2 ever be informed of your identity. Your final payment will depend on your decision and the decision of Participant 2.

Your decision in this section will be to choose an action between Left, Right or Middle. Participant 2 will receive 5 euros. Then, Participant 2 will decide where he/she would prefer to spend these 5 euros between one of the following options: An Amazon voucher, a Google Play voucher or an Apple Store voucher. You will not be notified of Participant 2's decision until you receive payment for

this experiment. The values below are numerical examples of how Participant 2's decision affects your payment.

- If you choose **Left** and Participant 2 chooses an **Amazon voucher**, you will receive **30 ECU**.
- If you choose **Left** and Participant 2 chooses a **Google Play voucher**, you will receive **20 ECU**.
- If you choose **Left** and Participant 2 chooses an **Apple Store voucher**, you will receive **16 ECU**.
- If you choose **Right** and Participant 2 chooses an **Amazon voucher**, you will receive **16 ECU**.
- If you choose **Right** and Participant 2 chooses a **Google Play voucher**, you will receive **30 ECU**.
- If you choose **Right** and Participant 2 chooses an **Apple Store voucher**, you receive **20 ECU**.
- If you choose **Middle** and Participant 2 chooses an **Amazon voucher**, you will receive **20 ECU**.
- If you choose **Middle** and Participant 2 chooses a **Google Play voucher**, you will receive **16 ECU**.
- If you choose **Middle** and Participant 2 chooses an **Apple Store voucher**, you will receive **30 ECU**.

Your possible payments (in ECU), depending on your decision and the decision of Participant 2, are summarized in the table below.

Participant 2				
		Amazon voucher	Google Play voucher	Apple Store voucher
Your decision	Left	30	20	16
	Right	16	30	20
	Middle	20	16	30

Note that Participant 2 is informed that his or her choice will affect you, but he or she does not know in what direction. This means that Participant 2 does not know how your payment changes based on his or her decision.

Example

Suppose you decide to choose the **Right** action and Participant 2 prefers to spend his or her 5 euros on a **Google Play voucher** (remember that you will not be informed of Participant 2's decision until you receive the payment for the experiment). The table below shows in **orange** the payment (in ECU) you will get in this scenario. If this decision is chosen at random for the payment, you earn 30 ECU.

Participant 2				
		Amazon voucher	Google Play voucher	Apple Store voucher
Your decision	Left	30	20	16
	Right	16	30	20
	Middle	20	16	30

Second stage

Instructions for the second sub-part of Part 1

In the second and final subpart of this part of the experiment, you will choose between several options. The options will be presented in 12 tables (see an

example of the table below). Each row represents one option. For each option, you will be asked to indicate whether you prefer Alternative A or Alternative B.

- **Alternative A** offers you a safe payment.
- **Alternative B** offers you a variable payment that depends on the decision made by Participant 2 in the first sub-part of this part of the experiment. This means that the payment you can receive varies depending on what Participant 2 decided between an **Amazon voucher**, a **Google Play voucher**, or an **Apple Store voucher**. This alternative changes from table to table, but it is the same for all rows in a given table.

Example of a table with payments (in ECU):

Safe payment of alternative A	Alternative A	Alternative B	Variable payment of alternative B
30	A1	B1	You get 30 ECU if Participant 2 chooses an Amazon voucher in the first sub-part of this part of the experiment or 16 ECU if Participant 2 chooses a Google Play voucher or an Apple Store voucher
28	A2	B2	
26	A3	B3	
24	A4	B4	
22	A5	B5	
20	A6	B6	
18	A7	B7	
16	A8	B8	

In each line you will be asked to indicate whether you prefer **Alternative A** or **Alternative B**.

Both alternatives are initially displayed in gray. You must click on one of the two alternatives to select it. Your selection will be highlighted in blue. You can change your selection at any time by clicking on the cell of the desired alternative, before moving on to the next screen. Once you confirm your decision, you cannot go back and change your previous decision.

If you select Alternative A for a given row, the computer will mark Alternative A for all previous rows (up to the first). Similarly, if you select Alternative B for a line, the computer will mark Alternative B for all subsequent lines (up to the last one).

Example

Suppose that the following option is randomly selected for payment:

Safe payment of alternative A	Alternative A	Alternative B	Variable payment of alternative B
26	A1	B1	You get 30 ECU if Participant 2 chooses an Amazon voucher in the first sub-part of this part of the experiment or 16 ECU if Participant 2 chooses a Google Play voucher or an Apple Store voucher

- If you select **Alternative A** for this line, you earn **26 ECU**.
- If you select **Alternative B** for this line, you can earn **30 ECU or 16 ECU**. Your payment depends on the decision of Participant 2 that you were associated with in sub-part 1 of this part of the experiment (the most recent task you completed). Payment is determined as follows:
 - If Participant 2 chooses an **Amazon voucher**, you earn **30 ECU**.
 - If Participant 2 chooses either a **Google Play voucher or an Apple Store voucher**, you earn **16 ECU**.

During this task, you will be able to use the back button to re-view the decisions that you and Participant 2 were asked to make in the first sub-part of this part of the experiment.

Strategic uncertainty - coordination game

You will now read the instructions for Part 2 of the experiment. Part 2 has two sub-parts. You will receive instructions for each sub-part before you make your decisions in each of them.

First stage

Instructions for the first sub-part of Part 2

In this part of the experiment, you are again randomly paired with another participant. We call this new person Participant 2. However, this Participant 2 is a **different person** than the one you were paired with in the previous part of the experiment. You will never be informed of Participant 2's identity, nor will Participant 2 be informed of your identity. Your final payment will depend on your decision and the decision of Participant 2.

You and Participant 2 will each choose one of three actions: **Left, Right and Middle**. You will not be informed of Participant 2's decision until the end of the experiment and Participant 2 will not be informed of your decision until the end of the experiment. A numerical example of the payments (in ECU) for you and for Participant 2 are presented in the table below. In each cell, the first amount is your payment, and the second amount is Participant 2's payment. These payments can be summarized as follows:

- If you choose **Left** and Participant 2 chooses **Left**, you receive **7 ECU**.
- If you choose **Left** and Participant 2 chooses **Right**, you receive **5 ECU**.
- If you choose **Left** and Participant 2 chooses **Middle**, you receive **4 ECU**.
- If you choose **Right** and Participant 2 chooses **Left**, you receive **4 ECU**.
- If you choose **Right** and Participant 2 chooses **Right**, you receive **7 ECU**.
- If you choose **Right** and Participant 2 chooses **Middle**, you receive **5 ECU**.
- If you choose **Middle** and Participant 2 chooses **Left**, you receive **5 ECU**.

- If you choose **Middle** and Participant 2 chooses **Right**, you receive **4 ECU**.
- If you choose **Middle** and Participant 2 chooses **Middle**, you receive **7 ECU**.

		Participant 2		
		Left	Right	Middle
Your decision	Left	7,7	5,9	4,11
	Right	4,11	7,7	5,9
	Middle	5,9	4,11	7,7

Example

Suppose you decide to choose the **Left** action and Participant 2 chooses the **Middle** action (remember that you will not be informed of Participant 2's decision until the end of the experiment). The table below shows in **orange** the payment (in ECU) that you and Participant 2 will have in this scenario. If this decision is chosen randomly for the payment, you will win 4 ECU and Participant 2 will win 11 ECU.

		Participant 2		
		Left	Right	Middle
Your decision	Left	7,7	5,9	4,11
	Right	4,11	7,7	5,9
	Middle	5,9	4,11	7,7

Second stage

Instructions for the second sub-part of Part 2

In the second and final sub-part of this part of the experiment, you will choose between several options. The options will be presented in 12 tables (see

an example of the table below). Each row represents one option. For each option, you will be asked to indicate whether you prefer Alternative A or Alternative B.

- **Alternative A** offers you a safe payment.
- **Alternative B** offers you a variable payment that depends on the decision made by Participant 2 in the first sub-part of this part of the experiment. This means that the payment you can receive varies depending on what Participant 2 decided between the **Left, Right or Middle** actions. This alternative changes from table to table, but it is the same for all rows in a given table.

Example of a table with payments (in ECU):

Safe payment of alternative A	Alternative A	Alternative B	Variable payment of alternative B
7	A1	B1	You get 7 ECU if Participant 2 chooses an Left in the first sub-part of this part of the experiment or 3.5 ECU if Participant 2 chooses a Right or Middle
6.5	A2	B2	
6	A3	B3	
5.5	A4	B4	
5	A5	B5	
4.5	A6	B6	
4	A7	B7	
3.5	A8	B8	

In each line you will be asked to indicate whether you prefer **Alternative A** or **Alternative B**.

Both alternatives are initially displayed in gray. You must click on one of the two alternatives to select it. Your selection will be highlighted in blue. You can change your selection at any time by clicking on the cell of the desired alternative, before moving on to the next screen. Once you confirm your decision, you cannot go back and change your previous decision.

If you select Alternative A for a given row, the computer will mark Alternative A for all previous rows (up to the first). Similarly, if you select Alternative B for a line, the computer will mark Alternative B for all subsequent lines (up to the last one).

Example

Suppose that the following option is randomly selected for payment:

Safe payment of alternative A	Alternative A	Alternative B	Variable payment of alternative B
6	A1	B1	You get 7 ECU if Participant 2 chooses an Left in the first sub-part of this part of the experiment or 3.5 ECU if Participant 2 chooses a Right or Middle

- If you select **Alternative A** for this line, you earn **6 ECU**.
- If you select **Alternative B** for this line, you can win **7 ECU or 3.5 ECU**. Your payment depends on the decision done by the Participant 2 which you were associated with in sub-part 1 of this part of the experiment (the most recent task you completed). Payment would be determined as follows:
 - If Participant 2 chooses **Left**, you earn **7 ECU**.
 - If Participant 2 chooses **Right or Middle**, you earn **3.5 ECU**.

During this task, you will be able to use the back button to re-view the decisions that you and Participant 2 were asked to make in the first sub-part of this part of the experiment.

Social ambiguity - trust game

You will now read the instructions for Part 3 of the experiment. Part 3 has two sub-parts. You will receive instructions for each sub-part before you make your decisions in each of them.

First stage

Instructions for the first sub-part of Part 3

In this part of the experiment, you are again randomly paired with another participant. We call this new person Participant 2. However, this Participant 2 is **a different person** than the ones you were paired with in the previous parts of the experiment. You will never be informed of Participant 2's identity, nor will Participant 2 be informed of your identity. Depending on your decision, your payment may or may not depend on Participant 2's decision.

Your decision in this sub-section will be to choose an action between the **Left or Right** possibilities. Participant 2 receives 5 euros. Participant 2 decides where he or she would prefer to spend the 5 euros between one of the following options: **an Amazon voucher, a Google Play voucher or an Apple Store voucher**. You will not be informed of Participant 2's decision until the end of the experiment. If you chose **Left**, you will receive a sure payment, and Participant 2's decision does not affect your payment. If you choose **Right**, your payment is determined by Participant 2's decision. Participant 2 knows that your payment may or may not depend on their decision. However, Participant 2 does not know how his or her decision is associated with your payment.

A numerical example of possible payments for this part of the experiment can be summarized as follows:

- If you choose **Left**, you receive **30 ECU** for sure.
- If you choose **Right**, your payment depends on the decision of Participant 2, as follows:
 - If Participant 2 chooses an **Amazon voucher**, you receive **45 ECU**.

- If Participant 2 chooses a **Google Play voucher**, you receive **30 ECU**.
- If Participant 2 chooses an **Apple Store voucher**, you will receive **24 ECU**.

Example

Suppose you decide to choose the **Right** action and Participant 2 prefers to spend his or her 5 euros on an **Amazon voucher** (remember that you will not be informed of Participant 2's decision until you receive the payment for the experiment).

Below you can see in **orange** the payment (in ECU) you will get in this scenario. If this decision is chosen randomly for the payment, you will earn 45 ECU.

- If you choose **Left**, you will receive **30 ECU** for sure.
- If you choose **Right**, your payment depends on Participant 2's decision, as follows:
 - If Participant 2 chooses an **Amazon voucher**, you receive **45 ECU**.
 - If Participant 2 chooses a **Google Play voucher**, you receive **30 ECU**.
 - If Participant 2 chooses an **Apple Store voucher**, you will receive **24 ECU**.

Second stage

Instructions for the second sub-part of Part 3

In the second and final sub-part of this part of the experiment, you will choose between several options. The options will be presented in 12 tables (see an example of the table below). Each row represents one option. For each option, you will be asked to indicate whether you prefer Alternative A or Alternative B.

- **Alternative A** offers you a safe payment.
- **Alternative B** offers you a variable payment that depends on the decision made by Participant 2 in the first sub-part of this part of the experiment. This means that the payment you can receive varies depending on what Participant 2 decided between an **Amazon voucher**, a **Google Play voucher**, or an **Apple Store voucher**. Alternative B changes from table to table, but it is the same for all rows in a given table.

Example of a table with payments (in ECU):

Safe payment of alternative A	Alternative A	Alternative B	Variable payment of alternative B
45	A1	B1	You get 45 ECU if Participant 2 chooses an Amazon voucher in the first sub-part of this part of the experiment or 24 ECU if Participant 2 chooses a Google Play or an Apple Store voucher
42	A2	B2	
39	A3	B3	
36	A4	B4	
33	A5	B5	
30	A6	B6	
27	A7	B7	
24	A8	B8	

In each line you will be asked to indicate whether you prefer **Alternative A** or **Alternative B**.

Both alternatives are initially displayed in gray. You must click on one of the two alternatives to select it. Your selection will be highlighted in blue. You can change your selection at any time by clicking on the cell of the desired alternative, before moving on to the next screen. Once you confirm your decision, you cannot go back and change your previous decision.

If you select Alternative A for a given row, the computer will mark Alternative A for all previous rows (up to the first). Similarly, if you select Alternative

B for a line, the computer will mark Alternative B for all subsequent lines (up to the last one).

Example

Suppose that the following option is randomly selected for payment:

Safe payment of alternative A	Alternative A	Alternative B	Variable payment of alternative B
39	A1	B1	You get 45 ECU if Participant 2 chooses an Amazon voucher in the first sub-part of this part of the experiment or 24 ECU if Participant 2 chooses a Google Play or an Apple Store voucher

- If you select **Alternative A** for this line, you earn **39 ECU**.
- If you select **Alternative B** for this line, you can earn **45 ECU** or **24 ECU**. Your payment depends on the decision of the Participant 2 you are associated with in the sub-part 1 of this part of the experiment (the most recent task you completed). The payment is determined as follows:
 - If Participant 2 chooses an **Amazon voucher**, you earn **45 ECU**.
 - If Participant 2 chooses either a **Google Play** or an **Apple Store voucher**, you earn **24 ECU**.

During this task, you will be able to use the back button to re-view the decisions that you and Participant 2 were asked to make in the first sub-part of this part of the experiment.

Betrayal aversion

You will now read the instructions for Part 4 of the experiment. Part 4 has two sub-parts. You will receive instructions for each sub-part before you make your decisions in each of them.

First stage

Instructions for the first sub-part of Part 4

In this part of the experiment, you are again randomly paired with another participant. We call this new person Participant 2. However, this Participant 2 is a **different person** than the ones you were paired with in the previous parts of the experiment. You will never be informed of Participant 2's identity, nor will Participant 2 be informed of your identity. Your decision will affect Participant 2's payment. In addition, depending on your decision, your payment may or may not depend on Participant 2's decision.

Your decision in this section is to choose an action between the **Left or Right** options. Participant 2 decides between three options: **Left, Right or Middle**. You will not be informed of Participant 2's decision until you receive payment for the experiment. If you choose **Left**, you and Participant 2 receive a sure payment, and Participant 2's decision does not affect your payment. In contrast, if you choose **Right**, the payments for you and Participant 2 are determined by Participant 2's decision.

A numerical example of the possible payments for this part of the experiment can be summarized as follows:

- If you choose **Left**, you and Participant 2 receive **20 ECU** for sure.

- If you choose **Right**, your payment depends on Participant 2's decision, as follows:
 - If Participant 2 chooses **Left**, you receive **25 ECU** and Participant 2 receives **25 ECU**.
 - If Participant 2 chooses **Right**, you receive **20 ECU** and Participant 2 receives **28 ECU**.
 - If Participant 2 chooses **Middle**, you receive **18 ECU** and Participant 2 receives **32 ECU**.

Example

Suppose you decide to choose the action **Right** and Participant 2 chooses the action **Right** (remember that you will not be informed of Participant 2's decision until you receive your payment).

Below you can see in **orange** the payment (in ECU) you will get in this scenario. If this decision is chosen at random for the payment, you win 20 ECU.

- If you choose **Left**, you and Participant 2 each get **20 ECU** for sure.
- If you choose **Right**, your payment depends on Participant 2's decision as follows:
 - If Participant 2 chooses **Left**, you receive **25 ECU** and Participant 2 receives **25 ECU**.
 - If Participant 2 chooses **Right**, you receive **20 ECU** and Participant 2 receives **28 ECU**.
 - If Participant 2 chooses **Middle**, you receive **18 ECU** and Participant 2 receives **32 ECU**.

Second stage

Instructions for the second sub-part of Part 4

In the second and final sub-part of this part of the experiment, you choose between several options. The options are presented in 12 tables (see an example of the table below). Each row represents an option. For each option, you must indicate whether you prefer Alternative A or Alternative B.

- **Alternative A** offers you a safe payment.
- **Alternative B** offers you a variable payment that depends on the decision made by Participant 2 in the first sub-part of this part of the experiment. This means that the payment you can receive varies depending on what Participant 2 decided between **Left**, **Right** or **Middle** actions.

Example of a table with payments (in ECU):

Safe payment of alternative A	Alternative A	Alternative B	Variable payment of alternative B
25	A1	B1	You get 25 ECU if Participant 2 chooses Left in the first sub-part of this part of the experiment or 18 ECU if Participant 2 chooses Right or Middle
24	A2	B2	
23	A3	B3	
22	A4	B4	
21	A5	B5	
20	A6	B6	
19	A7	B7	
18	A8	B8	

In each line you will be asked to indicate whether you prefer **Alternative A** or **Alternative B**.

Both alternatives are initially displayed in gray. You must click on one of the two alternatives to select it. Your selection will be highlighted in blue. You can change your selection at any time by clicking on the cell of the desired alternative, before moving on to the next screen. Once you confirm your decision, you cannot go back and change your previous decision.

If you select Alternative A for a given row, the computer will mark Alternative A for all previous rows (up to the first). Similarly, if you select Alternative B for a line, the computer will mark Alternative B for all subsequent lines (up to the last one).

Example

Suppose that the following option is randomly selected for payment:

Safe payment of alternative A	Alternative A	Alternative B	Variable payment of alternative B
23	A1	B1	You get 25 ECU if Participant 2 chooses Left in the first sub-part of this part of the experiment or 18 ECU if Participant 2 chooses Right or Middle

- If you select **Alternative A** for this line, you earn **23 ECU**.
- If you select **Alternative B** for this line, you can earn **25 ECU or 18 ECU**. Your payment depends on the decision done by the Participant 2's that you were associated with in sub-part 1 of this part of the experiment (the most recent task you completed). Payment is determined as follows:
 - If Participant 2 chooses **Left**, you earn **25 ECU**.
 - If Participant 2 chooses **Right or Middle**, you earn **18 ECU**.

During this task, you will be able to use the back button to re-view the decisions that you and Participant 2 were asked to make in the first sub-part of this part of the experiment.

Nature

In this part of the experiment, you must choose between several options. The options are presented in 12 tables (see an example of the table below). Each row represents an option. For each option, you must indicate whether you prefer Alternative A or Alternative B.

- **Alternative A** offers you a safe payment.
- **Alternative B** offers you a variable payment that depends on a random selection made by the computer. The computer chooses one of three options: **Left, Right or Middle**. Each option has an equal chance of being drawn. Alternative B changes from table to table, but is the same for all rows in a given table.

Example of a table with payments (in ECU):

Safe payment of alternative A	Alternative A	Alternative B	Variable payment of alternative B
20	A1	B1	You get 20 ECU if the computer randomly chooses Left or 13 ECU if the computer randomly chooses Right or Middle
19	A2	B2	
18	A3	B3	
17	A4	B4	
16	A5	B5	
15	A6	B6	
14	A7	B7	
13	A8	B8	

In each line you will be asked to indicate whether you prefer **Alternative A** or **Alternative B**.

Both alternatives are initially displayed in gray. You must click on one of the two alternatives to select it. Your selection will be highlighted in blue. You can change your selection at any time by clicking on the cell of the desired alternative, before moving on to the next screen. Once you confirm your decision, you cannot go back and change your previous decision.

If you select Alternative A for a given row, the computer will mark Alternative A for all previous rows (up to the first). Similarly, if you select Alternative

B for a line, the computer will mark Alternative B for all subsequent lines (up to the last one).

Example

Suppose that the following option is randomly selected for payment:

Safe payment of alternative A	Alternative A	Alternative B	Variable payment of alternative B
20	A1	B1	You get 20 ECU if the computer randomly chooses Left or 13 ECU if the computer randomly chooses Right or Middle

- If you select **Alternative A** for this line, you win **20 ECU**.
- If you select **Alternative B** for this line, you can win **20 ECU or 13 ECU**. Your payment depends on which option the computer randomly selects. Remember that each option has the same chance of being drawn. The payment is determined as follows:

- If the computer selects **Left**, you win **20 ECU**.
- If the computer selects **Right or Middle**, you win **13 ECU**.

1.D Comparison of multi-stage and one stage approaches

We propose a multistage method in which the utility function and the probability weighting function are specified sequentially.¹³ In this section, we compare our multi-stage approach with the one-stage approach in which the utility

¹³In case of continuous valued source of uncertainty, we also allow to specify the distribution of beliefs only in the third stage (see Appendix 1.A).

and weighting functions are specified simultaneously. To that end we conduct parameter recovery and misspecification exercises (e.g. [Gao et al., 2020](#); [Kpegli et al., 2022](#); [Nilsson et al., 2011](#)).

Simulated data

We consider six specifications resulting from the combination of two utility functions $u(\cdot)$ and three weighting functions $w(\cdot)$.¹⁴

The two utility functions $u(\cdot)$ are P(ower) (Eq. 1.16) and E(xponential) (Eq. 1.17):

$$U(z) = z^\alpha \tag{1.16}$$

$$u(z) = \frac{1 - \exp(-\alpha z)}{\alpha} \tag{1.17}$$

For the power utility, $\alpha < 1$ (resp. $\alpha > 1$) means concavity (resp. convexity) and $\alpha = 1$ corresponds to the linear case. For the exponential utility, $\alpha > 0$ (resp. $\alpha < 0$) means concavity (resp. convexity) and $\alpha \rightarrow 0$ corresponds to the linear case. To have a common measure of the utility curvature to facilitate comparisons, we adopt the following measure of the utility curvature over the range of outcomes $[0, \bar{q}]$ ([Kpegli et al., 2022](#); [Abdellaoui et al., 2016](#))

$$\beta = \frac{1}{\bar{q}u(\bar{q})} \int_0^{\bar{q}} u(t)dt$$

with $\beta > 0.5$ (resp. $\beta < 0.5$) meaning concavity (resp. convexity) and $\beta = 0.5$ corresponds to the linear case.

¹⁴The vast majority of specifications in ambiguity studies rely on one of these six combination of utility and weighting functions (e.g. [Li et al., 2018](#); [Gutierrez and Kemel, 2021](#)).

The three weighting functions $w(\cdot)$ are the specifications of GE87 (Eq. 1.18), P98 (Eq. 1.19) and CEG7 (Eq. 1.20)

$$W(P(E)) = \frac{\eta P(E)^\gamma}{\eta P(E)^\gamma + (1 - P(E))^\gamma} \quad (1.18)$$

$$W(P(E)) = \exp\left(-\eta\left(-\ln(P(E))\right)^\gamma\right) \quad (1.19)$$

$$W(P(E)) = \gamma P(E) + \eta \quad (1.20)$$

with $\gamma > 0$, $\eta > 0$.

For the specification of CEG7, the pessimism and insensitivity indexes are given by $1 - \eta - 2\gamma$ and $1 - \eta$, respectively (e.g. Abdellaoui et al., 2011a). For the specification of P98, the parameters η and γ are an index of pessimism and an anti-index of likelihood insensitivity, respectively (Abdellaoui et al., 2021a). For the specification of GE87, the parameters η and γ are an anti-index of pessimism and an anti-index of likelihood insensitivity, respectively (e.g. Gonzalez and Wu, 1999).¹⁵ Insensitivity makes weighting the function flatter in the range of intermediate subjective probability and steeper near the ends. Hence, the weighting function follows an inverse S-shaped. Pessimism determines the elevation of the weighting function.

The calibration of lotteries follows the outcomes in Li et al. (2019, 2020) and the ones from our experiment. We consider 12 lotteries $L = (x, y, E, E^c)$ that results from the combination of three pairs of outcomes $(x, y) = (10, 0)$, $(15, 0)$, and $(15, 8)$ and, four events $E = E_1, E_2, E_3$ and E_{12} .

Simulated data 1: P & GE87. We simulate data for 250 ($s = 1, 2, \dots, 250$) hypothetical subjects. For each subject s , we draw the parameters of weighting function η and γ of GE87 from $\mathcal{U}(0.1, 1.5)$. We draw the parameter of the power

¹⁵For this specification, the crossing point is given by $W(p^*) = p^* = \frac{1}{1+\eta^{\frac{1}{\gamma-1}}}$ and, $W(\cdot)$ is well defined over all the probability range including the boundary $W(0) = 0$ and $W(1) = 1$.

utility function α from an uniform distribution $\mathcal{U}(0.1, 2.1)$ (e.g. Abdellaoui et al., 2008; Spiliopoulos and Hertwig, 2019). For the beliefs, we draw $P(E_1)$ and $P(E_2)$ from $U(0, 1)$ and keep only the cases where $P(E_1) + P(E_2) < 1$. We derive then $P(E_3) = 1 - P(E_1) - P(E_2)$. Then, the simulated α , η , γ , $P(E_1)$, $P(E_2)$, and $P(E_3)$ are plugged into the RDU formulas to generate *noiseless* certainty equivalents of the 12 lotteries. In the last step of the data generation process, we draw 12 random values from a normal distribution with expected value 0 and standard deviation $\sigma = 0.25$, which we add to the previously generated 12 *noiseless* certainty equivalents to obtain the *noisy* ones.

Simulated data 2: P & P98. similar as simulated data 1, but in this case the two-parameter weighting function of P98 is used. We draw η and γ of P98 from $\mathcal{U}(0.1, 1.5)$.

Simulated data 3: P & CEG7. Similar as simulated data 2, but in this case the two-parameter weighting function of CEG7 is used. We draw η and γ of CEG7 from $\mathcal{U}(0, 1)$.

Simulated data 4: E & GE87. Similar as simulated data 1, but in this case the CARA utility function is used. We draw α from $\mathcal{U}(-0.15, 0.15)$.

Simulated data 5: E & P98. Similar as simulated data 2, but in this case the CARA utility function is used. We draw α from $\mathcal{U}(-0.15, 0.15)$.

Simulated data 6: E & CEG7. Similar as simulated data 3, but in this case the CARA utility function is used. We draw α from $\mathcal{U}(-0.15, 0.15)$.

Simulation results

We conduct two types of estimations for each approach by using the six simulated data. In the first type of estimation, we estimate by using the correct specification of the utility and weighting functions that are behind the simulated data. This first type of estimation corresponds to the parameter recovery exercise in which

the purpose is to assess the ability of the two approaches to identify the targeted parameters (Murphy and ten Brincke, 2018; Gao et al., 2020; Kpegli et al., 2022).

In the second type of estimation, we make the estimation on each of the simulated data by assuming the 5 other specifications of utility and weighting functions that are not behind the simulated data. This second type of estimation corresponds to the misspecification exercise in which the purpose is to assess the extend to which a wrong specification of utility and weighting functions will affect the estimation results (Gao et al., 2020; Kpegli et al., 2022).

Table 1.D.1 provides the average of the squared difference between the true values of the parameters and their estimated values over the 250 hypothetical subjects. Table 1.D.1 shows evidence of the fact that the two-stage approach leads to smaller error than the one-stage approach. These results can be explained by the use of a semi-parametric method in the first stage of our method. The first stage provides a semi-parametric estimates in which the utility function is specified and no parametric assumption is made on event weights. Previous simulation results (e.g. Kim et al., 2007; Mahmoud et al., 2016; Kpegli et al., 2022) have shown that semi-parametric methods are preferable to parametric methods due to misspecification issues. Furthermore, the two-stage approach based on the power utility function in combination with the two-parameter weighting function of GE87 leads to smaller errors.

Table 1.D.1: Result of parameter recovery and misspecification exercises

	Specification		one-stage				two-stage			
	$u()$	$w()$	$u()$	$w()$	$P()$	pool	$u()$	$w()$	$P()$	pool
Parameter recovery										
1	E	CEG87	0.0010	0.0012	0.0096	0.0039	0.0010	0.0012	0.0096	0.0039
2	E	GE87	0.0011	0.0012	0.0022	0.0015	0.0011	0.0012	0.0020	0.0014
3	E	PR98	0.0011	0.0012	0.0031	0.0018	0.0011	0.0013	0.0028	0.0017
4	P	CEG87	0.0005	0.0007	0.0189	0.0067	0.0005	0.0007	0.0189	0.0067
5	P	GE87	0.0004	0.0006	0.0034	0.0015	0.0004	0.0006	0.0026	0.0012
6	P	PR98	0.0005	0.0007	0.0037	0.0016	0.0005	0.0007	0.0033	0.0015
7	pool	pool	0.0008	0.0009	0.0068	0.0028	0.0008	0.0009	0.0065	0.0027
Misspecification										
1	E	CEG7	0.0028	0.0069	0.0070	0.0056	0.0029	0.0070	0.0070	0.0056
2	E	GE87	0.0023	0.0064	0.0100	0.0062	0.0026	0.0059	0.0083	0.0056
3	E	P98	0.0026	0.0070	0.0076	0.0057	0.0028	0.0067	0.0070	0.0055
4	P	CEG7	0.0017	0.0018	0.0061	0.0032	0.0017	0.0018	0.0061	0.0032
5	P	GE87	0.0018	0.0021	0.0090	0.0043	0.0018	0.0019	0.0076	0.0038
6	P	P98	0.0019	0.0020	0.0074	0.0038	0.0019	0.0018	0.0068	0.0035
7	pool	pool	0.0022	0.0044	0.0078	0.0048	0.0023	0.0042	0.0071	0.0045
Parameter recovery and Misspecification										
1	E	CEG7	0.0019	0.0040	0.0083	0.0048	0.0020	0.0041	0.0083	0.0048
2	E	GE87	0.0017	0.0038	0.0061	0.0038	0.0018	0.0035	0.0052	0.0035
3	E	P98	0.0018	0.0041	0.0053	0.0038	0.0019	0.0040	0.0049	0.0036
4	P	CEG7	0.0011	0.0012	0.0125	0.0049	0.0011	0.0012	0.0125	0.0049
5	P	GE87	0.0011	0.0014	0.0062	0.0029	0.0011	0.0012	0.0051	0.0025
6	P	P98	0.0012	0.0013	0.0056	0.0027	0.0012	0.0012	0.0051	0.0025
7	pool	pool	0.0015	0.0026	0.0073	0.0038	0.0015	0.0026	0.0068	0.0036

Chapter 2

On the Communication of Higher Order Ambiguity

This chapter is based on a paper co-authored with Camille Cornand, Béatrice Rey-Fournier, and Adam Zylbersztein.

Abstract

In a context-free preference situation, we conduct a laboratory experiment in which we test higher order ambiguity attitudes (order 2, order 3, and order 4) using a simple model with two states of nature (good or bad). We compare ambiguity attitudes when the random variable capturing ambiguity is introduced on the probability associated with the good state versus the bad state of nature. In addition, in the case of order 3, we compare ambiguity attitudes when the random variable capturing ambiguity is presented as two harms (as usual in decision theory) versus one harm and one favor. We find that empirical results are more in line with theory when ambiguity is introduced on the probability associated with the bad state of nature and in the form of one harm and one favor. We derive implications of our results in terms of news communication.

Keywords: Higher order preferences, risk preferences, ambiguity preferences, prudent attitudes, temperate attitudes.

2.1 Introduction

Risk aversion drives behavior in many economic contexts. This behavioral feature is however insufficient. We know since the end of the sixties that higher-order risk preferences – prudence and temperance – are just as decisive to explain for example precautionary savings (e.g. [Leland, 1968](#); [Sandmo, 1970](#); [Kimball, 1990, 1993](#); [Eeckhoudt and Schlesinger, 2008](#)), insurance decisions (e.g. [Fei and Schlesinger, 2008](#)), prevention (e.g. [Eeckhoudt and Gollier, 2005](#); [Crainich and Menegatti, 2021](#); [Courbage and Rey, 2016a](#); [Peter, 2017](#)) and portfolio choices (e.g. [Eeckhoudt and Gollier, 1996](#); [Kimball, 1992](#)). This literature on higher order attitudes has been theoretically extended to situations where probabilities are unknown, i.e. ambiguous situations.¹ For instance, ambiguity aversion, prudence and temperance have been found to be key to explain prevention behavior (e.g. [Treich, 2010](#); [Berger, 2016](#); [Baillon, 2017](#); [Bleichrodt et al., 2019](#)) and savings decisions (e.g. [Alary et al., 2013](#); [Berger, 2014](#)).

Many laboratory experiments have provided an experimental counterpart to theoretical works under risk, generally finding strong evidence for risk aversion, risk prudence and, to a lesser extent, for risk temperance (e.g. [Deck and Schlesinger, 2010, 2014](#); [Ebert and Wiesen, 2014](#); [Noussair et al., 2014](#); [Attema et al., 2019](#); [Bleichrodt and Bruggen, 2022](#)). Yet, only very few papers have provided experimental tests of higher order ambiguity attitudes. [Baillon et al. \(2018\)](#) consider a pure damage context, i.e. with two states of nature, a good state (no damage) and a bad state (damage). Introducing the hazard capturing ambiguity on the good state of nature, they report ambiguity aversion, ambiguity prudence and, to a lesser extent, ambiguity temperance.

¹While the hazard affects the revenue under risk, under ambiguity, it affects the probability distribution of the states of nature.

However, in the theoretical literature on pure damage, the announced probability refers to the occurrence of a damage.² Theoretical models of pure damage typically introduce the ambiguity parameter on the probability associated with the bad state of nature (e.g. Treich, 2010; Snow, 2011; Alary et al., 2013; Gollier, 2014; Bleichrodt et al., 2019). Under risk and under ambiguity when the probability is associated with the good state of nature, a stochastically dominated hazard in the sense of Ekern is considered more risky, respectively more ambiguous. A prudent (temperate) agent prefers a first hazard that stochastically dominates in the sense of Ekern at order 3 (4) a second hazard. It is the same for order 2. A risk averse (ambiguity averse) agent prefers a certain situation (a situation without ambiguity) to a situation with a zero-mean random variable, that is stochastically dominated in sense of Ekern at order 2 by zero.

In a theoretical paper, Courbage and Rey (2016b) show that when the hazard capturing ambiguity is introduced on the bad state of nature, these results are reversed for odd orders. An ambiguity prudent agent prefers the random variable that is stochastically dominated in the sense of Ekern at order 3, i.e. he considers it to be less ambiguous. It is an open empirical question whether at order 3 people are ambiguity prudent whatever the context, good or bad, to which the probability capturing ambiguity is associated.

We therefore conduct a context-free preference laboratory experiment in which we test higher order ambiguity attitudes: ambiguity aversion (order 2), ambiguity prudence (order 3), and ambiguity temperance (order 4), using a simple model with two states of nature (a good one and a bad one). We compare ambiguity attitudes when the random variable capturing ambiguity is introduced

²In the literature where the damage is non-pecuniary, for example in the Value of a Statistical Life (VSL) literature (Dreze, 1962), the announced probability is the probability of death, and in models of irreplaceable commodity (Cook and Graham, 1977), the announced probability is the probability of commodity loss. In the literature where the damage is pecuniary, the announced probability is the probability of the monetary loss.

on the probability associated with the good state versus the bad state of nature. In addition, in the case of order 3, we compare ambiguity attitudes when the random variable capturing ambiguity is presented as two harms (as usual in decision theory) versus one harm and one favor. This test under ambiguity mimics the comparison done under risk between attitudes in the loss versus gain domains (see e.g. [Attema et al., 2019](#)). We find that empirical results are more in line with theory when the ambiguity parameter is introduced on the probability associated with the bad state of nature. In the case of order 3, prudence trait is only observed when subjects face one harm and one favor.

Our results have implications in terms of news communication. Indeed, we may interpret a harm as bad news and a favor as good news (see Section 2 for more details). Since prudence trait is preponderant when the story is presented by the ambiguity introduced on the bad state and in the form of a good news and a bad news, the way the news are communicated influences the extent to which people are receptive of these news. Such effects have to be accounted for when communicating about damage in real life, be it about climate change, alcohol, driving or eating behaviors.

The remainder of this chapter is organized as follows. In the next section, we present the theoretical foundation of our measurements of higher order ambiguity attitudes. Section 3 describes the design of our experiment. The results are presented in Section 4. Section 5 concludes.

2.2 Theoretical background

Let us consider a decision maker (DM) with an initial wealth R and confronted with two states of nature. Following the theoretical damage literature, the presentation of the context is the following: a bad state (damage) that occurs

with probability p ($0 < p < 1$) and a good state that occurs with probability $(1 - p)$. The DM's expected utility writes as follows:

$$pu^B(R) + (1 - p)u^G(R) = p(u^B(R) - u^G(R)) + u^G(R) \equiv V^B(p; 0), \quad (2.1)$$

where utility functions u^B and u^G verify $u^{B''}(x) < 0 < u^{B'}(x)$, $u^{G''}(x) < 0 < u^{G'}(x) \forall x$ and $u^B(x) < u^G(x) \forall x$. So as to introduce ambiguity (see [Treich \(2010\)](#), [Snow \(2010\)](#), [Berger et al. \(2013\)](#), or [Bleichrodt et al. \(2019\)](#) for example), we introduce a zero-mean random variable $\tilde{\xi}$, and add it to the probability of the bad state of nature. This probability of the bad state of nature, $p + \tilde{\xi}$, is ambiguous in the sense that $\tilde{\xi}$ takes on values in $[\underline{\xi}, \bar{\xi}]$. Ambiguity arises because the DM lacks knowledge of the probability of being in the bad state or in the good state of nature, i.e. he does not know the value of the realization ξ .

According to the smooth ambiguity model axiomatized by [Klibanoff et al. \(2005\)](#), the DM's welfare writes as

$$\begin{aligned} \mathbb{E} \left[\Phi \left((p + \tilde{\xi})u^B(R) + (1 - (p + \tilde{\xi}))u^G(R) \right) \right] &= \mathbb{E} \left[\Phi \left((p + \tilde{\xi})(u^B(R) - u^G(R)) + u^G(R) \right) \right] \\ &\equiv V^B(p; \tilde{\xi}), \end{aligned} \quad (2.2)$$

where \mathbb{E} denotes the expectation operator over the random variable $\tilde{\xi}$ which probability distribution is assumed to be implicitly known. The function Φ captures the attitude towards ambiguity and is supposed to be smooth and increasing, i.e. $\Phi' > 0$. Modeling ambiguity perception according to [Klibanoff et al. \(2005\)](#), this boils down to check that $\Phi'' < 0$, $\Phi''' > 0$, and $\Phi'''' < 0$ to capture ambiguity aversion, ambiguity prudence and ambiguity temperance, respectively.

An alternative manner to present the context consists in associating p with the good state of nature. Then the DM's expected utility writes as follows:

$$pu^G(R) + (1 - p)u^B(R) = p(u^G(R) - u^B(R)) + u^B(R) \equiv V^G(p; 0). \quad (2.3)$$

Observe that there is a negative relation between $V^G(p; 0)$ and $V^B(p; 0)$: $V^G(p; 0) = u^G(R) + u^B(R) - V^B(p; 0)$. With ambiguity, the DM's welfare writes as

$$\begin{aligned} \mathbb{E} \left[\Phi \left((p + \tilde{\xi})u^G(R) + (1 - (p + \tilde{\xi}))u^B(R) \right) \right] &= \mathbb{E} \left[\Phi \left((p + \tilde{\xi})(u^G(R) - u^B(R)) + u^B(R) \right) \right] \\ &\equiv V^G(p; \tilde{\xi}). \end{aligned} \quad (2.4)$$

For the purpose of the experiment, the damage is taken as a monetary loss L ($L > 0$). Therefore, utility functions u^G and u^B are state-independent: $u^G(R) = u(R)$ and $u^B(R) = u(R - L)$ with u such that $u'' < 0 < u'$. We adopt the following notations (see Table 2.3.1: choice tasks). We denote the context captured by Equation (2.1) (respectively Equation (2.3)) by $(p : R_1, R_2)$ with $R_1 = R - L < R = R_2$ ($(p : R_1, R_2)$ with $R_1 = R > R_2 = R - L$). We denote the ambiguous context captured by Equation (2.2) (respectively Equation (2.4)) by $(p + \tilde{\xi} : R_1, R_2)$ with $R_1 = R - L < R = R_2$ ($(p + \tilde{\xi} : R_1, R_2)$ with $R_1 = R > R_2 = R - L$). With our notation, the probability is always assigned to the state with revenue R_1 .

Observe that in Equation (2.4), $\tilde{\xi}$ is multiplied by a positive term ($u^G(R) - u^B(R)$), as in Baillon et al. (2018), while it is multiplied by a negative one, ($u^B(R) - u^G(R)$), in Equation (2.2). This difference is crucial and explains why a greater level of ambiguity³ does not always coincide with a dominated context in the sense of Ekern dominance. The result may depend on the dominance order,

³When comparing two ambiguous contexts, a 'greater level of ambiguity' is associated to a welfare loss, e.g. an ambiguity averse, prudent, or temperate subject prefers the less ambiguous context.

even or odd (see [Courbage and Rey \(2016b\)](#)). For this reason, we separately analyze even orders ($n = 2, 4$) and the odd order ($n = 3$).⁴

2.2.1 Even orders: ambiguity aversion ($n = 2$) and ambiguity temperance ($n = 4$)

For even orders, whether the configuration corresponding to the probability $\tilde{p} = p + \tilde{\xi}$ associated to the bad state or the good state, a greater level of ambiguity coincides with a dominated context in the sense of Ekern dominance of order n . Formally, $\tilde{\xi}_2$ more ambiguous than $\tilde{\xi}_1$ coincides with $\tilde{\xi}_2 \preceq_{Ekern_n} \tilde{\xi}_1 \forall n = 2, 4$. This means that the DM's welfare when ambiguity is modeled by $\tilde{\xi}_2$ is smaller than the DM's welfare when ambiguity is modeled by $\tilde{\xi}_1$: $V^k(p, \tilde{\xi}_2) \leq V^k(p, \tilde{\xi}_1)$, with $k = G, B$.

More precisely, for an ambiguity averse DM: $V^k(p, \tilde{\xi}_2) \leq V^k(p, \tilde{\xi}_1)$ ($k = G, B$) with $\tilde{\xi}_2 \preceq_{Ekern_2} \tilde{\xi}_1$. For the experiment, as [Baillon et al. \(2018\)](#), to test ambiguity aversion, we compare a situation without ambiguity to a situation with ambiguity. More formally, we consider the particular case where $\tilde{\xi}_1$ is a degenerated random variable ($\tilde{\xi}_1 = 0$) and where $\tilde{\xi}_2$ is a zero-mean random variable $\tilde{\epsilon}$. Following our notations, ambiguity aversion is defined as preferring $(p : R_1, R_2)$ to $(p + \tilde{\epsilon} : R_1, R_2)$ with $R_1 < R_2$ or $R_1 > R_2$.

For an ambiguity temperate DM: $V^k(p, \tilde{\xi}_2) \leq V^k(p, \tilde{\xi}_1)$ ($k = G, B$) with $\tilde{\xi}_2 \preceq_{Ekern_4} \tilde{\xi}_1$. To model Ekern's dominance of order $n = 4$, we choose the classical specification used in experimental studies that is disaggregation versus aggregation of harms. Let's consider two independent zero-mean random variables $\tilde{\epsilon}_1$ and $\tilde{\epsilon}_2$. $\tilde{\xi}_1$ and $\tilde{\xi}_2$ write as two 50 – 50 lotteries: $\tilde{\xi}_1 = [\tilde{\epsilon}_1, \tilde{\epsilon}_2]$ and $\tilde{\xi}_2 = [0, \tilde{\epsilon}_1 + \tilde{\epsilon}_2]$. The two 50 – 50 lotteries involve two “harms”, the zero-mean

⁴As will become clear below, in the experiment, we do not consider $n = 5$ because [Deck and Schlesinger \(2014\)](#) do not find any statistical difference with random behavior for orders larger than $n = 4$.

$\tilde{\epsilon}_1$ and $\tilde{\epsilon}_2$. Ambiguity temperance can be defined as always preferring $\tilde{\xi}_1$ to $\tilde{\xi}_2$ for all zero-mean random variables $\tilde{\epsilon}_1$ and $\tilde{\epsilon}_2$, hence preferring disaggregating the two harms. We adopt the following notations: $(\{p + \tilde{\epsilon}_2, p + \tilde{\epsilon}_2\} : R_1, R_2)$ preferred to $(\{p, p + \tilde{\epsilon}_1 + \tilde{\epsilon}_2\} : R_1, R_2)$ with $R_1 < R_2$ or $R_1 > R_2$.

2.2.2 Odd order: ambiguity prudence ($n = 3$)

For the odd order $n = 3$, we have to distinguish the configuration in which \tilde{p} is associated to the good state from the configuration in which \tilde{p} is associated to the bad state. In the configuration in which \tilde{p} is associated to the good state, as for even orders, a greater level of ambiguity coincides with a dominated context in the sense of Ekern dominance. This means that the DM's welfare when ambiguity is modeled by $\tilde{\xi}_2$ is smaller than the DM's welfare when ambiguity is modeled by $\tilde{\xi}_1$ with $\tilde{\xi}_2 \preceq_{Ekern_3} \tilde{\xi}_1$. More precisely, for an ambiguity prudent DM: $V^G(p, \tilde{\xi}_2) \leq V^G(p, \tilde{\xi}_1)$. By contrast, in the configuration in which \tilde{p} is associated to the bad state, a greater level of ambiguity does not coincide with a dominated context in the sense of Ekern dominance. The result is explained by the fact that \tilde{p} is multiplied by a negative term (see remark above before section 2.1 and Courbage and Rey (2016b) for more details). This means that, in this configuration, $\tilde{\xi}_2$ is less ambiguous than $\tilde{\xi}_1$ when $\tilde{\xi}_2 \preceq_{Ekern_3} \tilde{\xi}_1$. The DM's welfare when ambiguity is modeled by $\tilde{\xi}_2$ is then larger than the DM's welfare when ambiguity is modeled by $\tilde{\xi}_1$. Thus, for an ambiguity prudent DM: $V^B(p, \tilde{\xi}_2) \geq V^B(p, \tilde{\xi}_1)$ with $\tilde{\xi}_2 \preceq_{Ekern_3} \tilde{\xi}_1$.

First, let us focus on the configuration in which \tilde{p} is associated to the good state. Consider a choice between $\tilde{\xi}_1 = [-k, \tilde{\epsilon}]$ and $\tilde{\xi}_2 = [0, -k + \tilde{\epsilon}]$ with $k > 0$ and $\tilde{\epsilon}$ a zero-mean random variable. The two 50–50 lotteries involve two “harms”, the zero-mean random variable $\tilde{\epsilon}$ and the certain loss $-k$. Ambiguity prudence can be defined as always preferring $\tilde{\xi}_1$ to $\tilde{\xi}_2$, hence preferring disaggregating

the two harms. We denote it as follows: $(\{p - k, p + \tilde{\epsilon}\} : R_1, R_2)$ preferred to $(\{p, p - k + \tilde{\epsilon}\} : R_1, R_2)$ with $R_1 > R_2$.

Second, let us now focus on the configuration in which \tilde{p} is associated to the bad state. In this configuration, a certain harm is $+k$ with $k > 0$. Indeed, increasing by $+k$ the probability of the bad state is a bad news. Consider a choice between $[+k, \tilde{\epsilon}]$ and $[0, +k + \tilde{\epsilon}]$ and $\tilde{\epsilon}$ a zero-mean random variable. The two 50–50 lotteries involve two “harms”, the zero-mean random variable $\tilde{\epsilon}$ and the certain increment $+k$. Ambiguity prudence can be defined as always preferring $[+k, \tilde{\epsilon}]$ to $[0, +k + \tilde{\epsilon}]$, hence preferring disaggregating the two harms. Note that $[+k, \tilde{\epsilon}] = \tilde{\xi}_2 \preceq_{\text{Ekernel}_3} [0, +k + \tilde{\epsilon}] = \tilde{\xi}_1$: the DM prefers the dominated lottery. With our notations, this becomes: $(\{p + k, p + \tilde{\epsilon}\} : R_1, R_2)$ preferred to $(\{p, p + k + \tilde{\epsilon}\} : R_1, R_2)$ with $R_1 < R_2$.

It is also interesting to compare ambiguity attitudes according to the communication of the news. The idea is to compare attitudes in the loss versus gain domains under ambiguity (as [Attema et al. \(2019\)](#) do under risk). Let us return to lotteries $[-k, \tilde{\epsilon}]$ and $[0, -k + \tilde{\epsilon}]$. These lotteries involve two harms in the configuration of the good state. However, in the configuration in which \tilde{p} is associated to the bad state, $-k$ is not a harm but a favor (good news). An ambiguity prudent DM prefers to disaggregate harms, e.g. he prefers to combine one harm $\tilde{\epsilon}$ with one favor k and to combine one favor 0 (0 is one favor compared to $\tilde{\epsilon}$) with one harm 0 (0 is one harm compared to k) rather than to combine two harms, $\tilde{\epsilon}$ with 0, and two favors, 0 and k . Formally, he prefers $[0, -k + \tilde{\epsilon}] = \tilde{\xi}_2$ to $[-k, \tilde{\epsilon}] = \tilde{\xi}_1$ (recall that $\tilde{\xi}_2 \preceq_{\text{Ekernel}_3} \tilde{\xi}_1$), which rewrites with our notations: $(\{p, p - k + \tilde{\epsilon}\} : R_1, R_2) \succeq (\{p - k, p + \tilde{\epsilon}\} : R_1, R_2)$ with $R_1 < R_2$. Symmetrically, in the configuration in which \tilde{p} is associated to the good state, a certain favor (good news) writes as $+k$ and an harm (bad news) as $\tilde{\epsilon}$. An ambiguity prudent DM that is a DM preferring disaggregated harms prefers $[0, +k + \tilde{\epsilon}] = \tilde{\xi}_1$ to

$[+k, \tilde{\epsilon}] = \tilde{\xi}_2$ (recall that $\tilde{\xi}_2 \preceq_{E\text{kern}_3} \tilde{\xi}_1$). With our notations, this preference relation writes as: $(\{p, p + k + \tilde{\epsilon}\} : R_1, R_2) \succeq (\{p + k, p + \tilde{\epsilon}\} : R_1, R_2)$ with $R_1 > R_2$.

2.3 Experimental design

We recruited 227 students to participate in a computerized experiment⁵ conducted at GATE-Lab in Lyon. According to our criteria of outliers, 18 subjects were removed from the sample because they failed to answer correctly to more than half of the questions in the understanding questionnaire.⁶ Hence, our final sample size is 209. Subjects were told that the experiment could last up to 90 minutes, that they would receive €5 as a participation fee, and they could additionally earn a variable amount depending on random draws and their own decisions. The mean age of subjects is 21 years, 44% are female, and 45% study economics or finance.

The experiment consisted of two parts. In the first part, we elicited risk attitudes in 15 choices. In the second part, we elicited ambiguity attitudes in 40 choices. Each part started with its specific instructions, which were presented on the screen⁷. Within each part, the order of the choices was randomized across subjects.

Table 2.3.1 displays the 55 choice tasks, which are divided into sets of 5 choices each. The first 30 choice tasks in Table 2.3.1 replicate the tasks implemented by [Baillon et al. \(2018\)](#). Accordingly, the first 15 tasks are risk choice tasks, and each of the sets corresponds to risk orders 2, 3, and 4. Tasks from 16 to 30 are ambiguous choice tasks of order 2, 3, and 4, in which the variable capturing

⁵The design and behavioral conjectures have been pre-registered at AsPredicted (#78997).

⁶Our definition criteria of outliers is specified in the pre-registration.

⁷The full content of the instructions can be found in Appendix 2.A.

ambiguity is introduced on the probability associated with the good state of nature. In addition, we include 25 choices. Lines 31 to 45 in Table 2.3.1 present 15 ambiguous lotteries, in which, contrary to Baillon et al. (2018), the random variable capturing ambiguity is introduced on the probability associated with the bad state of nature. These 15 choice tasks represent the counterparts of choice tasks 16 to 30, ambiguity being now introduced on the bad state. The last 10 choice tasks in Table 2.3.1 aim at comparing ambiguity prudence choices with ambiguity presented as one harm and one favor in the bad state of nature (lines 46-50) versus ambiguity prudence with ambiguity presented as one harm and one favor on the good state (lines 51-55).⁸

In the experiment, we presented the two alternatives for each task graphically, using diagrams of circles representing both options A and B, which were framed as option Left (L) and Right (R), respectively. The position in the screen (left or right) for options A and B is randomized across subjects. Figure 2.3.1 displays the screen of task 11 in Table 2.3.1. Subjects' task is to choose an option between A and B. To make their selection, subjects click on one of the texts (Option L, Option R) positioned on the top of the image. As Figure 2.3.1 displays, the final outcomes in the risk task, are shown in yellow. These yellow circles only appear on the screen after 10 seconds.

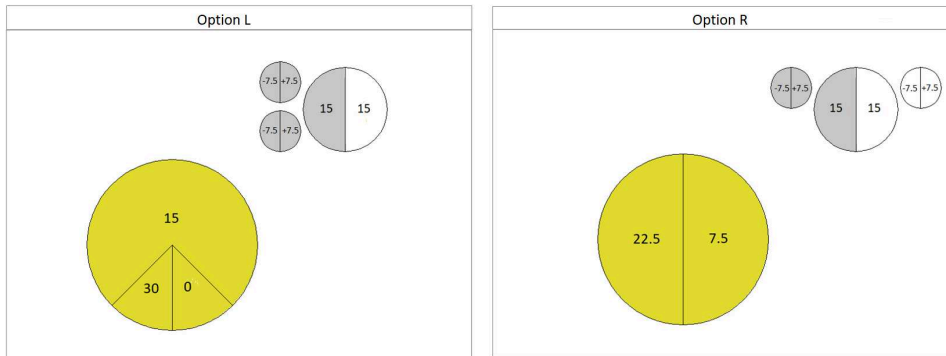
In the ambiguous choices, circles have two different colors representing the good or bad state of nature, the circles are gradually being colored to illustrate the variation of the probabilities, capturing ambiguity. The green color represents the bad state of nature, and the blue color represents the good state of nature. Figure 2.3.2 shows the screen of task 31 in Table 2.3.1. The arrow⁹ around the

⁸We did not consider comparing the loss versus gain domains at order 2. Indeed, we test ambiguity aversion (order 2) by comparing a context without ambiguity to a context with ambiguity rather than comparing two ambiguous contexts.

⁹The arrow is included in this chapter for illustration purposes. However, it is not part of the screen in the experiment. Instead, the colors move automatically. A video

circle in the left panel represents the fact that the circle is progressively colored in green from 0° to 360° to illustrate ambiguity.¹⁰

Figure 2.3.1: Task 11



Example of decision screen under risk in the experiment. Option A on the right and option B on the left.

recording of the examples of ambiguity tasks referred to in the instructions is provided at: <https://page.hn/w61e8e>.

¹⁰The implementation of the moving proportions in the circles, partially relies on Garcia et al. (2020)'s design.

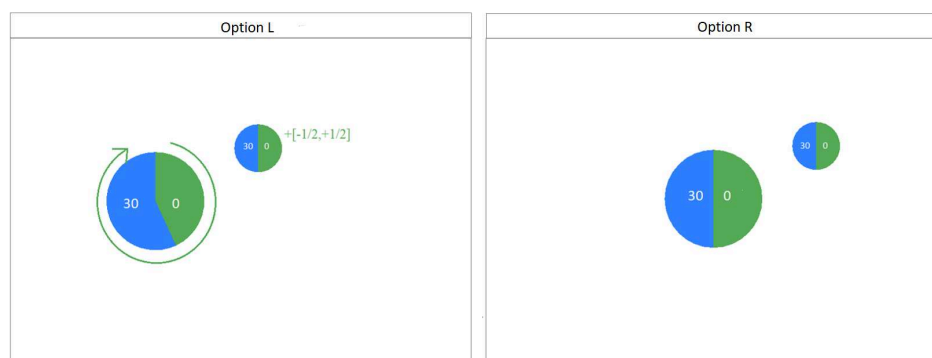
Table 2.3.1: Choice tasks

Task	Dom	Ord	Option A	Option B
	Risk	2	$(p : R_1, R_2)$	R
1	Risk	2	$(1/2 : 30, 0)$	15
2	Risk	2	$(1/2 : 45, 15) = 1A + 15$	$1B + 15$
3	Risk	2	$(1/2 : 45, 0) = 1A \times 1.5$	$1B \times 1.5$
4	Risk	2	$(1/3 : 30, 0)$	10
5	Risk	2	$(2/3 : 30, 0)$	20
	Risk	3	$(p : R, R - k + \bar{\epsilon})$	$(p : R + \bar{\epsilon}, R - k)$
6	Risk	3	$(1/2 : 15, 15 - 7.5 + [-7.5, +7.5])$	$(1/2 : 15 + [-7.5, +7.5], 15 - 7.5)$
7	Risk	3	$6A + 15 = (1/2 : 30, 30 - 7.5 + [-7.5, +7.5])$	$6B + 15 = (1/2 : 30 + [-7.5, +7.5], 30 - 7.5)$
8	Risk	3	$6A \times 2 = (1/2 : 30, 30 - 15 + [-15, +15])$	$6B \times 2 = (1/2 : 30 + [-15, +15], 30 - 15)$
9	Risk	3	$(1/2 : 10, 10 - 5 + (1/3 : 10, -5))$	$(1/2 : 10 + (1/3 : 10, -5), 10 - 5)$
10	Risk	3	$(1/2 : 25, 25 - 15 + (2/3 : 5, -10))$	$(1/2 : 25 + (2/3 : 5, -10), 25 - 15)$
	Risk	4	$(p : R, R + \bar{\epsilon}_1 + \bar{\epsilon}_2)$	$(p : R + \bar{\epsilon}_1, R + \bar{\epsilon}_2)$
11	Risk	4	$(1/2 : 15, 15 + [7.5, -7.5] + [7.5, -7.5])$	$(1/2 : 15 + [7.5, -7.5], 15 + [7.5, -7.5])$
12	Risk	4	$11A + 15 = (1/2 : 30, 30 + [7.5, -7.5] + [7.5, -7.5])$	$11B + 15 = (1/2 : 30 + [7.5, -7.5], 30 + [7.5, -7.5])$
13	Risk	4	$11A \times \frac{3}{2} = (1/2 : 22.5, 22.5 + [11.25, -11.25] + [11.25, -11.25])$	$11B \times \frac{3}{2} = (1/2 : 22.5 + [11.25, -11.25], 22.5 + [11.25, -11.25])$
14	Risk	4	$(1/2 : 10, 10 + (1/3 : 10, -5) + (1/3 : 10, -5))$	$(1/2 : 10 + (1/3 : 10, -5), 10 + (1/3 : 10, -5))$
15	Risk	4	$(1/2 : 20, 20 + (2/3 : 5, -10) + (2/3 : 5, -10))$	$(1/2 : 20 + (2/3 : 5, -10), 20 + (2/3 : 5, -10))$
	Amb	2	$(p + \bar{\epsilon} : R_1, R_2)$ with $R_1 > R_2$	$(p : R_1, R_2)$ with $R_1 > R_2$
16	Amb	2	$(1/2 + [-1/2, +1/2] : 30, 0)$	1A
17	Amb	2	$16A + 15 = (1/2 + [-1/2, +1/2] : 45, 15)$	2A
18	Amb	2	$(1/2 + [-1/2, +1/2] : 45, 0)$	3A
19	Amb	2	$(1/3 + [-1/3, +1/3] : 30, 0)$	4A
20	Amb	2	$(2/3 + [-1/3, +1/3] : 30, 0)$	5A
	Amb	3	$(\{p, p - k + \bar{\epsilon}\} : R_1, R_2)$ with $R_1 > R_2$	$(\{p - k, p + \bar{\epsilon}\} : R_1, R_2)$ with $R_1 > R_2$
21	Amb	3	$(\{1/2, 1/2 - 1/4 + [-1/4, +1/4]\} : 30, 0)$	$(\{1/2 - 1/4, 1/2 + [-1/4, +1/4]\} : 30, 0)$
22	Amb	3	$21A + 15$	$21B + 15$
23	Amb	3	$21A \times 1.5$	$21B \times 1.5$
24	Amb	3	$(\{1/3, 1/3 - 1/6 + [-1/6, +1/6]\} : 30, 0)$	$(\{1/3 - 1/6, 1/3 + [-1/6, +1/6]\} : 30, 0)$
25	Amb	3	$(\{2/3, 2/3 - 1/6 + [-1/6, +1/6]\} : 30, 0)$	$(\{2/3 - 1/6, 2/3 + [-1/6, +1/6]\} : 30, 0)$
	Amb	4	$(\{p, p + \bar{\epsilon}_1 + \bar{\epsilon}_2\} : R_1, R_2)$ with $R_1 > R_2$	$(\{p + \bar{\epsilon}_1, p + \bar{\epsilon}_2\} : R_1, R_2)$ with $R_1 > R_2$
26	Amb	4	$(\{1/2, 1/2 + [-1/8, 1/8] + [-1/8, 1/8]\} : 30, 0)$	$(\{1/2 + [-1/8, 1/8], 1/2 + [-1/8, 1/8]\} : 30, 0)$
27	Amb	4	$26A + 15$	$26B + 15$
28	Amb	4	$26A \times 1.5$	$26B \times 1.5$
29	Amb	4	$(\{1/3, 1/3 + [-1/6, 1/6] + [-1/6, 1/6]\} : 30, 0)$	$(\{1/3 + [-1/6, 1/6], 1/3 + [-1/6, 1/6]\} : 30, 0)$
30	Amb	4	$(\{2/3, 2/3 + [-1/6, 1/6] + [-1/6, 1/6]\} : 30, 0)$	$(\{2/3 + [-1/6, 1/6], 2/3 + [-1/6, 1/6]\} : 30, 0)$
	Amb	2	$(p + \bar{\epsilon} : R_1, R_2)$ with $R_1 < R_2$	$(p : R_1, R_2)$ with $R_1 < R_2$
31	Amb	2	$(1/2 + [-1/2, +1/2] : 0, 30)$	$(1/2 : 0, 30)$
32	Amb	2	$(1/2 + [-1/2, +1/2] : 15, 45)$	$(1/2 : 15, 45)$
33	Amb	2	$(1/2 + [-1/2, +1/2] : 0, 45)$	$(1/2 : 0, 45)$
34	Amb	2	$(1/3 + [-1/3, +1/3] : 0, 30)$	$(1/3 : 0, 30)$
35	Amb	2	$(2/3 + [-1/3, +1/3] : 0, 30)$	$(2/3 : 0, 30)$
	Amb	3	$(\{p, p + k + \bar{\epsilon}\} : R_1, R_2)$ with $R_1 < R_2$	$(\{p + k, p + \bar{\epsilon}\} : R_1, R_2)$ with $R_1 < R_2$
36	Amb	3	$(\{1/2, 1/2 + 1/4 + [-1/4, +1/4]\} : 0, 30)$	$(\{1/2 + 1/4, 1/2 + [-1/4, +1/4]\} : 0, 30)$
37	Amb	3	$(\{1/2, 1/2 + 1/4 + [-1/4, +1/4]\} : 15, 45)$	$(\{1/2 + 1/4, 1/2 + [-1/4, +1/4]\} : 15, 45)$
38	Amb	3	$(\{1/2, 1/2 + 1/4 + [-1/4, +1/4]\} : 0, 45)$	$(\{1/2 + 1/4, 1/2 + [-1/4, +1/4]\} : 0, 45)$
39	Amb	3	$(\{1/3, 1/3 + 1/6 + [-1/6, +1/6]\} : 0, 30)$	$(\{1/3 + 1/6, 1/3 + [-1/6, +1/6]\} : 0, 30)$
40	Amb	3	$(\{2/3, 2/3 + 1/6 + [-1/6, +1/6]\} : 0, 30)$	$(\{2/3 + 1/6, 2/3 + [-1/6, +1/6]\} : 0, 30)$
	Amb	4	$(\{p, p + \bar{\epsilon}_1 + \bar{\epsilon}_2\} : R_1, R_2)$ with $R_1 < R_2$	$(\{p + \bar{\epsilon}_1, p + \bar{\epsilon}_2\} : R_1, R_2)$ with $R_1 < R_2$
41	Amb	4	$(\{1/2, 1/2 + [-1/8, 1/8] + [-1/8, 1/8]\} : 0, 30)$	$(\{1/2 + [-1/8, 1/8], 1/2 + [-1/8, 1/8]\} : 0, 30)$
42	Amb	4	$(\{1/2, 1/2 + [-1/8, 1/8] + [-1/8, 1/8]\} : 15, 45)$	$(\{1/2 + [-1/8, 1/8], 1/2 + [-1/8, 1/8]\} : 15, 45)$
43	Amb	4	$(\{1/2, 1/2 + [-1/8, 1/8] + [-1/8, 1/8]\} : 0, 45)$	$(\{1/2 + [-1/8, 1/8], 1/2 + [-1/8, 1/8]\} : 0, 45)$
44	Amb	4	$(\{1/3, 1/3 + [-1/6, 1/6] + [-1/6, 1/6]\} : 0, 30)$	$(\{1/3 + [-1/6, 1/6], 1/3 + [-1/6, 1/6]\} : 0, 30)$
45	Amb	4	$(\{2/3, 2/3 + [-1/6, 1/6] + [-1/6, 1/6]\} : 0, 30)$	$(\{2/3 + [-1/6, 1/6], 2/3 + [-1/6, 1/6]\} : 0, 30)$
	Amb	3	$(\{p - k, p + \bar{\epsilon}\} : R_1, R_2)$ with $R_1 < R_2$	$(\{p, p - k + \bar{\epsilon}\} : R_1, R_2)$ with $R_1 < R_2$
46	Amb	3	$(\{1/2 - 1/4, 1/2 + [-1/4, +1/4]\} : 0, 30)$	$(\{1/2, 1/2 - 1/4 + [-1/4, +1/4]\} : 0, 30)$
47	Amb	3	$46A + 15$	$46B + 15$
48	Amb	3	$46A \times 1.5$	$46B \times 1.5$
49	Amb	3	$(\{1/3 - 1/6, 1/3 + [-1/6, +1/6]\} : 0, 30)$	$(\{1/3, 1/3 - 1/6 + [-1/6, +1/6]\} : 0, 30)$
50	Amb	3	$(\{2/3, 2/3 - 1/6 + [-1/6, +1/6]\} : 0, 30)$	$(\{2/3, 2/3 - 1/6 + [-1/6, +1/6]\} : 0, 30)$
	Amb	3	$(\{p + k, p + \bar{\epsilon}\} : R_1, R_2)$ with $R_1 > R_2$	$(\{p, p + k + \bar{\epsilon}\} : R_1, R_2)$ with $R_1 > R_2$
51	Amb	3	$(\{1/2 + 1/4, 1/2 + [-1/4, +1/4]\} : 30, 0)$	$(\{1/2, 1/2 + 1/4 + [-1/4, +1/4]\} : 30, 0)$
52	Amb	3	$(\{1/2 + 1/4, 1/2 + [-1/4, +1/4]\} : 45, 15)$	$(\{1/2, 1/2 + 1/4 + [-1/4, +1/4]\} : 45, 15)$
53	Amb	3	$(\{1/2 + 1/4, 1/2 + [-1/4, +1/4]\} : 45, 0)$	$(\{1/2, 1/2 + 1/4 + [-1/4, +1/4]\} : 45, 0)$
54	Amb	3	$(\{1/3 + 1/6, 1/3 + [-1/6, +1/6]\} : 30, 0)$	$(\{1/3, 1/3 + 1/6 + [-1/6, +1/6]\} : 30, 0)$
55	Amb	3	$(\{2/3 + 1/6, 2/3 + [-1/6, +1/6]\} : 30, 0)$	$(\{2/3, 2/3 + 1/6 + [-1/6, +1/6]\} : 30, 0)$

Note: The probability always refers to the first wealth level.

A zero-mean random variable $\bar{\epsilon}$ represented by $\{-a, +a\}$ means that $\bar{\epsilon}$ is a discrete random variable, e.g. that it takes the value $-a$ with probability $\frac{1}{2}$ and the value $+a$ with probability $\frac{1}{2}$. A zero-mean random variable $\bar{\epsilon}$ represented by $[-a, +a]$ means that $\bar{\epsilon}$ is a random variable distributed according to a uniform distribution taking values in $[-a, +a]$.

Figure 2.3.2: Task 31



Example of decision screen under ambiguity in the experiment. Option A on the right and option B on the left. *Note:* the green arrow in the left panel illustrates that the circle is gradually being colored in green progressively from 0° to 360° on the screen during the experiment. The arrow is included in this image for illustration purposes only, but it is not part of the screen subjects see in the experiment.

The big circles in Figure 2.3.2 represent the aggregate outputs for each option. They appear after 7 seconds and the button to confirm the decision is only available after 12 additional seconds. These features of the tasks are implemented in order to let subjects focus on the aggregated or disaggregated news.

Each choice task corresponds to a sealed envelope that was prepared before the experiment. The content of the envelopes is described to the subjects in the instructions. The envelopes contain all the possible outcomes from choices A and B of each task. For instance, the envelope corresponding to risk task 11 contains two smaller envelopes that represent each of the options A and B. The envelope representing option A has inside eight tags: six tags indicating €15, one tag indicating €0, and one tag indicating €30. Therefore, the tags illustrate that if option A is chosen, the probability of winning €15, €0, or €30

is $3/4$, $1/8$, and $1/8$, respectively (as shown in the left panel of Figure 2.3.1). The second smaller envelope representing option B contains two tags. One of them indicates €22.5 and the other one €7.5. Therefore, for option B, the probability of winning €22.5 and €7.5 is $1/2$ (see right panel of Figure 2.3.1).

Similarly, the envelope corresponding to ambiguity task 31 contains two smaller envelopes for options A and B. Inside the envelope for option A, there are five smaller envelopes, each of them representing different probabilities of obtaining the outcome of the bad state of nature. The probabilities are 0, $1/4$, $1/2$, $3/4$, and 1. Each of these envelopes has inside different amounts of tags showing the final payoff. For instance, the envelope with probability $1/4$ contains four tags: one indicating €0 and three tags indicating €30. The envelope representing option B contains two tags: one displaying the value €30 and another one displaying €0. This corresponds to the probability of winning the two possible outcomes of this option, as shown in the right panel of Figure 2.3.2.

All the 55 envelopes were stored in a box located in the laboratory within sight of the subjects. The envelopes did not have visible identification of the task they represented. At the beginning of each experimental session, one subject was randomly selected to pick one of the envelopes from the box and was asked to sign it. Subsequently, the envelope was left within sight of all the subjects. At the end of the experiment, the selected envelope was opened by the subject who signed it to determine the payoffs. As pointed out by [Baillon et al. \(2018\)](#), ambiguity opens up the possibility that results are affected by subjects' beliefs. A priori subjects do not have reasons to expect one outcome to be more likely than another. This concern is related to suspicion. Subjects may suspect the experimenter to voluntarily influence the outcome. To avoid suspicion: we manually implemented the above described procedure in front of the subjects.

Also, subjects were told that, if they wish, they could open and check all the envelopes at the end of the experiment. Once subjects finished the choice tasks, they proceeded to answer a battery of questions, including self-evaluation of personality traits, cognitive reflection test, and demographic.

2.4 Results

In this section, we establish subjects' preferences for ambiguity of order 2, 3, and 4.¹¹ We analyze the difference between the decisions in the experiment and the choices that would be observed if subjects chose randomly. Following the methodology of [Deck and Schlesinger \(2010\)](#), [Noussair et al. \(2014\)](#), and [Baillon et al. \(2018\)](#), we use the number of choices (out of 5) that subjects answered in a averse/prudent/temperate way to state their preferences. All the statistical tests in this analysis are Wilcoxon signed-rank tests, unless otherwise stated. In section 2.4.4, we examine the determinants of higher order ambiguity attitudes in a regression analysis.¹²

2.4.1 Ambiguity of order 2: Aversion

Figure 2.4.1 presents the distribution of ambiguity averse choices for lotteries where the probability capturing ambiguity is associated with the good state of nature (left panel) and bad state of nature (right panel), that is the percentage of subjects choosing 0, 1, 2, 3, 4 or 5 times option B rather than option A in

¹¹Results about risk are reported in Appendix 2.C. In line with previous literature (see [Eeckhoudt and Loubergé, 2012](#), for a review), subjects are risk averse and risk prudent (as in [Deck and Schlesinger, 2014](#); [Baillon et al., 2018](#); [Attema et al., 2019](#); [Haering et al., 2020](#)) (see Appendices 2.C.1 and 2.C.2). We also find that they are risk temperate (see Appendix 2.C.3), which is in line with [Noussair et al. \(2014\)](#) and [Heinrich and Mayrhofer \(2018\)](#), but contrasts with [Deck and Schlesinger \(2014\)](#) and [Baillon et al. \(2018\)](#) who find risk intemperance, and [Attema et al. \(2019\)](#) who do not observe a significant deviation from neutrality for temperance.

¹²In Appendix 2.D, we present the results concerning mixed attitudes to analyze the link between the various orders of ambiguity aversion and risk aversion.

lotteries 16 to 20 for the left panel and 31 to 35 for the right panel. The observed distribution of ambiguity averse choices is significantly different from what would be observed if subjects chose randomly (χ^2 test, p – value < 0.001) for both panels.

The left panel of Figure 2.4.1 shows that subjects behave neutrally towards ambiguity when the probability is associated with the good state of nature. On average, subjects choose the ambiguity averse option 2.5 out of 5 times, which is not significantly different from what would be observed if they chose randomly (p – value = 0.620).¹³

Contrary to the findings supporting risk aversion presented in Appendix 2.C.1, subjects are neutral towards ambiguity aversion. However, ambiguity neutral preferences disappear once we discard task 19, in which most of the subjects (138 out of 209) preferred the ambiguity seeking option, when the probability of winning was in the interval $[0, 2/3]$. In line with previous literature [Trautmann and Van De Kuilen \(2015\)](#), this finding corroborates that subjects are ambiguity seeking when facing lower likelihoods. Figure 2.4.2 presents the distribution of ambiguity averse choices after excluding task 19. As shown in this figure, subjects are ambiguity averse. On average, subjects choose the ambiguity averse option 2.2 out of 4 times, which is significantly different from random choices (p – value = 0.024).¹⁴ Evidence in favor of ambiguity aversion has been broadly reported in the literature (see [Oechssler and Roomets, 2015](#), for a review).

The right panel of Figure 2.4.1 shows that subjects are ambiguity averse when the probability capturing ambiguity is associated with the bad state of nature. On average, subjects chose the ambiguity averse option 2.8 out of 5

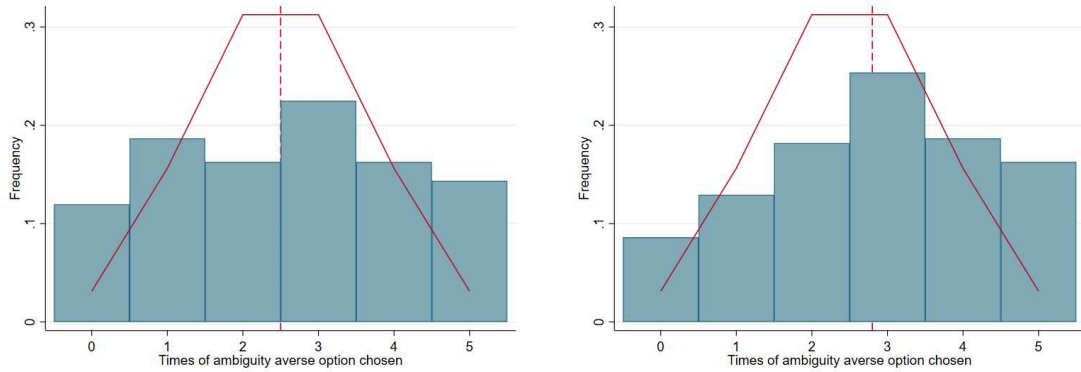
¹³All Wilcoxon signed-rank tests are based on the number of times subjects chose the averse/prudent/temperate option compared to 2.5.

¹⁴Here again, the resulting distribution of ambiguity averse choices is significantly different from what would be observed if subjects chose randomly (χ^2 test, p – value < 0.001).

times, which is significantly higher than what would be observed if subjects made random choices ($p - value = 0.003$). Findings of ambiguity aversion when a random probability is associated with the bad state of nature are consistent with the theoretical results of Section 2.2.

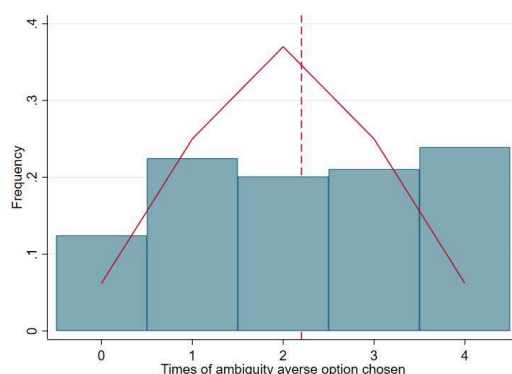
Comparing the left and right panels, we observe that including a probability associated with the good or bad state of nature, affects ambiguity aversion preferences. Precisely, a probability associated with the bad state of nature increases ambiguity aversion. Such increase in ambiguity aversion is significant ($p - value = 0.014$).

Figure 2.4.1: Distribution of ambiguity averse choices



Note: Decisions over lotteries 16-20 with probability associated with the good state of nature (left), decisions over lotteries 31-35 with probability associated with the bad state of nature (right). The solid line indicates the frequency with which a given number of choices would be expected to occur if subjects choose randomly. The dashed line indicates the average of times subjects chose the ambiguity averse option.

Figure 2.4.2: Distribution of ambiguity averse choices excluding lottery 19



Note: Decisions over lotteries 16, 17, 18, and 20 with probability associated with the good state of nature. The solid line indicates the frequency with which a given number of choices would be expected to occur if subjects choose randomly. The dashed line indicates the average of times subjects chose the ambiguity averse option.

2.4.2 Ambiguity of order 3: Prudence

For order 3, there are typically three possible types of comparisons. First, as for orders 2 and 4, it is possible to compare choices when the hazard capturing ambiguity is presented as two harms and introduced on the good *versus* bad state of nature (section 2.4.2.1). Second, it is possible to compare choices when the hazard capturing ambiguity is presented as one harm and one favor and once introduced on the good state or once introduced in the bad state of nature (section 2.4.2.2).

2.4.2.1 Good state *versus* bad state

Figure 2.4.3 presents the distribution of ambiguity prudent choices when the hazard capturing ambiguity is introduced on the good state of nature as in [Baillon et al. \(2018\)](#) (left panel) and when it is introduced on the bad state of

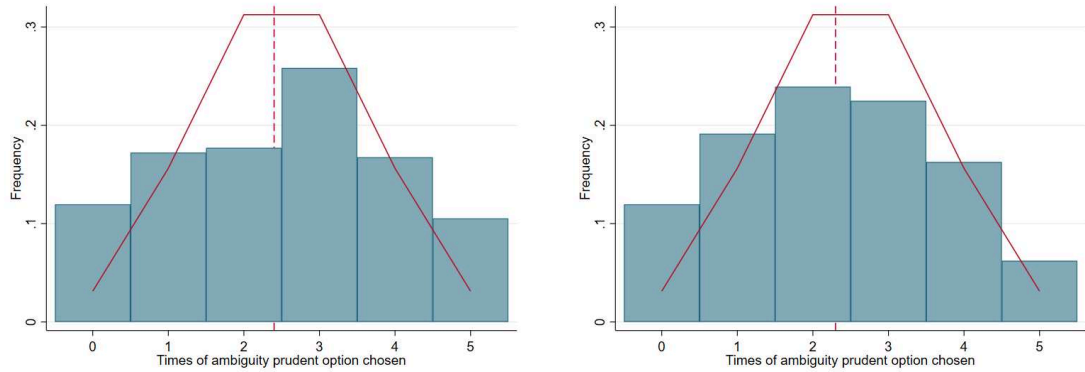
nature (right panel). The observed distribution of ambiguity averse choices is significantly different from what would be observed if subjects chose randomly (χ^2 test, p -value < 0.001) for both panels.

The left panel of Figure 2.4.3 exhibits a neutral behavior towards ambiguity prudence, which means that subjects seem ambiguity neutral at order 3 when the hazard capturing ambiguity is introduced on the good state of nature. On average, subjects chose the ambiguity prudent option 2.4 out of 5 times, which is not significantly different from what would be observed if they chose randomly (p -value = 0.955). These results differ from the notable risk prudent behavior presented in Appendix 2.C.2 and are different from the findings of ambiguity prudence reported by [Baillon et al. \(2018\)](#).

However, the right panel of Figure 2.4.3 shows that when the probability capturing ambiguity is associated with the bad state of nature, subjects are ambiguity imprudent. On average, subjects chose the ambiguity prudent option 2.3 out of 5 times, which is significantly different from what would be observed if he chose randomly (p -value = 0.059).

Comparing the left and right panels, we observe that ambiguity prudence behavior varies depending on whether the probability capturing ambiguity is associated with the good or bad state of nature. Specifically, subjects become ambiguity imprudent when the probability is on the bad state (p -value = 0.057).

Figure 2.4.3: Distribution of ambiguity prudent choices



Note: Decisions over lotteries 21-25 with probability associated with the good state of nature (left), decisions over lotteries 36-40 with probability associated with the bad state of nature (right). The solid line indicates the frequency with which a given number of choices would be expected to occur if subjects choose randomly. The dashed line indicates the average of times subjects chose the ambiguity prudent option.

Imprudence means that subjects prefer to aggregate the harms (which is the same as saying that statistically they prefer $[0, +k + \tilde{\epsilon}]$ to $[+k, \tilde{\epsilon}]$), that is the lottery that dominates in the sense of Ekern at order 3. This result seems surprising. In the case where the news concern the bad state of nature, we may think that subjects prefer to regroup them. When news are communicated differently, do subjects always prefer to group them together? This is the subject of the next section where we test how communicating news under ambiguity as is done under risk (with $-k$ and $+\tilde{\epsilon}$), that is in the form of one favor and one harm, affects preferences. A preference for regrouping the news will coincide with a preference for disaggregating harms. This amounts to considering a comparison somewhat similar to the comparison made under risk between the gain (benefit) and loss domains.

2.4.2.2 Communication about news: two harms *versus* one harm and one favor

Figure 2.4.4 presents the distribution of ambiguity choices at order 3 when the random variable capturing ambiguity is presented as one harm and one favor¹⁵ on the bad state (right panel) and on the good state (left panel). The observed distribution of ambiguity prudent choices is significantly different from what would be observed if subjects chose randomly (χ^2 test, p -value < 0.001) for both panels.¹⁶

The right panel of Figure 2.4.4 shows that subjects are ambiguity prudent. On average, subjects choose the ambiguity prudent option 2.8 out of 5 times, which is significantly higher than what would be observed if subjects chose randomly (p -value < 0.001). Ambiguity prudence means that subjects prefer to regroup news that coincide to a preference for disaggregating the two harms (they prefer $[0, k + \tilde{\epsilon}]$ to $[k, \tilde{\epsilon}]$).

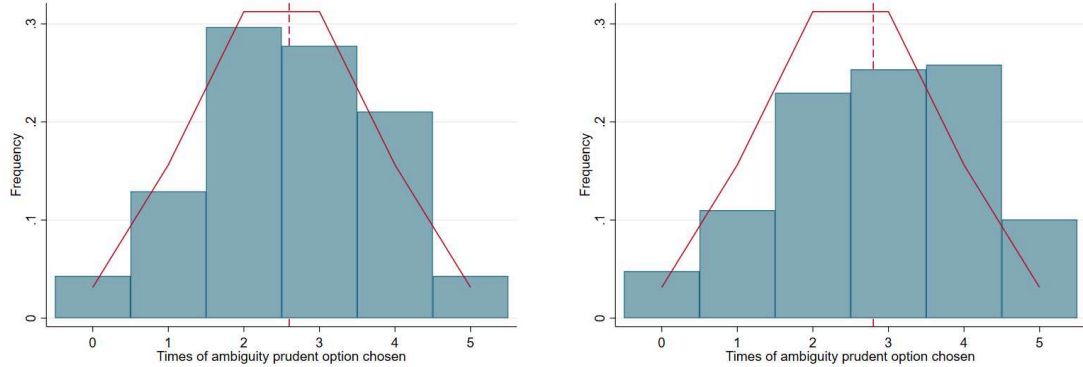
The left panel of Figure 2.4.4 shows that subjects behave neutral towards ambiguity prudence when the random variable capturing ambiguity is presented as one harm and one favor. On average, subjects chose the ambiguity prudent option 2.6 out of 5 times, which is not significantly different from what would be observed if he chose randomly (p -value = 0.156). Overall, there is a significant difference between the distribution of the left and right panels (p -value = 0.018).¹⁷

¹⁵We did not test ambiguity aversion using one harm and one favor since doing so would have lengthen an already long-lasting experiment.

¹⁶Comparing lotteries 36-40 (right panel of Figure 2.4.3) to lotteries 46-50 (right panel of Figure 2.4.4), there is a significant difference between the two distributions (p -value < 0.001).

¹⁷Comparing lotteries 21-25 (left panel of Figure 2.4.3) to lotteries 51-55 (left panel of Figure 2.4.4), there is no significant difference between the two distributions (p -value = 0.345).

Figure 2.4.4: Distribution of ambiguity prudent choices with one harm and one favor



Note: Decisions over lotteries 51-55 in which ambiguity is presented as one harm and one favor on the good state of nature (left) and decisions over lotteries 46-50 in which ambiguity is presented as one harm and one favor on the bad state of nature (right). The solid line indicates the frequency with which a given number of choices would be expected to occur if subjects choose randomly. The dashed line indicates the average of times subjects chose the ambiguity prudent option.

Overall, subjects are neutral toward ambiguity prudence when the hazard capturing ambiguity is associated with the good state of nature, whatever the way news are communicated (two harms or one harm and one favor). In the case of two harms, this result stands in contrast to [Baillon et al. \(2018\)](#) and may be attributed to our specific design features. Indeed, our design shares two characteristics. First, it intended to capture ambiguity visually. Second, apportionment of news is presented in two steps: lotteries are described in an exhaustive manner (in a raw form that clearly identifies news) before being presented in a reduced form (see design Section 2.3). However, when the hazard capturing ambiguity is associated with the bad state of nature, preferences towards ambiguity prudence depend on the way the story is presented. Communication about news affects the outcome: when the random variable capturing ambiguity mixes one harm

and one favor, subjects are ambiguity prudent, while they are imprudent when the random variable capturing ambiguity consists in two harms. Note that, the hazard $\tilde{\epsilon}$ is symmetric: it takes on realization $-a$ with probability $1/2$ and $+a$ with probability $1/2$. Thus $-\tilde{\epsilon} = +\tilde{\epsilon}$. Introducing the hazard $[+k, \tilde{\epsilon}]$ on the probability associated with the bad state of nature is then equivalent to introducing the hazard $[-k, -\tilde{\epsilon}] = [-k, \tilde{\epsilon}]$ on the probability associated with the good state of nature. Theoretically, we could expect a symmetry in choice behaviors. However, the experiment shows that it is not the case: facing two harms, subjects are imprudent (bad state) versus neutral (good state) and facing one harm and one favor, they are prudent (bad state) versus neutral (good state).

2.4.3 Ambiguity of order 4: Temperance

Figure 2.4.5 displays the distribution of ambiguity temperate choices when the probability capturing ambiguity is associated with the good (left panel) and bad (right panel) state of nature.¹⁸ The observed distribution of choices is significantly different from what would be observed if subjects chose randomly (χ^2 test, p -value = 0.001) for both panels.

The left panel of Figure 2.4.5 shows ambiguity temperance neutrality when the probability capturing ambiguity is associated with the good state of nature. On average, subjects choose the ambiguity temperate alternative 2.4 out of 5 times, which is not significantly different from what would be observed if they chose randomly (p -value = 0.344). This result stands in contrast to [Baillon et al. \(2018\)](#) who find them temperate.

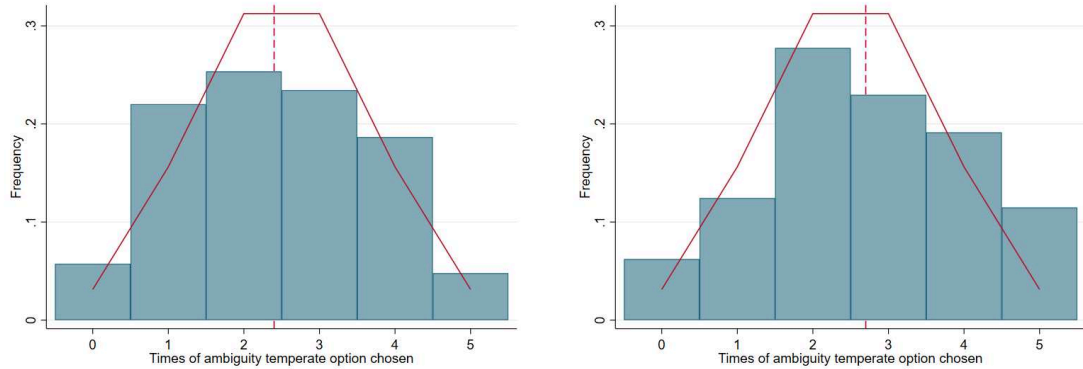
However, we find a preference for ambiguity temperance when the random probabilities are associated with the bad state of nature, as shown by the right

¹⁸Recall that for order 4, we focus on two harms only.

panel of Figure 2.4.5. On average, subjects chose the ambiguity temperate option 2.7 out of 5 times, which is significantly different from random choices ($p - value = 0.040$).¹⁹

Finally, when the probabilities are associated with the bad state of nature, subjects' preferences significantly move towards ambiguity temperance compared to the neutral behavior observed when the probabilities are associated with the good state of nature ($p - value = 0.004$).

Figure 2.4.5: Distribution of ambiguity temperate choices



Note: Decisions over lotteries 26-30 with probabilities associated with the good state of nature (left), decisions over lotteries 41-46 with probabilities associated with the bad state of nature (right). The solid line indicates the frequency with which a given number of choices would be expected to occur if subjects choose randomly. The dashed line indicates the average of times subjects chose the ambiguity temperate option.

¹⁹The observed preference for risk temperance, presented in Appendix 2.C.3, does not extend to ambiguity when ambiguities are associated with the good state of nature, but it does extend when the ambiguities are associated with the bad state of nature. One possible reason for the findings of ambiguity neutrality at order 4 when the probabilities are associated with the good state of nature and the relatively weak evidence for ambiguity temperance when probabilities are introduced on the bad state of nature, could be the level of complexity of the task. This task involves the combination of two independent random variables, which is more cognitive demanding and therefore, subjects could be more prone to errors or random choices.

2.4.4 Regression analysis

To analyze the determinants of higher order ambiguity attitudes, we run logit regressions²⁰ on choices, with a preference for Option A coded as 0 and for Option B coded as 1. The regression results can be interpreted in terms of the probability to choose the averse/prudent/temperate option according to each lottery type. Our regression models do not include a constant, i.e. all the coefficients equal to zero imply random choices. Table 2.4.1 reports the results in terms of marginal effects. Since the regressions are done on mutually exclusive categorical explanatory variables,²¹ each coefficient is the same as it would be if estimated through separate regressions. This analysis is done with two aims: *i*) Perform a robustness check of the nonparametric analysis previously presented through Model 1, and *ii*) control for one of the characteristics of the experiment (Model 2) and demographic variables (Models 3 and 4).

In Model 1, we regress choices on binary variables capturing whether these choices concern ambiguity aversion, prudence or temperance. Model 1 confirms all the results of the non-parametric analysis. Accordingly, subjects prefer the averse/prudent/temperate option in the following cases. First, for ambiguity aversion when the ambiguity parameter is associated with the bad state of nature, on average, subjects are 6.3 percentage points more likely to choose the ambiguity averse option than if they were choosing randomly. Second, for ambiguity prudence with ambiguity presented as one harm and one favor on the bad state, on average, subjects are 7.3 percentage points more likely to choose the ambiguity prudence option than if they choose randomly. Lastly, for ambiguity temperance when the ambiguity parameter is associated with the bad state of nature, on average, subjects are 4.2 percentage points more likely to

²⁰Clustering standard errors at the individual level.

²¹Each category of the mutually exclusive categorical variable represents a type of lottery. Each type of lottery corresponds to one of the eight sets of 5 choices presented in Table 2.3.1.

choose the prudent option than if they were choosing randomly. In addition, for cases of ambiguity prudence when the ambiguity parameter is associated with the bad state of nature, on average, subjects are 3.9 percentage points less likely to choose the ambiguity prudence option than if they were choosing randomly. Finally, subjects have a neutral behavior in the following cases. First, ambiguity aversion when the ambiguity parameter is associated with the good state of nature. Second, ambiguity prudence when the ambiguity parameter is associated with the good state of nature. Third, ambiguity prudence when the ambiguity parameter is presented as one harm and one favor on the good state of nature. Fifth ambiguity temperance when the ambiguity parameter is associated with the good state of nature.

In Model 2, we interact the variables of Model 1 with a variable capturing whether the ambiguous averse/prudent/temperate option is on the left side of the screen in the experiment. Subjects who saw the averse/prudent/temperate options on the left side of the screen are 5.4 percentage points more likely to choose the ambiguity averse option when the ambiguity parameter is associated with the bad state of nature than if they were choosing randomly. Although subjects who observed the averse/prudent/temperate options on the right side of the screen are only 1.7 percentage points more likely to choose the ambiguity averse option when the ambiguity parameter is associated with the bad state of nature than if they were choosing randomly, Model 2 shows that the implemented randomization of the position of the options on the screen works well: the position of the options (L or R) on the the screen does not have an influence on subjects' decisions.

Model 3 interacts the variables of Model 1 with a gender variable, in which male is coded as 1 and women is coded as 0. Female are 9.6 percentage points more likely to choose the ambiguity averse option when the ambiguity parameter

is associated with the bad state of nature than if they were choosing randomly. Although males are 5.9 percentage points less likely to choose the ambiguity averse option when the ambiguity parameter is associated with the bad state of nature than if they were choosing randomly, we do not find significant evidence of gender effect on ambiguity decisions. Previous research ([Borghans et al., 2009](#)) supports that as ambiguity increases, men and women ambiguity preferences become closer to each other.

In Model 4, we interact the variables of Model 1 with the variable field of study, which is equal to 1 if subjects study economics or finance and equal to 0 otherwise. Subjects who do not study economics or finance are 7.0 percentage points more likely to choose the ambiguity prudent option presented as one harm and one favor one the bad state of nature than if they were choosing randomly. Also, subjects who study economics or finance are significantly more likely (8.0 percentage points) to choose the ambiguity averse option when the ambiguity parameter is associated with the bad state of nature.

Finally, Model 5 includes all the variables. In this model, we confirm the effects previously described for position of the lottery, gender, and field of study. Compared to Model 1, the following variables turn insignificant. First, ambiguity aversion when the ambiguity parameter is associated with the bad state of nature. Second, ambiguity prudence when the ambiguity parameter is associated with the good state of nature. Third, ambiguity temperance when the ambiguity parameter is associated with the bad state of nature. This means that the reference category does not make choices different from what would be observed if subjects decided randomly. However, such reference category concerns a small

sample size (around 12% of the total sample size).²² Finally, we find older subjects tend to choose more the averse/prudent/temperate option.²³

²²The reference category involves females, who do not study economics or finance and who had the averse/prudent/temperance option on the right side of the screen in the experiment.

²³In Appendix 2.E, we present results regarding the correlation between ambiguity attitudes, cognitive abilities, and psychological traits. We find that higher cognitive abilities are associated with ambiguity aversion when the probability is associated with the good state of nature. Also, risk propensity tends to be negatively correlated with risk and ambiguity. Finally, high scores in prudence personality traits are associated with higher prudent behavior when the probability is associated both with the good and bad states of nature.

Table 2.4.1: Analysis of ambiguity choices with logit regressions, with and with

	Model 1		Model 2		Model 3		Model 4
	Margin	s.d.	Margin	s.d.	Margin	s.d.	
Amb. averse ⁱ	0.011	(0.022)	0.023	(0.027)	-0.026	(0.032)	-0.035
Amb. averse ⁱⁱ	0.063	(0.021)	0.096	(0.026)	0.096	(0.028)	0.026
Amb. prud. ⁱⁱⁱ	-0.000	(0.021)	0.015	(0.025)	-0.007	(0.032)	0.033
Amb. prud. ^{iv}	-0.039	(0.020)	-0.055	(0.026)	-0.024	(0.030)	-0.032
Amb. prud. ^v	0.073	(0.018)	0.066	(0.026)	0.087	(0.028)	0.070
Amb. prud. ^{vi}	0.022	(0.017)	0.022	(0.023)	0.013	(0.023)	-0.007
Amb. temp. ^{vii}	-0.017	(0.018)	0.001	(0.023)	-0.009	(0.028)	-0.035
Amb. temp. ^{viii}	0.042	(0.019)	0.034	(0.027)	0.065	(0.029)	0.023
<i>Impact of position</i>							
Amb. averse ⁱ x pos.			-0.025	(0.032)			
Amb. averse ⁱⁱ x pos.			0.017	(0.031)			
Amb. prud. ⁱⁱⁱ x pos.			-0.030	(0.030)			
Amb. prud. ^{iv} x pos.			0.032	(0.033)			
Amb. prud. ^v x pos.			0.015	(0.032)			
Amb. prud. ^{vi} x pos.			0.002	(0.031)			
Amb. temp. ^{vii} x pos.			-0.036	(0.030)			
Amb. temp. ^{viii} x pos.			0.014	(0.036)			
<i>Impact of gender</i>							
Amb. averse ⁱ x male			0.066	(0.044)			
Amb. averse ⁱⁱ x male			-0.059	(0.041)			
Amb. prud. ⁱⁱⁱ x male			0.011	(0.042)			
Amb. prud. ^{iv} x male			-0.027	(0.040)			
Amb. prud. ^v x male			-0.025	(0.037)			
Amb. prud. ^{vi} x male			0.017	(0.033)			
Amb. temp. ^{vii} x male			-0.014	(0.036)			
Amb. temp. ^{viii} x male			-0.042	(0.038)			

Table continues in the next page

	Model 1		Model 2		Model 3		Model 4	
	Margin	s.d.	Margin	s.d.	Margin	s.d.	Margin	s.d.
<i>Impact of study field</i>								
Amb. averse ⁱ x econ.							0.101 **	(0.0)
Amb. averse ⁱⁱ x econ.							0.080 *	(0.0)
Amb. prud. ⁱⁱⁱ x econ.							-0.074 *	(0.0)
Amb. prud. ^{iv} x econ.							-0.016	(0.0)
Amb. prud. ^v x econ.							0.007	(0.0)
Amb. prud. ^{vi} x econ.							0.065 **	(0.0)
Amb. temp. ^{vii} x econ.							0.040	(0.0)
Amb. temp. ^{viii} x econ.							0.041	(0.0)
χ^2	425.8***		414.28***		481.68***		480.05***	
N	11495		11495		11495		11495	

Logit regression on choices, with a preference for Option L coded as 0 and for Option R coded as 1. The results can be interpreted as the probability of choosing Option L. The variable *position* (*pos.*) is on the left side of the screen in the experiment; *economics* (*econ.*) is 1 if the subject studies economics or finance.

* $p < 0.1$

** $p < 0.05$

*** $p < 0.01$

- ⁱ Lotteries from 16 to 20 with probability associated with the good state of nature.
ⁱⁱ Lotteries from 31 to 35 with probability associated with the bad state of nature.
ⁱⁱⁱ Lotteries from 21 to 25 with probability associated with the good state of nature.
^{iv} Lotteries from 36 to 40 with probability associated with the bad state of nature.
^v Lotteries from 46 to 50 with ambiguity presented as one harm and one favor on the bad state of nature.
^{vi} Lotteries from 51 to 55 with ambiguity presented as one harm and one favor on the good state of nature.
^{vii} Lotteries from 26 to 30 with probabilities associated with the good state of nature.
^{viii} Lotteries from 41 to 45 with probabilities associated with the bad state of nature.

2.5 Conclusion

We have proposed a laboratory experiment to test higher order ambiguity attitudes (order 2, order 3, and order 4) using a simple model with two states of nature (good and bad). When the hazard capturing ambiguity is introduced on the good state of nature and in the form of two harms (which is the case considered in [Baillon et al. \(2018\)](#)), our experiment shows that subjects are neutral toward ambiguity. These results contrast with those of [Baillon et al. \(2018\)](#), suggesting that our design features may be responsible for the observed neutrality. Indeed, our design shares two characteristics. First, it intended to capture ambiguity visually. Second, apportionment of harms is presented in two steps: lotteries are described in an exhaustive manner (in a raw form that clearly identifies harms) before being presented in a reduced form.

Our experiment also shows that when the hazard capturing ambiguity is introduced differently, i.e. on the bad state of nature, results depend on the way news are communicated: facing two harms, subjects prefer to aggregate them and are thus imprudent; facing one harm and one favor, they prefer to disaggregate them and are thus prudent.

Our experiment therefore shows that the way news are communicated is not neutral. For subjects to become aware and behave averse and temperate toward ambiguity, one should communicate by presenting probability on the bad state. In the case of prudence, presenting probability in the bad state is only good in the case of one harm and one favor.

In real life, when scientific experts talk about damage (global warming, natural disasters, nuclear accidents, etc.), they communicate about the frequency of the damage, i.e. the probability associated with the bad state. In the case where the scientists' information would be presented as a sure reduction (one favor) and a hazard (one harm), our experiment suggests that it would be better

to keep this presentation by communicating about the bad state (because the experiment shows that subjects behave prudent). By contrast, in the case where the scientists' information would be presented as a sure increase (one harm) and a hazard (one harm), it would be better to rephrase this presentation in an equivalent way by telling the story on the good state of nature as follows. A sure decrease (one harm) and a hazard (one harm) (because while they are neutral in our experiment, subjects behave prudent in [Baillon et al. \(2018\)](#)).

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2.A Instructions

This appendix presents an English translation from the original instructions in French.

General instructions

This experiment involves 55 choices between two options involving amounts of money and chance. At the end of the experiment, 1 of your choices will be paid. One of you will now randomly draw a sealed envelope containing one of the choices (a number from 1 to 55).²⁴

The envelope will be opened at the end of the experiment and the option that you have chosen in that particular choice will then be resolved and paid for real. If you wish, we can verify the content of the envelope at the end of the experiment. Each choice has an equal chance to be selected. As such, it is in your best interest to make each decision as if it was the one that will be chosen. On top of this payment, you will receive a show-up fee of €5, provided that you make all choices and complete a short questionnaire at the end of the experiment.

There will be two sets of choices. In the first set, you will have 15 choices and, in the second one, there will be 40 choices. We will wait for everybody to make the first 15 choices before proceeding to the next 40 choices; you might have to wait a while before the new set of 40 choices appears on your screen. We will provide the instructions corresponding to the 15 and 40 choices at the beginning of each set. Before you start making your choices, we ask you to fill an understanding questionnaire about the tasks corresponding to each set. The 55 choices concern two options, called Option L (left) and Option R (right).

²⁴One of the subjects is randomly selected to pick one of the envelopes and sign it.

First set of 15 choices

In the first set of 15 choices, you have to decide between Option L and Option R, like in the examples²⁵ below. After providing the examples, the payment process is explained in the event that the envelope drawn and signed at the start of the session corresponds to a choice from this first series.

Example 1

As a first (fictitious) example for choices 1 to 15, let's consider the choice between the two options depicted below. The explanation related to this example are presented in the instructions on paper.

Figure 2.A.1: Image example 1



The example 1 presented on the screen, reads as follow.

For option L:

- The payoff is €10 with probability $\frac{1}{2}$;
- The payoff is €40 with probability $\frac{1}{2}$.

For option R:

The payoff is €25 for sure.

²⁵The written explanation of the examples was given in paper.

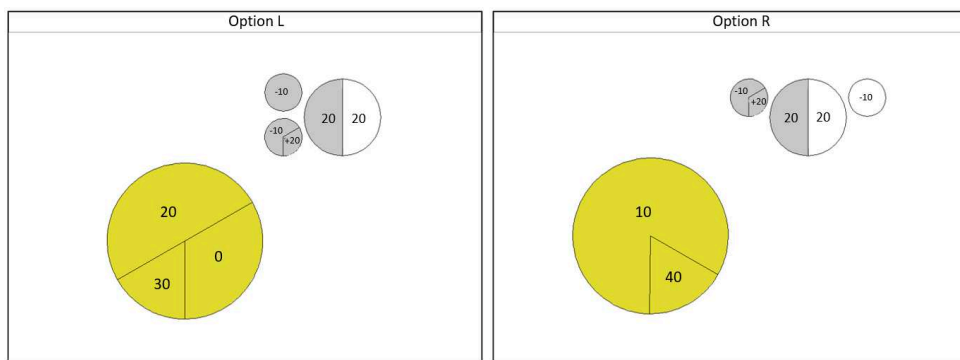
When you move the mouse over the disk on the screen, the probabilities associated with the payoffs are displayed.

Note that in each choice, the expected payoff (i.e. the amount you would earn on average if you selected the same option over a large number of times) of both options is identical. In the example, the expected payoff is 25 € for both options. However, the potential payoffs, and the chances to win these payoffs, differ between the two options.

Example 2

As a second (fictitious) example for choices 1 to 15, let's consider the choice between the two options depicted below. The explanation related to this example are presented in the instructions on paper.

Figure 2.A.2: Image example 2



The example 2 presented on the screen, reads as follow.

For option L:

Let's consider the intermediate size disk at the top right. This disk represents the initial situation:

- The payoff on the gray area is €20 with probability $\frac{1}{2}$;
- The payoff on the white area is €20 with probability $\frac{1}{2}$.

To the left of the intermediate size disk, two small gray disks represent two changes in the payoff of the gray area:

- a definite reduction of €10 (small gray disk at the top);
- and a reduction of €10 with probability $\frac{2}{3}$ and an increase of €20 with probability $\frac{1}{3}$ (small gray disk at the bottom).

No small white disk appears to the right of the white payoff of €20, which means that this payoff is not modified.

The final result of this process is described by the large yellow disk. The probability of winning €20 is $\frac{1}{2}$, the probability of winning €30 is $\frac{1}{6}$, and the probability of winning €0 is $\frac{1}{3}$.

For option R:

Let's consider the intermediate size disk at the top right. This disk represents the initial situation:

- the payoff on the gray area is €20 with probability $\frac{1}{2}$;
- the payoff on the white area is €20 with probability $\frac{1}{2}$.

To the left of the intermediate size disk, a small gray disk represents a change in the payoff of the gray area:

- a reduction of €10 with probability $\frac{2}{3}$ and an increase of €20 with probability $\frac{1}{3}$.

To the right of the intermediate size disk, a small white disk represents a change in the payoff of the white area:

- a definite reduction of €10.

The final result of this process is described by the large yellow disk. The probability of winning €10 is $\frac{5}{6}$ and the probability of winning €40 is $\frac{1}{6}$.

Remember that when you move the mouse over the large yellow disk, the probabilities associated with the payoffs are displayed.

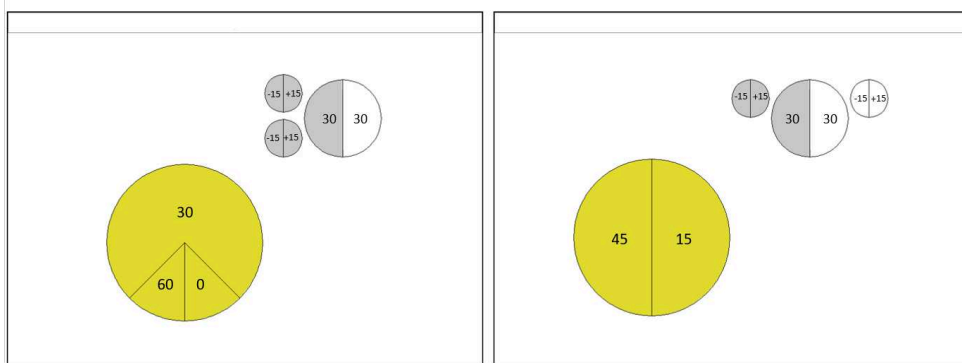
There is a waiting time for the display of the final results (large yellow disk), so that you can get a good idea of how these final results are composed.

Recall that in each choice, the expected payoff (i.e. the amount you would earn on average if you selected the same option over a large number of times) of both options is identical. In the example, the expected payoff is €15 for both options. However, the potential payoffs, and the chances to win these payoffs, differ between the two options.

Example 3

As a third and last (fictitious) example for choices 1 to 15, let's consider the choice between the two options depicted below. The explanation related to this example are presented in the instructions on paper.

Figure 2.A.3: Image example 3



The example 3 presented on the screen, reads as follows.

For option L:

Let's consider the intermediate size disk at the top right. This disk represents the initial situation:

- the payoff on the gray area is €30 with probability $\frac{1}{2}$;
- the payoff on the white area is €30 with probability $\frac{1}{2}$.

To the left of the intermediate size disk, two small gray disks represent two changes in the payoff of the gray area:

- a reduction of €15 with probability $\frac{1}{2}$ and an increase of €15 with probability $\frac{1}{2}$ (small gray disk at the top);
- and a reduction of €15 with probability $\frac{1}{2}$ and an increase of €15 with probability $\frac{1}{2}$ (small gray disk at the bottom).

No small white disc appears to the right of the white payoff of €30, which means that this payoff is not modified.

The final result of this process is described by the large yellow disk. The probability of winning €30 is $\frac{3}{4}$, the probability of winning €60 is $\frac{1}{8}$ and the probability of winning €0 is $\frac{1}{8}$.

For option R:

Let's consider the intermediate size disk at the top right. This disk represents the initial situation:

- the payoff on the gray area is €30 with probability $\frac{1}{2}$;
- the payoff on the white area is €30 with probability $\frac{1}{2}$.

To the left of the intermediate size disk, a small gray disk represents a change in the payoff of the gray area:

- a reduction of €15 with probability $\frac{1}{2}$ and an increase of €15 with probability $\frac{1}{2}$.

To the right of the intermediate size disk, a small white disk represents a change in the payoff of the white area:

- a reduction of € 15 with probability $\frac{1}{2}$ and an increase of € 15 with probability $\frac{1}{2}$.

The final result of this process is described by the large yellow disk. The probability of winning € 45 is $\frac{1}{2}$ and the probability of winning € 15 is $\frac{1}{2}$.

Remember that when you move the mouse over the large yellow disk, the probabilities associated with the payoffs are displayed.

Also, there is a waiting time for the display of the final results (large yellow disk), so that you can get a good idea of how these final results are composed.

Recall that in each choice, the expected payoff (i.e. the amount you would earn on average if you selected the same option over a large number of times) of both options is identical. In the example, the expected payoff is € 30 for both options. However, the potential payoffs, and the chances to win these payoffs, differ between the two options.

Envelopes for payoffs (set of lotteries from 1 to 15)

Let's consider again the example 3 for choices 1 to 15. We now explain the composition of the corresponding (fictitious) envelope to this choice.

As we previously explained in the screen, an envelope will be used to proceed with the payoff of the lottery. Its composition exactly follows the description of the lottery. In the case of example 3, the envelope contains the following.

Besides containing the number that identifies the lottery, the envelope contains two smaller envelopes, one for each option (L and R).

In the small envelope depicting the situation that is on the left of the screen (option L), there would be 8 tags, six indicating € 30, one indicating € 60, and 1 indicating € 0.

In the other small envelope, the one depicting the situation that is on the right of the example screen (option R), there would be 2 tags, one indicating €45, and another one indicating €15.

So, the resulting probabilities of yielding a prize (owing to the draw from the envelope) precisely correspond to those reported on the example of the screen in both options.²⁶

Second set of 40 choices

In the second set of 40 choices, you will be asked to make a choice between Option L (left) and Option R (right). For these 40 choices, there are always two types of payoffs: low payoff and high payoff. The probability of low payoff is always indicated in green, and the probability of high payoff is always indicated in blue.

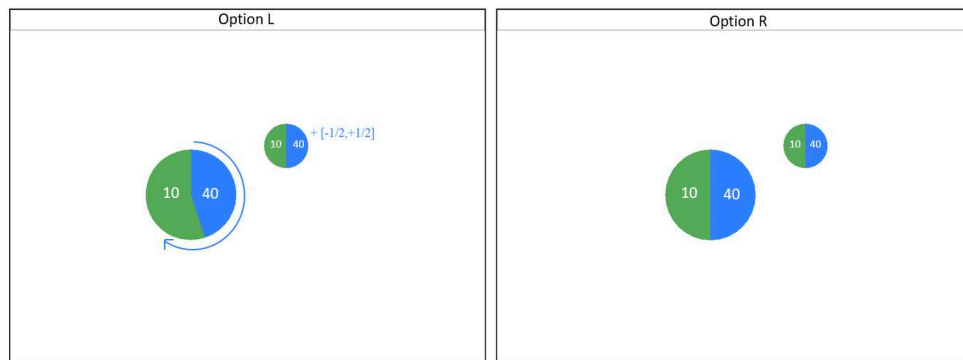
After providing the examples, the payment process is explained in the event that the envelope drawn and signed at the start of the session corresponds to a choice from this second series.

Example 1

As a first (fictitious) example for choices 16 to 55, let's consider the choice between the two options depicted below. The explanation related to this example are presented in the instructions on paper.

²⁶At the end of this part of the instructions, subjects proceed with an understanding questionnaire and perform the 15 choices corresponding to this type of lotteries.

Figure 2.A.4: Image example 1



The example 1 presented on the screen, reads as follows.

For option L:

Let's consider the small disk at the top right of the large disk. This small disk represents the initial situation:

- a low payoff (green color) of €10 with a probability $\frac{1}{2}$;
- a high payoff (blue color) of €40 with a probability $\frac{1}{2}$.

$+\left[-\frac{1}{2}, +\frac{1}{2}\right]$ means that the probability associated with the high payoff of €40, initially equal to $\frac{1}{2}$, becomes equal to $\frac{1}{2}$ (initial probability) $+\left[-\frac{1}{2}, +\frac{1}{2}\right]$;

Also, $+\left[-\frac{1}{2}, +\frac{1}{2}\right]$ means that the value that will be added to modify the initial probability of $\frac{1}{2}$ is randomly selected between $-\frac{1}{2}$ and $\frac{1}{2}$. Each value inside the interval has the same chance to be selected.

Note that $+\left[-\frac{1}{2}, +\frac{1}{2}\right]$ is displayed in blue color to clearly show that it is the probability associated with the high payoff the one modified.

The final result of this process is described on the large disk at the bottom left. The probability of winning the high payoff of €40, is between 0 and 1. The fact that there is an equal change for each of the values between 0 and 1 to be selected, is represented by the blue color continuously coloring the disk.

For option R:

Let's consider the small disk at the top right of the large disk. This small disk represents the initial situation:

- a **low payoff (green color)** of €10 with a probability $\frac{1}{2}$;
- a **high payoff (blue color)** of €40 with a probability $\frac{1}{2}$.

This initial situation is not affected. The result of the final situation, represented by the large disk, is identical to that of the initial situation.

When you move the mouse over the small disks, the initial probabilities associated with the payoffs are displayed.

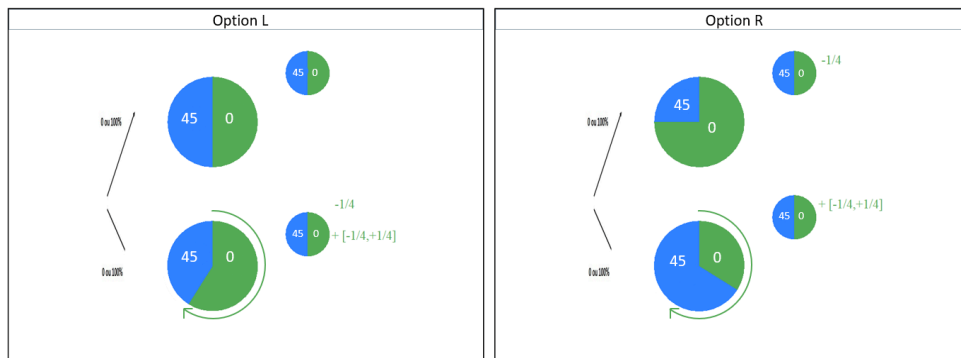
There is a waiting time for the display of the final results (large disk), so that you can get a good idea of how these final results are composed.

Note that in each choice, the expected payoff (i.e. the amount you would earn on average if you selected the same option over a large number of times) of both options is identical. In the example, the expected payoff is €25 for both options. However, the potential payoffs, and the chances to win these payoffs, differ between the options.

Example 2

As a second (fictitious) example for choices 16 to 55, let's consider the choice between the two options depicted below. The explanation related to this example are presented in the instructions on paper.

Figure 2.A.5: Image example 2



The example 2 presented on the screen, reads as follows.

For option L:

The 2 branches, 0 or 100%, mean that there is the same probability of being in the scenario described by the top branch of the screen or in the scenario described by the bottom branch of the screen.

Let's first consider the scenario described by the branch at the top of the screen. The small disk represents the initial situation:

- a low payoff (green color) of €0 with a probability $\frac{1}{2}$;
- a high payoff (blue color) of €45 with a probability of $\frac{1}{2}$.

There is not value written next to the small disk. Then, the initial situation is not affected. The initial probability of winning the low payoff of €0 remains equal to $\frac{1}{2}$. The result of the final situation, represented by the large disk, is identical to the initial situation,

Let's now consider the scenario described by the branch at the bottom of the screen.

The small disk represents the initial situation:

- a low payoff (green color) of €0 with a probability $\frac{1}{2}$;

- a high payoff (blue color) of €45 with a probability of $+\frac{1}{4}$.

$+\frac{1}{4}$ and $[-\frac{1}{4}, +\frac{1}{4}]$ mean that the probability associated with the low payoff of €0, initially equal to $\frac{1}{2}$, becomes equal to $\frac{1}{2}$ (initial probability) $+\frac{1}{4} + [-\frac{1}{4}, +\frac{1}{4}]$. The probability undergoes two modifications:

$+\frac{1}{4}$ means that the value of the initial probability is increased by $\frac{1}{4}$ with certainty;

$[-\frac{1}{4}, +\frac{1}{4}]$ means that the value that will be added to modify the initial probability of $\frac{1}{2}$ is randomly selected between $-\frac{1}{4}$ and $+\frac{1}{4}$. Each value inside of the interval has the same chance to be selected.

Note that $+\frac{1}{4}$ and $[-\frac{1}{4}, +\frac{1}{4}]$ are displayed in green color to clearly show that it is the probability associated with the low payoff that is the one modified.

The final result of this process is described on the large disk at the bottom left. The probability of winning the low payoff €0, is between $\frac{1}{2}$ and 1. The fact that there is an equal chance for each of the values between $\frac{1}{2}$ and 1 to be selected, is represented by the green color continuously coloring the disk.

For option R:

The 2 branches, 0 or 100%, mean that there is the same probability of being in the scenario described by the top branch of the screen or in the scenario described by the bottom branch of the screen.

Let's first consider the scenario described by the branch at the top of the screen. The small disk represents the initial situation:

- a low payoff (green color) of €0 with probability $\frac{1}{2}$;
- a high payoff (blue color) of €45 with probability of $\frac{1}{2}$.

$+\frac{1}{4}$ means that the probability associated with the low payoff of €0, initially equal to $\frac{1}{2}$, becomes $\frac{1}{2}$ (initial probability) $+\frac{1}{4}$.

Note that $+\frac{1}{4}$ is displayed in green color to clearly show that it is the probability associated with the low payoff the one modified.

The final result of this process is described on the large disk at the bottom left: the probability associated with the low payoff of €0 is equal to $\frac{3}{4}$.

Let's now consider the scenario described by the branch at the bottom of the screen.

The small disk represents the initial situation:

- a low payoff (green color) of €0 with probability $\frac{1}{2}$;
- a high payoff (blue color) of €45 with probability $\frac{1}{2}$.

$+\left[-\frac{1}{4}, +\frac{1}{4}\right]$ means that the probability associated with the low payoff of €0, initially equal to $\frac{1}{2}$, becomes $\frac{1}{2}$ (initial probability) $+\left[-\frac{1}{4}, +\frac{1}{4}\right]$.

Also, $\left[-\frac{1}{4}, +\frac{1}{4}\right]$ means that the value that will be added to modify the initial probability is randomly selected between $-\frac{1}{4}$ and $\frac{1}{4}$. Each value inside the interval has the same chance to be selected.

Note that $+\left[-\frac{1}{4}, +\frac{1}{4}\right]$ is displayed in green color to clearly show that it is the probability associated with the low payoff the one modified.

The final result of this process is described on the large disk at the bottom left. The probability of winning the low payoff of €0 is between $\frac{3}{4}$ and 1. The fact that there is an equal chance that each of the values between $\frac{1}{4}$ and $\frac{3}{4}$ is selected is represented by the fact that the green color is continuously coloring the disk.

Remember that when you move the mouse over the small disks, the initial probabilities associated with the payoffs are displayed.

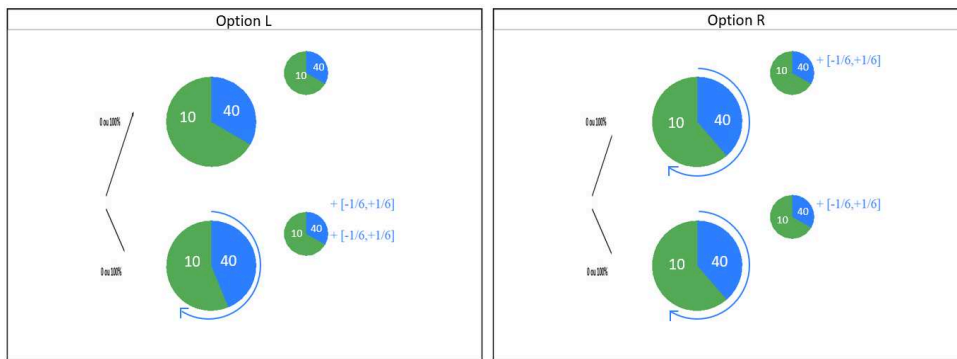
Also, there is a waiting time for the display of the final results (large disks), so that you can get a good idea of how these final results are composed.

Note that in each choice, the expected payoff (i.e. the amount you would earn on average if you selected the same option over a large number of times) of both options is identical. In this example, the expected payoff is € 16.8 for both options. However, the potential payoffs, and the chances to win these payoffs, differ between the options.

Example 3

As a third (fictitious) example for choices 16 to 55, let's consider the choice between the two options depicted below. The explanation related to this example are presented in the instructions on paper.

Figure 2.A.6: Image example 3



The example 3 presented on the screen, reads as follows.

For option L:

The 2 branches, 0 or 100%, mean that there is the same probability of being in the scenario described by the top branch of the screen or in the scenario described by the bottom branch of the screen.

Let's first consider the scenario described by the branch at the top of the screen. The small disk represents the initial situation:

- a low payoff (green color) of € 10 with probability $\frac{2}{3}$;
- a high payoff (blue color) of € 40 with probability of $\frac{1}{3}$.

There is not value written next to the small disk. Then, the initial situation is not affected. The initial probability of winning the high payoff of €40 remains equal to $\frac{1}{3}$. The result of the final situation, represented by the large disk, is identical to that of the initial situation.

Let's now consider the scenario described by the branch at the bottom of the screen.

The small disk represents the initial situation:

- a **low payoff (green color)** of €10 with probability $\frac{2}{3}$;
- a **high payoff (blue color)** of €40 with probability of $\frac{1}{3}$.

$+\left[-\frac{1}{6}, +\frac{1}{6}\right]$ and $+\left[-\frac{1}{6}, +\frac{1}{6}\right]$ mean that the probability associated with the high payoff of €40, initially equal to $\frac{1}{3}$, becomes equal to $\frac{1}{3}$ (initial probability) $+\left[-\frac{1}{6}, +\frac{1}{6}\right] + \left[-\frac{1}{6}, +\frac{1}{6}\right]$. The probability undergoes two random modifications (of the same type): $+\left[\frac{1}{6}, +\frac{1}{6}\right]$):

The first modification, coming from one of the intervals $+\left[-\frac{1}{6}, +\frac{1}{6}\right]$, means that the value that will be added to modify the initial probability of $\frac{1}{3}$, is randomly selected between $-\frac{1}{6}$ and $\frac{1}{6}$. Each value inside the interval has the same chance to be selected.

The second modification, coming from the other interval $+\left[-\frac{1}{6}, +\frac{1}{6}\right]$, means that the value that will be added to modify the probability that has become random and equal to $\left[\frac{1}{6}, +\frac{1}{2}\right]$ because of the first modification explained above, is randomly selected between $-\frac{1}{6}$ and $\frac{1}{6}$. Each value inside the interval has the same chance to be selected;

Note that $+\left[-\frac{1}{6}, +\frac{1}{6}\right]$ and $+\left[-\frac{1}{6}, +\frac{1}{6}\right]$ are displayed in blue color to clearly show that it is the probability associated with the **high payoff** that is the one modified.

The final result of this process is described on the large disk at the bottom left. The probability of winning the high payoff of €40, is between 0 and $\frac{2}{3}$. The fact that there is an equal chance for each of the values between 0 and $\frac{2}{3}$ to be selected, is represented by the blue color continuously coloring the disk.

For option R:

The 2 branches, 0 or 100%, mean that there is the same probability of being in the scenario described by the top branch of the screen or in the scenario described by the bottom branch of the screen.

Let's first consider the scenario described by the branch at the top of the screen. The small disk represents the initial situation:

- a low payoff (green color) of €10 with probability $\frac{2}{3}$;
- a high payoff (blue color) of €40 with probability of $\frac{1}{3}$.

$+\left[-\frac{1}{6}, +\frac{1}{6}\right]$ means that the probability associated with the high payoff of €40, initially equal to $\frac{1}{3}$, becomes $\frac{1}{3}$ (initial probability) $+\left[-\frac{1}{6}, +\frac{1}{6}\right]$.

Also, $+\left[-\frac{1}{6}, +\frac{1}{6}\right]$ means that the value that will be added to modify the initial probability is randomly selected between $-\frac{1}{6}$ and $\frac{1}{6}$. Each value inside the interval has the same chance to be selected.

Note that $+\left[-\frac{1}{6}, +\frac{1}{6}\right]$ is displayed in blue color to clearly show that the probability associated with the high payoff is the one modified.

The final result of this process is described on the large disk at the bottom left. The probability of winning the high payoff of €40, is between $\frac{1}{6}$ and $\frac{1}{2}$. The fact that there is an equal chance that each of the values between $\frac{1}{6}$ and $\frac{1}{2}$ is selected is represented by the blue color continuously coloring the disk.

Let's now consider the scenario described by the branch at the bottom of the screen.

It is identical to the one described by the top branch.

Remember that when you move the mouse over the small disks, the initial probabilities associated with the payoffs are displayed.

Also, there is a waiting time for the display of the final results (large disks), so that you can get a good idea of how these final results are composed.

Note that in each choice, the expected payoff (i.e. the amount you would earn on average if you selected the same option over a large number of times) of both options is identical. In this example, the expected payoff is €20 for both options. However, the potential payoffs, and the chances to win these payoffs, differ between the options.

Envelopes for payoffs (set of lotteries from 16 to 55)

Let's consider again the example 3 for choices 16 to 55. We now explain the composition of the corresponding (fictitious) envelope to this choice.

As we previously explained in the screen, an envelope will be used to proceed with the payoff of the lottery. Its composition exactly follows the description of the lottery. In the case of example 3, the envelope contains the following.

Besides containing the number that identifies the lottery, the envelope contains two smaller envelopes, one for each option (L and R).

Inside of the envelope depicting option L, there would be 2 smaller envelopes. One of these, would depict the top branch of option L and the other envelope would depict the bottom branch of option L. Each of these envelopes would contain the following.

- The envelope depicting the top branch: there would be three tags, 2 indicating €10 and 1 indicating €40.
- The envelope depicting the bottom branch: there would be five smaller envelopes, one for each probability value 0 , $\frac{1}{6}$, $\frac{2}{6}$, $\frac{3}{6}$, and $\frac{4}{6}$. Each of these five envelopes would be marked with a tag indicating the randomly drawn

probability value and have inside tags indicating the value of the payoff. For examples, if the chosen envelope is marked with a probability value $\frac{1}{6}$, there would be inside six tags, 5 tags indicating €0 and 1 tag indicating €40.

Inside the envelope depicting option R, there would be also 2 smaller envelopes. One would depict the top branch of option R and the other one would depict the bottom branch of option R. The content of each of these 2 envelopes is the following.

- The envelope depicting the top branch: there would be five smaller envelopes, one for each probability value $\frac{2}{12}$, $\frac{3}{12}$, $\frac{4}{12}$, $\frac{5}{12}$, $\frac{6}{12}$. Each of these five envelopes would be marked with a tag indicating the randomly drawn probability value and have inside tags indicating the value of the payoff. For example, if the chosen envelope is marked with a probability value $\frac{4}{12}$, which is equal to $\frac{1}{3}$, the envelope would have three tags inside, 2 tags indicating €0 and 1 tag indicating €40.
- The envelope depicting the bottom branch: the content would be identical to the one of envelope depicting the top branch.

So, the resulting probabilities of yielding a prize (owing to the draw from the envelope) precisely correspond to those reported on the example of the screen in both options.

2.B Cognitive abilities and psychological traits questionnaires

2.B.1 Cognitive Reflection Test (CRT)

We administered the original three questions CRT ([Frederick, 2005](#)). Our measure of cognitive reflection is given by the total number of correct answers (from 0 to 3).

We used the following questions taken from [Frederick \(2005\)](#):

1. A bat and a ball cost €1.10 in total. The bat costs an euro more than the ball. How much does the ball cost? [Correct answer: 5 cents; intuitive answer: 10 cents]
2. If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets? [Correct answer: 5 minutes; intuitive answer: 100 minutes]
3. In a lake, there is a patch of lily pads. Every day, the patch double in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? [Correct answer: 47 days; intuitive answer: 24 days]

2.B.2 General Risk Propensity Scale (GRiPS)

We administer the GRiPS developed and validated by [Zhang et al. \(2019\)](#). This test comprises the following statements. For each statement, subjects answered using a 5-level Likert scale from strongly disagree (1) to strongly agree (5).

1. Taking risks makes life more fun.

2. My friends would say that I'm a risk taker.
3. I enjoy taking risks in most aspects of my life.
4. I would take a risk even if it meant I might get hurt.
5. Taking risks is an important part of my life.
6. I commonly make risky decisions.
7. I am a believer of taking chances.
8. I am attracted, rather than scared, by risk.

2.B.3 Hexaco Personality Inventory test

Basic information and materials for the HEXACO Personality Inventory-Revised [Ashton and Lee \(2009\)](#), a test that assesses the six major dimensions of personality (Honesty-Humility, Emotionality, eXtraversion, Agreeableness (versus Anger), Conscientiousness, Openness to Experience) is made available by Kibeom Lee and Michael C. Ashton at <http://hexaco.org/hexaco-inventory>.

From the 100-item version of the test, we used the following four questions related to the prudence facet measured in the Conscientiousness dimension. For each statement, subjects answered using a 5-level Likert scale from strongly disagree (1) to strongly agree (5).

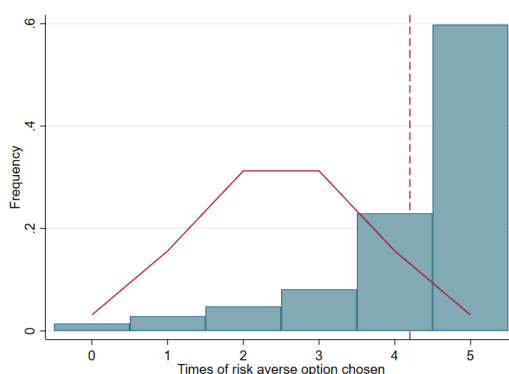
1. I make decisions based on the feeling of the moment rather than on careful thought.
2. I make a lot of mistakes because I don't think before I act.
3. I don't allow my impulses to govern my behavior.
4. I prefer to do whatever comes to mind, rather than stick to a plan.

2.C Results for risk

2.C.1 Order 2: Aversion

Figure 2.C.1 presents the distribution of risk averse choices subjects made in the experiment. In line with previous literature (see [Eeckhoudt and Loubergé, 2012](#), for a review), subjects are risk averse. On average, subjects choose the risk averse option 4.2 out of 5 times, which is significantly different from the average that would be observed if subjects chose randomly (p -value < 0.001).²⁷ Additionally, the observed distribution of risk averse choices is significantly different from what would be observed if subjects chose randomly (χ^2 test, p -value < 0.001).

Figure 2.C.1: Number of times the risk averse option is chosen



Note: individual decisions of choices over lotteries from 1 to 5. The solid line indicates the frequency with which a given number of choices would be expected to occur if subjects choose randomly. The dashed line indicates the average of times subjects chose the risk averse option.

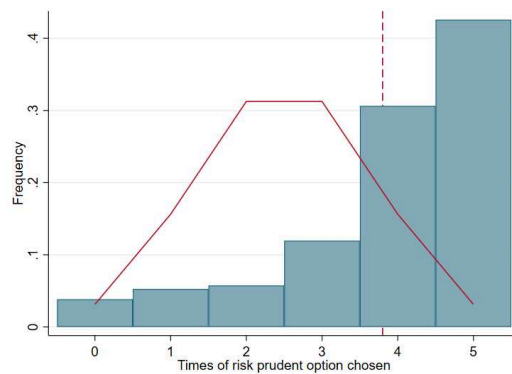
2.C.2 Order 3: Prudence

The distribution of risk prudent choices made by the subjects in the experiment is presented in Figure 2.C.2. In line with previous research ([Deck and Schlesinger](#),

²⁷All Wilcoxon signed-rank tests are based on the number of times subjects chose the averse/prudent/temperate option compared to 2.5.

2014; Baillon et al., 2018; Attema et al., 2019; Haering et al., 2020), we find that subjects are risk prudent. On average, subjects choose the risk prudent option 3.8 out of 5 times, which is significantly different from the average that would be observed if subjects chose randomly (p – value < 0.001). In addition, the observed distribution of risk prudent choices is significantly different from what would be observed if subjects chose randomly (χ^2 test, p – value < 0.001).

Figure 2.C.2: Number of times the risk prudent option is chosen



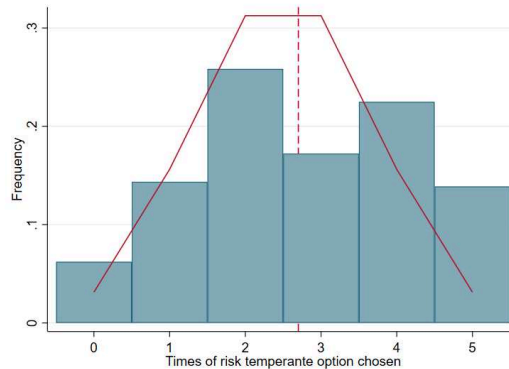
Note: individual decisions of choices over lotteries from 6 to 10. The solid line indicates the frequency with which a given number of choices would be expected to occur if subjects choose randomly. The dashed line indicates the average of times subjects chose the risk prudent option.

2.C.3 Order 4: Temperance

Figure 2.C.3 displays the distribution of risk temperate choices. As the figure shows, we observe risk temperance. On average, subjects chose the risk temperate option 2.7 out of 5 times, which is significantly above the average that would be observed if subjects make random choices (p – value = 0.010). Also, the observed distribution of risk temperate choices is significantly different from what would be observed if subjects chose randomly (χ^2 test, p – value < 0.001). Previous

evidence regarding risk temperance is mixed. Our results are in line with [Heinrich and Mayrhofer \(2018\)](#) who find evidence for risk temperance. Contrary, [Deck and Schlesinger \(2014\)](#) and [Baillon et al. \(2018\)](#) find risk intemperance.

Figure 2.C.3: Number of times the risk temperate option is chosen



Note: individual decisions of choices over lotteries from 11 to 15. The solid line indicates the frequency with which a given number of choices would be expected to occur if subjects choose randomly. The dashed line indicates the average of times subjects chose the risk temperate option.

2.D Mixed attitudes

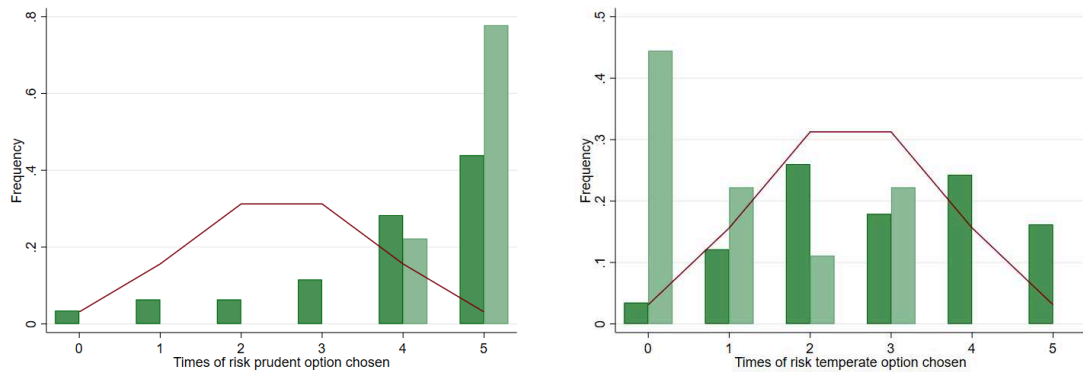
To test predictions regarding the link between the various orders of risk aversion and ambiguity aversion, we analyze the choices of risk and ambiguity averters and risk and ambiguity seekers separately. Following [Baillon et al. \(2018\)](#), we classify as risk and ambiguity averters (seekers) subjects who choose the averse option 4 or 5 (0 or 1) out of 5 times. Under this classification, we find that 9 subjects are risk seekers and 173 are risk averters. We created two sub-groups for ambiguity preferences. In the first one, we classify subjects based on their ambiguity preferences when the probability is associated with the good state of nature. For this case, 64 subjects are ambiguity averse and 64 are ambiguity

seeking. The second sub-group is determined based on ambiguity preferences when the probability is on the bad state of nature. In this subgroup, 73 subjects are ambiguity averters and 45 are ambiguity seekers.

The left panel of Figure 2.D.1 shows the distribution of risk prudent choices made by risk averters (dark bars) and risk seekers (light bars). In line with previous findings (Baillon et al., 2018; Deck and Schlesinger, 2014), risk averters are significantly prudent (p -value < 0.001). On the other hand, contrary to this previous evidence, risk seekers are also significantly prudent (p -value = 0.005). The right panel of Figure 2.D.1 shows that risk seekers are significantly risk intemperate (p -value = 0.026), which corroborates the findings of Baillon et al. (2018). However, we find that risk averters have a preference for temperance (p -value < 0.001).

We provide further evidence of mixed attitudes, by analyzing the correlation of individual behavior between choice tasks of different orders. We find that risk aversion is positively correlated with risk temperance (Spearman $\rho = 0.25$; p -value < 0.001), as well as risk prudence with risk temperance (Spearman $\rho = 0.25$; p -value < 0.001), which corroborates the findings of Baillon et al. (2018). On the other hand, the correlation between risk aversion and risk prudence is not significant (Spearman $\rho = 0.02$; p -value = 0.712).

Figure 2.D.1: Distribution of risk prudent and temperate choices by risk type



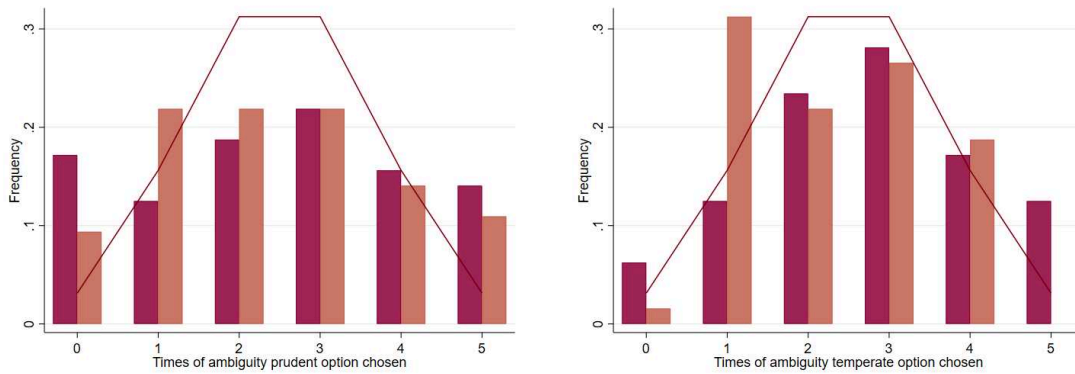
Risk prudent choices over lotteries 6-10 (left) and risk temperate choices over lotteries 11-15 (right). Dark (lights) bars represent risk averters (seekers). *Note:* the solid line indicates the frequency with which a given number of choices would be expected to occur if subjects choose randomly.

Figures 2.D.2 and 2.D.3 display the choices made by ambiguity averters (dark bars) and ambiguity seekers (light bars). The classification of ambiguity type is based on subjects' ambiguity preferences when the probability is on the good state of nature.²⁸ The left panel of Figure 2.D.2 shows that both ambiguity averters and seekers are neutral towards ambiguity prudence with probability associated with the good state of nature ($p - value = 0.970$) and ($p - value = 0.629$), respectively. As shown in the right panel of Figure 2.D.2, ambiguity averters tend to make more temperate choices than ambiguity seekers when the probabilities are associated with the good state of nature. However, ambiguity averters' decisions are not significantly different from random choices ($p - value = 0.157$), as well as choices done by ambiguity seekers ($p - value = 0.172$). These results are partially in line with the ones provided by [Baillon et al. \(2018\)](#), who also find that ambiguity-seekers are neutral towards prudence and temperance.

²⁸Ambiguity preferences when probability is associated with the good state are recovered from subjects' decisions regarding the choice tasks of lotteries from 16 to 20.

Analysis of individual choices between tasks of different orders reveals that there is a positive correlation between ambiguity aversion and temperance (Spearman $\rho = 0.13$; p -value = 0.048) and ambiguity prudence and temperance (Spearman $\rho = 0.17$; p -value = 0.009). The correlation between ambiguity aversion and prudence is not significant (Spearman $\rho = 0.27$; p -value = 0.688).

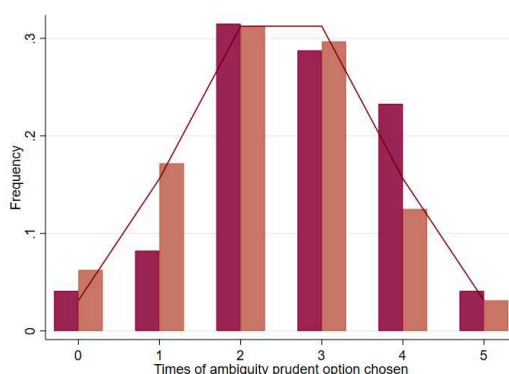
Figure 2.D.2: Distribution of ambiguity prudent and temperate choices by ambiguity type



Ambiguity prudent choices over lotteries 21-25 (left) and ambiguity temperate choices over lotteries 26-30 (right). Dark (light) bars represent ambiguity averters (seekers). *Note:* the solid line indicates the frequency with which a given number of choices would be expected to occur if subjects choose randomly.

Figure 2.D.3 shows the distribution of prudent choices with ambiguity presented as one harm and one favor on the good state of nature by prudent type. Dark (light) bars represent the ambiguity averters (seekers) subjects. Ambiguity-averters are significantly prudent (p -value = 0.034). Although ambiguity-seekers tend to choose more the imprudent option, their choices are not significantly different from random decisions (p -value = 0.316). The correlation between ambiguity aversion and prudence is not significant (Spearman $\rho = 0.12$; p -value = 0.077).

Figure 2.D.3: Distribution of ambiguity prudent choices by ambiguity type



Ambiguity prudent choices over lotteries 51-55. Dark (light) bars represent ambiguity averters (seekers). *Note:* the solid line indicates the frequency with which a given number of choices would be expected to occur if subjects choose randomly.

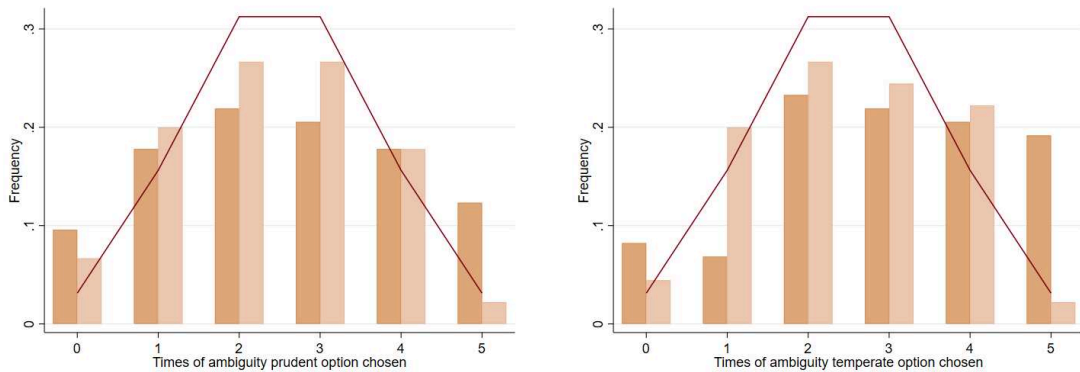
Figures 2.D.4 and 2.D.5 show the distribution of prudent choices with probability associated with the bad state of nature, and temperate choices with probabilities associated with the bad state of nature made by ambiguity-averters (dark bars) and ambiguity-seekers (light bars). Subjects were classified based on their ambiguity preferences when the probability is associated with the bad state of nature.²⁹ The left panel of Figure 2.D.4 shows that although ambiguity-seekers tend to choose less times the imprudent option than ambiguity-averters, both ambiguity averters and seekers are ambiguity prudent neutral (p -value = 0.747) and (p -value = 0.487), respectively. As the right panel of Figure 2.D.4 shows, ambiguity-averters are ambiguity temperate (p -value = 0.009), while ambiguity seekers are neutral towards ambiguity temperance (p -value = 0.894).

The analysis between task of different orders, shows that ambiguity aversion and temperance with probabilities associated with the bad state of nature are positively correlated (Spearman $\rho = 0.16$; p -value = 0.020), as well as ambiguity

²⁹Ambiguity preferences when probability is associated with the bad state are recovered from subjects' decisions regarding the choice tasks of lotteries from 31 to 35.

prudence and temperance (Spearman $\rho = 0.26$; p -value < 0.001). On the other hand, the correlation between ambiguity aversion and prudence with probability associated with the bad state of nature is not significant (Spearman $\rho = 0.06$; p -value $= 0.331$).

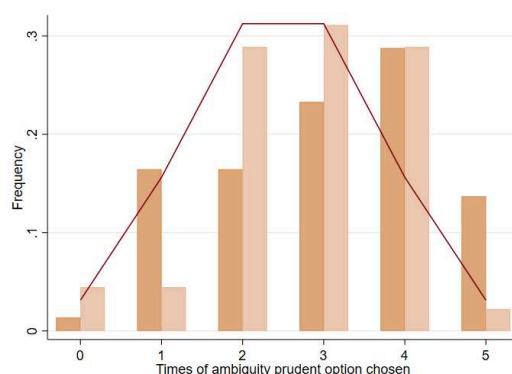
Figure 2.D.4: Distribution of ambiguity prudent and temperate choices by ambiguity type



Ambiguity prudent choices over lotteries 36-40 (left) and ambiguity temperate choices over lotteries 41-45 (right). Dark (light) bars represent ambiguity averters (seekers). *Note:* the solid line indicates the frequency with which a given number of choices would be expected to occur if subjects choose randomly.

Figure 2.D.5 displays the distribution of prudent choices with ambiguity presented as one harm and one favor on the bad state of nature by ambiguity type. Ambiguity averters (seekers) are represented by dark (light) bars. Ambiguity-averters are significantly prudent (p -value $= 0.002$). Ambiguity-seekers also have a preference for prudent options. However, their choices are not significantly different from random choices (p -value $= 0.388$). Finally, ambiguity aversion is not significantly correlated with prudence (Spearman $\rho = 0.07$; p -value $= 0.265$).

Figure 2.D.5: Distribution of ambiguity prudent choices by ambiguity type



Ambiguity prudent choices over lotteries 46-50. Dark (light) bars represent ambiguity averters (seekers). *Note:* the solid line indicates the frequency with which a given number of choices would be expected to occur if subjects choose randomly.

2.E Ambiguity attitudes, cognitive abilities, and psychological traits

To study the effect of cognitive abilities and psychological traits on higher order ambiguity attitudes, we run logit regressions.³⁰ We follow the same approach as the one done for the regression analysis presented in Section 2.4.4. As such, preference for Option A is coded as 0 and for Option B is coded as 1. The results of these regressions represent the probability to choose the averse/prudent/temperate option. We report the results in terms of marginal effects in Table 2.E.1.

We measure cognitive abilities through the Cognitive Reflection Test (CRT), which evaluates the ability to reflect on a question and resist reporting the first response that comes to mind (Frederick, 2005). In Model 7, we interact the

³⁰Clustering standard errors at the individual level. The regression models do not include a constant (i.e., all the coefficients equal to zero imply random choices).

variables of Model 1 (see section 2.4.4)³¹ with a proxy of cognitive abilities, which is a variable representing the number of correct answers (from 0 to 3) provided in the CRT test. We find that subjects with higher scores in the CRT are more ambiguity averse when the probability is associated with the good state of nature.

We estimate risk propensity throughout the General Risk Propensity Scale (GRiPS). The GRiPS measures individual's general propensity for risk taking, rather than risk taking in specific domains (e.g., recreation or health) (Zhang et al., 2019). Model 8 presents the interaction between Model 1 and *risk*, which is a continuous variable that captures the level of risk propensity. We find that individuals scoring high levels of risk propensity are less likely to make the following choices. First, risk averse and risk temperate choices. Second, the ambiguity averse choice when the probability is associated both with the good and bad state of nature. Third, choose the ambiguity prudent option with probability associated with the bad state of nature. Fourth, chose the ambiguity prudence alternative with ambiguity presented as one harm and one favor on the good state of nature. Finally, select the ambiguity temperate option when probabilities associated with the bad state of nature.

To estimate prudence propensity, we implement the questions related to the prudence facet from the 100-items from the Hexaco Personality Inventory test Ashton and Lee (2009). This prudence scale assesses a tendency to deliberate and to inhibit impulses. Individuals who score low tend to act on impulse and not to consider consequences, whereas individuals with high scores consider their options carefully and tend to be cautious and self-controlled. In Model 9, we interact Model 1 with the scores of prudence propensity. We find that subjects

³¹Results regarding risk lotteries are excluded from the Model 1 presented in Section 2.4.4. Nevertheless, results remain the same because the regressions are done on mutually exclusive categorical explanatory variables. Hence, each coefficient is the same as it would be by finding it through separate regressions.

with high prudence scores are more likely to chose the ambiguity prudent option with probability associated both with the good and bad states of nature.

Finally, Model 10 includes all the variables in Table 2.E.1. We confirm the effect previously described for the CRT. Also, all the effects of risk propensity remain, except the significant result for the probability of choosing the ambiguity prudent option with probability associated with the bad state of nature. Regarding the impact of prudence propensity, the interaction between prudence propensity and choosing the risk averse option becomes significant, and the effect of prudence propensity on the probability of choosing the ambiguity prudent option with probability associated with the good state of nature becomes insignificant.

Table 2.E.1: Analysis of choices with logit regressions, with cognitive abilities and psy variables

	Model 7		Model 8		Model 9	
	Margin	s.d.	Margin	s.d.	Margin	s.d.
Risk averse ⁱ	0.357 ***	(0.016)	0.372 ***	(0.014)	0.357 ***	(0.015)
Risk prud. ⁱⁱ	0.276 ***	(0.019)	0.276 ***	(0.019)	0.277 ***	(0.019)
Risk temp. ⁱⁱⁱ	0.054 ***	(0.020)	0.055 ***	(0.020)	0.054 ***	(0.020)
Amb. averse ^{iv}	0.011	(0.022)	0.011	(0.022)	0.011	(0.022)
Amb. averse ^v	0.063 ***	(0.021)	0.063 ***	(0.021)	0.063 ***	(0.021)
Amb. prud. ^{vi}	-0.000	(0.021)	-0.000	(0.021)	-0.000	(0.021)
Amb. prud. ^{vii}	-0.039 **	(0.020)	-0.039 **	(0.020)	-0.039 **	(0.020)
Amb. prud. ^{viii}	0.073 ***	(0.018)	0.073 ***	(0.018)	0.073 ***	(0.018)
Amb. prud. ^{ix}	0.023	(0.017)	0.023	(0.016)	0.023	(0.017)
Amb. temp. ^x	-0.017	(0.018)	-0.017	(0.018)	-0.017	(0.018)
Amb. temp. ^{xi}	0.042 **	(0.019)	0.042 **	(0.019)	0.042 **	(0.019)
<i>Impact of CRT</i>						
Risk averse ⁱ x CRT	-0.018	(0.017)				
Risk prud. ⁱⁱ x CRT	-0.011	(0.018)				
Risk temp. ⁱⁱⁱ x CRT	-0.029	(0.019)				
Amb. averse ^{iv} x CRT	0.055 ***	(0.018)				
Amb. averse ^v x CRT	-0.023	(0.018)				
Amb. prud. ^{vi} x CRT	0.027	(0.019)				
Amb. prud. ^{vii} x CRT	0.022	(0.018)				
Amb. prud. ^{viii} x CRT	0.020	(0.017)				
Amb. prud. ^{ix} x CRT	0.021	(0.016)				
Amb. temp. ^x x CRT	0.025	(0.017)				
Amb. temp. ^{xi} x CRT	0.016	(0.018)				
<i>Impact of risk propensity</i>						
Risk averse ⁱ x risk			-0.101 ***	(0.021)		
Risk prud. ⁱⁱ x risk			0.013	(0.025)		
Risk temp. ⁱⁱⁱ x risk			-0.086 ***	(0.027)		
Amb. averse ^{iv} x risk			-0.064 **	(0.029)		
Amb. averse ^v x risk			-0.042 *	(0.024)		
Amb. prud. ^{vi} x risk			-0.043	(0.031)		
Amb. prud. ^{vii} x risk			-0.049 *	(0.027)		
Amb. prud. ^{viii} x risk			-0.030	(0.026)		
Amb. prud. ^{ix} x risk			-0.052 **	(0.023)		
Amb. temp. ^x x risk			-0.006	(0.025)		
Amb. temp. ^{xi} x risk			-0.053 **	(0.023)		

Table continues in the next page

	Model 7	Model 8	Model 9
	Margin	Margin	Margin
	s.d.	s.d.	s.d.
<i>Impact of prudence propensity</i>			
Risk averse ⁱ x prud.			-0.028 (0.022)
Risk prud. ⁱⁱ x prud.			0.027 (0.025)
Risk temp. ⁱⁱⁱ x prud.			-0.022 (0.027)
Amb. averse ^{iv} x prud.			-0.009 (0.028)
Amb. averse ^v x prud.			-0.008 (0.025)
Amb. prud. ^{vi} x prud.			0.047 * (0.027)
Amb. prud. ^{vii} x prud.			0.064 ** (0.025)
Amb. prud. ^{viii} x prud.			0.018 (0.025)
Amb. prud. ^{ix} x prud.			0.018 (0.020)
Amb. temp. ^x x prud.			-0.009 (0.024)
Amb. temp. ^{xi} x prud.			0.031 (0.025)

χ^2	444.33***	438.21***	430.10***
N	11495	11495	11495

Logit regression on choices, with a preference for Option L coded as 0 and for Option R coded as 1. The res probability to choose the averse/prudent/temperate option. There is no constant, i.e., all coefficients equal to zero variables *risk* and *prudence* (*prud.*) represent risk and prudence propensity, respectively. The variable CRT is provided in this test.

* $p < 0.1$

** $p < 0.05$

*** $p < 0.01$

* $p < 0.1$

** $p < 0.05$

*** $p < 0.01$

ⁱ Lotteries from 1 to 5 of risk aversion.

ⁱⁱ Lotteries from 6 to 10 of risk aversion.

ⁱⁱⁱ Lotteries from 11 to 15 of risk temperance.

^{iv} Lotteries from 16 to 20 with probability associated with the good state of nature.

^v Lotteries from 31 to 35 with probability associated with the bad state of nature.

^{vi} Lotteries from 21 to 25 with probability associated with the good state of nature.

^{vii} Lotteries from 36 to 40 with probability associated with the bad state of nature.

^{viii} Lotteries from 46 to 50 with ambiguity presented as one harm and one favor on the bad state of nature.

^{ix} Lotteries from 51 to 55 with ambiguity presented as one harm and one favor on the good state of nature.

^x Lotteries from 26 to 30 with probabilities associated with the good state of nature.

^{xi} Lotteries from 41 to 45 with probabilities associated with the bad state of nature.

Chapter 3

Trading and Cognition in Asset Markets: An Eye-tracking Experiment

This chapter is based on a paper co-authored with Camille Cornand and Adam Zylbersztejn.

Abstract

We use an experimental asset market with eye-tracker measurements for a novel exploration of the cognitive validity of a classic heterogeneous trader taxonomy. Following a top-down approach, we assume that the patterns of attention and information acquisition are governed by one of the three trading strategies, either feedback, passive, or speculative. In line with our first hypothesis, speculators seek information about market expectations. Notwithstanding the two other hypotheses, feedback traders reveal patterns of attention and information acquisition that could *ex ante* be expected from passive traders, and *vice versa*.

Keywords: Experiments, asset markets, attention, information acquisition, eye-tracking.

3.1 Introduction

Expectations are critical for asset price dynamics. To formalize the expectation-formation process in an internally consistent manner, standard economic theory posits that agents form Rational Expectations (RE). Although appealing from the theoretical perspective, this approach has found little support in experimental evidence (see [Arifovic and Duffy, 2018](#), for a survey). The failure of RE has led to the development of a variety of expectation-formation heuristics as a descriptive attempt to rationalize behavioral data. Relying on [De Long et al. \(1990\)](#), [Haruvy and Noussair \(2006\)](#) classify traders according to three types – feedback, passive and speculators – in an asset market experiment studying the effect of short sales on both the incidence and magnitude of market bubbles. These three trader types apply strategies requiring different sources of information: either past, present or future market outcomes. Feedback trader’s decisions are based on the momentum: their demand for assets increases when prices rise.¹ Passive traders account for fundamental values: they buy (sell) when prices are below (above) fundamentals. Finally, speculator traders base their decisions on the expected price fluctuations in near future: they purchase more when there is an expected increase in prices.² In this study, we use an experimental asset market with eye-tracker measurements to explore the cognitive underpinnings of this classic behavioral taxonomy. We are interested in assessing the degree of consistency between the observed behavior and the patterns of attention and information acquisition.

¹Decision-making errors made by feedback traders foster market bubbles ([Lei et al., 2001](#)).

²The presence of speculator traders is in line with the hypothesis of the lack of common knowledge of expectations ([Smith, 1994](#)).

Previous research has shown that ways in which individuals sample and process information predict subsequent decisions.³ The broad use of the eye-tracking technique across domains has proven its adequacy to investigate different cognitive aspects in decision-making processes (see [Rahal and Fiedler, 2019](#), for a review). In economics, this technique has been employed in studies of strategic interactions in games (e.g. [Knoepfle et al., 2009](#); [Devetag et al., 2016](#); [Polonio and Coricelli, 2019](#); [Marchiori et al., 2021](#)) as well as financial decision-making (e.g. [Gödker and Lukas, 2021](#); [Bose et al., 2022](#)). However, the eye-tracking technique is barely applied in market settings. To our knowledge, [Powell \(2010\)](#) offers the only asset market experiment with eye-tracking. While he provides evidence that the information sought by subjects predicts trading behavior, his design falls short of linking the observed trading behavior to the type-specific patterns of information seeking.⁴ We conduct an asset market experiment in which we analyze trading and forecasts decisions to classify subjects as one of the three trade types (feedback, passive, and speculators) and evaluate the patterns of attention and information acquisition by monitoring cognition through eye-tracking.

We find limited support for the existence of a relationship between trading strategies and the patterns of attention and information acquisition. Our experimental data suggests that, in line with our initial hypothesis, speculators base their decisions on the incoming information about market expectations. Notwithstanding the two other hypotheses we formulated, feedback traders

³For example, gaze direction during the search process can predict choices in moral dilemmas ([Pärnamets et al., 2015](#)). Patterns of attention have also been used to study food choices (e.g. [Krajbich et al., 2010](#); [Towal et al., 2013](#)). [Krajbich et al. \(2012\)](#) show that attention dedicated to looking at a product rather than its price is predictive of purchasing decisions.

⁴Our study differs from his in several ways. First, his market is a continuous double auction while ours is a call market. Thus, we have a single market price per period (whenever a clearing price exists). Second, unlike us, he does not elicit market expectations and does not provide visual information allowing to discriminate speculators from the two other types.

reveal patterns of attention and information acquisition that could *ex ante* be expected from passive traders, and *vice versa*.

The remainder of the chapter is organized as follows. Section 3.2 presents our empirical strategy and research hypotheses. Section 3.3 describes the design of our experiment. In Section 3.4, we outline the main results. Section 3.5 concludes.

3.2 Empirical strategy

Our empirical strategy is based on two implicit assumptions. First, we assume that each participant to our experiment represents one of the three trader types which can be identified from the observed decisions. Second, the strategy underlying each trader type governs the patterns of attention resulting in a top-down information acquisition process.

3.2.1 Behavioral measurements

We classify traders using the standard taxonomy proposed by [Haruvy and Noussair \(2006\)](#). There are three types of traders – feedback, passive, and speculator – characterized by a demand function in period t :

- *feedback trader*: $constant + \beta(p_{t-1} - p_{t-2})$, where p_{t-1} and p_{t-2} are the average transaction prices in periods $t - 1$ and $t - 2$;
- *passive trader*: $constant - \alpha(p_{t-1} - fv_{t-1})$, where fv is the fundamental value;
- *speculator trader*: $constant + \gamma\mathbb{E}(p_{t+1} - p_t)$;

where $\alpha \geq 0$, $\beta \geq 0$, and $\gamma \geq 0$. Although different from [Haruvy and Noussair \(2006\)](#), our classification method remains descriptive.⁵ Each demand function yields a (constrained) linear regression model which can be estimated from the experimental data. For each subject, we estimate three regression models, compare their goodness of fit (R^2) and assign the type associated with the best-fitting model.

3.2.2 Eye-tracker measurement of attention

The literature on attention distinguishes between two coexisting processes underlying visual information acquisition: top-down and bottom-up. [Coricelli et al. \(2020\)](#) note that the fact that *attention can be mediated by bottom-up or top-down mechanisms has important implications for the interpretation of the process data because an observed information search pattern may be the result of a predetermined information search strategy (top-down analysis) or mainly determined by some features of the visual scene (bottom-up analysis)*. (p. 77). As mentioned in the opening paragraph of this section, herein we focus on the top-down processes. Although we cannot fully rule out the parallel presence of bottom-up factors, our design is aimed at minimizing their potential role through a standardized and balanced screen free of attractors or focal points (see [Figure 3.3.1](#)).⁶

⁵Their method can be summarized as follows (p. 1143): *[e]ach subject receives a score with respect to each of the three types, with the score for each type equal to the number of periods in which subject's behavior is consistent with that type. A subject is classified as the type that receives the highest score, provided that the score is greater than 8 [out of 15], and as "other" otherwise. Ties are broken by assigning the corresponding fraction to each type. In addition, [t]he proportion classified as "other" is randomly assigned to the three behavioral types with probabilities equal to their proportions in the population.* Our comparison, in turn, is based on a goodness-of-fit criterion thus ruling out the problem of ties and thus providing an unambiguous outcome in principle (unless all models have null capacity to explain the data).

⁶On the same page, [Coricelli et al. \(2020\)](#) note that *[i]n eye-tracking experiments, the characteristics of the task and of the decision maker may significantly affect how attention*

We use the SR-Research EyeLink 1000 Plus eye-tracking system, a high-accuracy video-based eye-tracker with binocular sampling rate of up to 2000 Hz. Following standard protocols, the eye-to-monitor distance is 1.8 times the display width.⁷ For the sake of the quality of eye-movement data, all eye-tracked participants use a chinrest and a forehead rest throughout the experimental session. In addition, we perform two calibrations during the experimental session: one before the beginning of the training task, and another one in the middle of the experiment. Our analysis of the eye-tracking data uses a standard metric: fixations location and their duration. During fixations the eyes extract information from the visual scene for further processing. We consider fixations lasting for at least 50 milliseconds to calculate dwell times, i.e. the overall duration of all the fixations falling into a given Area of Interest (AOI).⁸ The Areas of Interest (AOIs) on the screen, in turn, are determined using the aforementioned trader typology. AOIs relate to backward-looking information consisting in realized prices (echoing feedback trader's demand function), current information consisting in fundamental values (echoing passive trader's demand function), and forward-looking information consisting in market expectations of price evolution (echoing speculative trader's demand function). Each AOI has a rectangular shape with an area of 20800 pixels. AOIs never overlap and all the fixations that are not located inside of the AOIs are discarded for the analysis. Note that the set of AOIs expands as the experimental asset market unfolds over periods (see the next section for details).

is allocated in a visual scene. For example, a bottom-up analysis may be promoted by the presence of attractors or focal points [...].

⁷For eye-tracking setup standard protocol, see [EyeLink \(2013\)](#).

⁸Dwell times have been previously used to study eye-movement in both strategic interactions (e.g. [Halevy and Chou, 2014](#); [Polonio et al., 2015](#); [Peshkovskaya et al., 2017](#)) and individual decisions (e.g. [Engelmann et al., 2021](#)).

3.2.3 Hypotheses

While entering the demand function of all the three types of traders, the past prices constitute the unique determinant of the feedback type's decisions. This leads us to formulating our first hypothesis:

Hypothesis 1: Compared to other types, feedback traders devote more attention to the information about past prices.

Second, fundamental values only enter the demand function of the passive traders, making this information particularly relevant for this type:

Hypothesis 2: Compared to other types, passive traders devote more attention to the information about fundamental values.

Finally, an analogous intuition applies to a speculator's use of the information about market expectations:

Hypothesis 3: Compared to other types, speculators devote more attention to the information about the market expectations on price evolution.

3.3 Experimental design

We recruited 186 students to participate in 31 computerized (zTree, [Fischbacher, 2007](#)) experimental sessions conducted at the GATE-Lab in Lyon.⁹ Each session involves 6 participants: 5 that are seated in a regular cubicle, and one that is seated in a separate eye-tracker room. The usual duration is around 2h (which includes the experimental instructions and the post-experimental questionnaires).

⁹This project has been approved by the GATE-Lab Review Board for ethical standards in research, under the reference number 2020-09. The design and behavioral conjectures have been preregistered at AsPredicted (#106714).

The average age is 21 years, 32.25% of our participants are female. The average payoff is 29 EUR (including the 5 EUR show-up fee).

An experimental session unfolds as follows. First, one subject (among those not wearing glasses or contact lenses) is randomly assigned for eye-tracking. Then, everyone is seated in front of their computers and instructions are given to the subjects and read aloud which is followed by a series of comprehension questions.¹⁰ The experiment does not continue unless every participant managed to correctly answer every comprehension question. We then launch a practice market for four periods to familiarize the participants with trading decisions and the market environment. We provide feedback after each period, yet this part is not considered for the final earnings (which is common knowledge).

The main part of the experiment consists of two independent markets (that only differ in terms of calibration, as summarized in Table 3.3.1), each lasting for 8 periods.¹¹ As illustrated in Figure 3.3.1, the number of periods we use is also compatible with the requirements of the eye-tracking technology: it allows us to construct distinguishable and non-overlapping AOIs.

At the beginning of each market, all subjects receive the same initial endowment in terms of *i*) assets holdings and *ii*) cash to spend in Experimental Currency Units (ECU).¹² We implement a call market environment, as in [Van Boening et al. \(1993\)](#), [Haruvy et al. \(2007\)](#), [Akiyama et al. \(2017\)](#), and [Hanaki et al. \(2018\)](#). In a call market, all buying and selling orders are submitted simultaneously, aggregated into the market demand and supply curves that determine the

¹⁰The complete instructions can be found in Appendix 3.A.

¹¹As previously observed by [Hanaki et al. \(2018\)](#), prices in market experiments tend to converge to the asset's fundamental value as traders gain experience over periods. To avoid such convergence (which would make the behaviors from the later market periods highly homogeneous and thus hardly exploitable for our purposes) and increase the number of observation per subject, we opted for having two short and distinct (yet related) markets. Market 2 was calibrated to ensure enough similarities with Market 1 for making reasonable comparisons of decisions across markets.

¹²The exchange rate is such that 1 ECU = 0.015 euros.

Table 3.3.1: Summary of parameters in Markets 1 and 2.

	Market 1	Market 2
Dividend distribution	$\{0, 8, 28, 60\}$	$\{0, 1, 8, 28, 98\}$
Expected dividend	24	27
Fundamental value in period t	$24 \times (8 - t)$	$27 \times (8 - t)$
Initial number of assets	4	3
Initial cash in ECU	1040	1190

market clearing price (provided that they intersect). The market is cleared at a uniform price for all transactions of each period.

The calibration of Market 1 has been directly adopted from “design 4” in the seminal study of [Smith et al. \(1988\)](#). At the end of each period and independently for each asset, the computer randomly picks one of the four equiprobable dividend values: 0, 8, 28, 60 ECU. Thus, the expected dividend in any period is equal to 24 ECU. Dividends are the only source of value for the asset. Therefore, the fundamental value of an asset during period t is equal to the expected future dividend stream ($24 \times (8 - t)$) ECU. The initial cash endowment in this market is 1040 ECU.

Then, Market 2 is reparameterized in terms of the dividends: the distribution now contains five possible values (0, 1, 8, 28, and 98 ECU), so that in a given period t the expected dividend equals 27 ECU and the fundamental value of is given by $27 \times (8 - t)$ ECU. Subjects receive an initial cash endowment of 1190 ECU.

Each period consists of two tasks (and distinct sources of profit): *i*) forecasting market prices and *ii*) asset trading. For each task, profits are aggregated over all market periods; for trading, this includes the earnings from both asset trading and asset dividends. These profits are not transferred between Market 1 and Market 2. Following [Hanaki et al. \(2018\)](#), subjects are paid based on either their trading or forecasting performance: the final payoff at the end of the experiment

is randomly determined by the computer and corresponds to a single source of earnings (either price forecasting or asset trading) in one of the two markets.¹³

In the forecast task happening in the first stage of every period (except for the final period 8), subjects are asked to provide their forecast regarding two market prices: the price realized in the second stage of the present period and the price realized in the following period. For instance, in the beginning of period 1 subjects are first asked to indicate their forecast for the market price in period 1 and the market price in period 2. Since the market ends after eight periods, in period 8 subjects only indicate their forecast for the final period. If the forecast lies within a fixed interval of ± 25 around the actual realized price, the subject earns 250 ECU, so that the maximum earning from a total of 15 forecasts (two per period in periods 1-7 and one in period 8) amounts to $250 \times 15 = 3750$ ECU.

The asset trading task constitutes the second stage of every period during which each subject has the opportunity to submit one buy order and one sell order on the market. A buy order consists in providing the maximum price at which the subject is willing to buy and the maximum number of assets she wishes to buy at that price. A sell order consists in indicating the minimum price at which she is willing to sell and the number of assets she wishes to sell at such price.

¹³Hanaki et al. (2018) show that this payment method does not induce mispricing, as opposed to the alternative of paying subjects for both trading and forecasting performance.

Figure 3.3.1: Experimental screen for stage 2 and AOIs

Period	Realized price	Fundamental value
1	151	192
2		168
3		144
4		120
5		96
6		72
7		48
8		24

Profit from predictions: 250
 Profit from transactions: 0
 Profit from dividends: 32

Your ECU: 1072
 Your assets: 4

Distribution of dividends: (0, 8, 28, 60)
 Last realized dividend: 8

Highest price at which to buy
 Number of units to buy

Lowest price at which
 Number of units

Note. Example of the decision-making screen in period 2 translated from French to English. For the sake of clarity, the AOIs are highlighted by red rectangles.

Subjects do not observe other traders' orders before the end of every period. Once all subjects submit their orders, the computer calculates the market price. The market price is defined as the lowest price at which there is an equal number of assets offered for buying and selling, or the lowest price at which there is a greater number of assets offered for selling than for buying. Subjects who submit a buy (sell) order at a price equal to or above (equal to or below) the market price purchase (sell) assets. If there are any ties between accepted buy or sell orders, the computer randomly selects those that trade.

While deciding about their buying and selling orders, subjects have access to different bits of information displayed on the screen (see Figure 3.3.1):

- feedback information about the previous periods: *i)* realized prices, *ii)* aggregate earning from the two sources of profit, and *iii)* last realized dividend;
- fundamental values of assets;
- median price forecasts made by the six market participants.

Such design of the information structure enables us to operationalize the empirical strategy laid out in Section 3.2: previously realized prices are the sole determinant of feedback trader's behavior, passive trader also takes into account the fundamental value, while a speculator only cares about market expectations on price evolution which is proxied by the median price forecast.¹⁴

¹⁴We are grateful to Brice Corgnet and Charles Noussair for suggesting the use of median forecast as a proxy of market expectations. This approach also follows the recent learning-to-forecast literature (e.g., [Petersen and Kryvtsov, 2021](#); [Arifovic and Petersen, 2017](#)) in the sense that making use of median rather than average forecasts minimizes the ability of a single participant to manipulate aggregate expectations. We also note that this approach does not lack external validity. There are different publicly available surveys that provide median expectations to market participants (such as the Survey of Professional Forecasters for inflation expectations that provides median forecasts).

To avoid data contamination due to a possible center bias (Tseng et al., 2009) or bottom-left/top-right biases (Hagenbeek and Van Strien, 2002), the position of the columns containing the “realized prices”, “fundamental values”, and “median forecasts” was randomized between-subjects. Subjects introduce their trading choices at the bottom of the screen.

Finally, before leaving the lab, subjects perform the standard 3-item Cognitive Reflection Test (CRT, Frederick, 2005) and fill in a short socio-demographic questionnaire.¹⁵

3.4 Results

In what follows, we first conduct the behavioral classification of traders based on the decisions observed in the experimental asset market. Second, following our Hypotheses 1-3, we measure the relationship between these trading strategies and the patterns of attention revealed through the eye-tracking data. Overall, we find limited empirical support for our research hypotheses: the data corroborate only Hypothesis 3 according to which speculators base their decisions on the incoming information about market expectations.

3.4.1 Behavioral classification of traders

The left-hand side of Table 3.4.1 presents the results of our classification exercise for the final sample of 182 subjects.¹⁶ The decisions of 46.45%, 28.96%, 16.94%, and 7.65% of traders are best described as feedback, passive, speculators, and

¹⁵In Appendix 3.B we show that there is no systematic association between trader types and cognitive abilities (measured by the CRT score) or socio-demographic characteristics. Furthermore, in Appendix 3.C, we report the systematic association between patterns of attention and these two sets of individual characteristics.

¹⁶Out of the initial sample of 186 subjects, three were removed as they abstained from over the course of the experiment. Another subject was removed from the analyses due to the incompleteness of the eye-tracking data.

“other”, respectively.¹⁷ Altogether, the outcomes of our classification exercise are close to those reported in [Haruvy and Noussair \(2006\)](#).

The right-hand side of Table 3.4.1 breaks down these data into two categories: the non-eye-tracked and the eye-tracked individuals. Fisher’s exact test suggests that the two samples are not different ($p - value = 0.795$) meaning that the randomization procedure of the assignment to the eye-tracking condition has been successful and the behavior of eye-tracked subjects is representative of the larger population of traders in the experiment. In the remainder of this section we focus on the sub-sample of eye-tracked participants who were using the eye-tracker device while performing the experiment.

Table 3.4.1: Trader type classification

Trader type	Entire sample	Not eye-tracked	Eye-tracked
Feedback	84 (46.15%)	69 (45.39%)	15 (50%)
Passive	53 (29.12%)	43 (28.29%)	10 (33.33%)
Speculator	31 (17.03%)	27 (17.76%)	4 (13.33%)
Other	14 (7.69%)	13 (8.55%)	1 (3.33%)
Total	182 (100%)	153 (100%)	30 (100%)

3.4.2 Trader types and patterns of attention

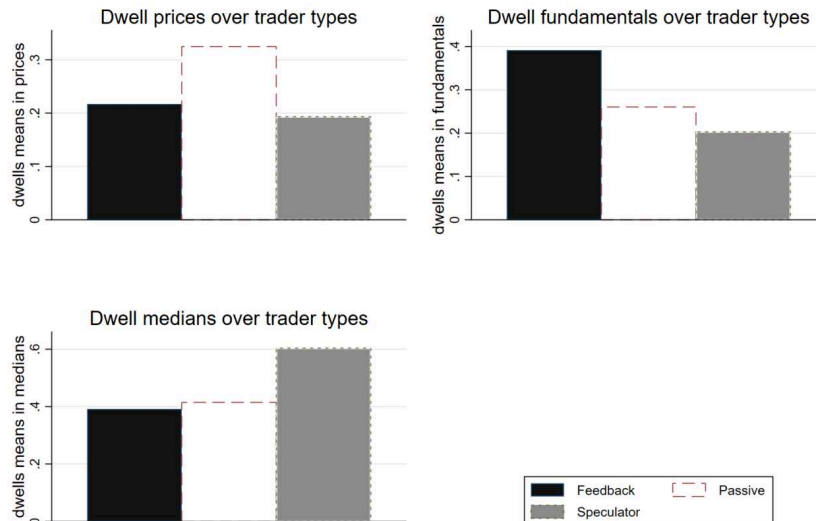
We use dwell times to measure the patterns of attention. Following [Polonio and Coricelli \(2019\)](#) we ignore fixations located outside the AOIs and transform absolute dwell times into relative ones, i.e the share of time spent looking at a given AOI out of the total time spent looking at all the AOIs on the screen.

¹⁷“Other” corresponds to a null R^2 coefficient in each of three models discussed in Section 3.2. For other categories, let us note that the demand function of feedback traders in period t depends on the average realized price in periods $t - 1$ and $t - 2$. Since realized prices of periods $t - 1$ and $t - 2$ are only available after period 3, we discard periods 1 and 2 from this analysis. Furthermore, a speculator’s demand relies on the market expectation of price evolution. Since period 8 is the last period of the market, we do not use it in the classification exercise. As a result, for each participant we have a total of 10 periods (5 per market). Regression models control for the (average) period and market fixed effects.

In addition, we aggregate these relative dwell times corresponding to each of the three information sets presented on the screen: realized prices, fundamental values and median forecasts. We then perform the analysis of patterns of attention based on the three main sets of information along with their relative dwell times.

Figure 3.4.1 gives an overview of the mean relative dwell times for each set of information across trader types. We interpret this descriptive evidence as pointing to differences in the patterns of attention which, however, do not mesh well with our initial hypotheses. On average, passive traders spend more time than others looking at the realized prices, while feedback traders devote more attention to the fundamental values (notwithstanding Hypotheses 1 and 2). Speculators, in turn, show the highest interest in inspecting median forecasts (in line with Hypothesis 3).

Figure 3.4.1: Mean relative dwell times in AOIs over trader types



For complementary nonparametric tests, we turn to the medians of relative dwell times summarized in the upper part of Table 3.4.2. Figures in bold

Table 3.4.2: Trader types and patterns of attention

	Prices	Fundamentals	Median forecasts
	Median dwell time		
Feedback	0.204	0.343	0.364
Passive	0.311	0.303	0.434
Speculators	0.200	0.216	0.610
	<i>p</i> – values		
Feedback vs. passive	0.036	0.046	
Feedback vs. speculators	0.727		0.037
Passive vs. speculators		0.532	0.074

Note. Median dwell times in bold correspond to the hypothesized dominant source of information of each trader type.

correspond to the hypothesized dominant source of information of each trader type. The bottom part of Table 3.4.2 shows the results from between-subject comparisons based on the two-sided Wilcoxon ranksum test.¹⁸

Notwithstanding Hypothesis 1, the median relative dwelling time for realized prices is significantly shorter in feedback than in passive traders (p – value = 0.036) and not significantly different as compared to speculators (p – value = 0.727).

The results of nonparametric tests also contradict Hypothesis 2. Passive traders pay less attention to the fundamentals than feedback traders (p – value = 0.046), and do not differ significantly in this regard from speculator traders (p – value = 0.532).

Solely Hypothesis 3 finds full empirical support both in descriptive and statistical terms: speculator traders spend substantially more time looking at

¹⁸We note that within-subject comparisons are also possible, yet less informative for our analyzes. The reason for which we avoid these comparisons is that the number of AOIs is not constant across our variables of interest (i.e., realized prices, fundamentals and median forecasts) and evolves over periods, as can be seen in Figure 3.3.1. Thus, relative dwell times may vary within-subject in a purely mechanical manner: independently of their subjective strategic relevance and the level of attention they attract, exploring some sources of information simply require inspecting more AOIs (and thus is more time-consuming) than others.

the median forecasts than both feedback ($p - value = 0.037$) and passive traders ($p - value = 0.074$).¹⁹

3.5 Conclusion

Our study provides a first piece of empirical evidence on (and limited support for) the cognitive validity of the classic heterogeneous trader classification due to [De Long et al. \(1990\)](#); [Haruvy and Noussair \(2006\)](#). We see these results as a promising starting point for future research.

Our experimental design is embedded in a predefined behavioral taxonomy of traders and focuses on the top-down processes in which trading strategy governs attention and information acquisition. Future designs could go beyond these two paradigms. First, they could allow for richer structures of heterogeneity in strategies, including multiple types and switching heuristics. Such enriched taxonomy has been shown to perform well in describing the patterns of belief formation in markets (see, e.g., [Hommes, 2021](#); [Bulutay et al., 2022](#)). Relatedly, the reason for the discrepancy between the hypothesized and the observed decisions may not be purely behavioral (e.g., due to the substantial heterogeneity in trading strategies, the role of trembles, or the presence of heuristic switching), but also cognitive: strategies may be also governed by the bottom-up processes in attention and information acquisition. Addressing these points is a challenge for future experimental designs.

¹⁹Although the magnitude of these differences is meaningful on its own, we note that these comparisons may suffer from low statistical power given that only 4 in 30 eye-tracked subjects are classified as speculators. As shown in [Table 3.4.1](#), speculators constitute the rarest type, accounting for 17% of all traders. Taking these figures at face value, increasing the number of eye-tracked speculators in the dataset is extremely resource-intensive. In expectancy, increasing the sub-sample of eye-tracked speculators by one observation would require running more than 5 additional experimental sessions of 6 subjects.

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3.A Instructions

This appendix presents an English translation from the original instructions in French.

General instructions

In this experiment, you will participate in a market where you trade units of a fictitious asset with the other 5 participants of the experiment.

The experiment consists of two rounds, each round represents a different market. Each market consists of 8 periods. In each period you have the opportunity to predict the market price for such period and to trade in the market (i.e., to buy and sell). Specific instructions for your predictions and trading tasks will be provided later in the instructions.

You will receive 5 euros, provided that you make all the choices and complete a short questionnaire at the end of the experiment. You can earn extra money depending on the accuracy of your predictions and your trading decisions. Your objective in this experiment is to make as much profit as you can.

You will see two different screens in each period. In the first screen, you will introduce your predictions for the market price. In the second screen you will be able to trade your assets in the market, you can also obtain dividends for the assets you hold in each period (earnings from dividends are included in the trading profit). You will have two separate sources of profit: predictions and trading. The total profit from each source is the sum of **all your earnings along the 8 periods of each market**. However, **your profit does not transfer across markets**, meaning that at the end of the experiment, you will have 4 different possible payoffs (i.e., 2 profits from predictions and 2 profits from trading), each of the predictions and trading profits correspond to your decisions in the 2 markets.

Your final payoff is determined as follows. At the end of the experiment, the computer will first select randomly one of the markets, with equal probability for each market being selected. Then, the computer will select either the sum of your predictions' profit along the 8 periods within the selected market or the sum of your trading profit (which includes profit from dividends) along the 8 periods within the selected market, once again with equal chance of being selected. As such, it is in your best interest to make each decision as if it was the one that will be chosen.

Payoffs for your decisions will be expressed in experimental currency units (ECU). Please note that each ECU is equal to 0.015 euros.

Earning profit from predictions

You can earn money by **predicting the market price of the current and the next period**. Later in the instructions, we present a detailed explanation of how the market price is determined. For now, we just explain to you how you can make profit from predictions.

Before starting to trade your assets, you will be asked to predict the market price of the same period and one period ahead. If your prediction lies within a fixed interval of ± 25 around the actual realized market price, you earn 250 ECU. Note that in the last period (period 8), you will be asked to predict only the price for such period.

Example:

For example, suppose you are in period 2. You predict that the market price is going to be 90 ECU in the current period (period 2) and 120 ECU in the next period (period 3). Assume that after all the transactions the market price in

period 2 realized as 100 ECU and the market price in period 3 realized as 180 ECU.

You will earn 250 ECU for your prediction regarding period 2 and 0 ECU for your prediction regarding period 3. For period 2, any prediction between 75 and 125 leads to earnings. For period 3, any prediction between 155 and 205 leads to earnings. The maximum earning from predictions you can accumulate during a market is thus $250 \times 15 = 3750$ ECU.

Experimental interface

Figure 3.A.1: First screen of each period



The screenshot shows a light gray rectangular window. At the top center, the text reads: "Please introduce below your predictions of the market price for the current period and the next period." Below this text, there are two horizontal input fields. The first field is preceded by the text "Your market price prediction for the current period" and the second by "Your market price prediction for the next period". Both fields are currently empty. In the bottom right corner of the window, there is a red rectangular button with the white text "OK".

Figure 3.A.1 illustrates the interface of the first screen of each period. In this stage, your task is to predict the market price of the current period and the next period, according to the rules stated in the instructions previously presented. Remember that in the last period (period 8), you will be asked to predict only the price for such period. Please click on the button OK to confirm

your prediction. You can only submit once.

Earning profit from trading

Trading assets generates two sums of profit: one from buying and selling in the market and another one from dividends.

How to buy and sell assets

At the beginning of every market, you receive an endowment of a number of assets and ECU. You can use this endowment to trade in the market. Every trader begins this market with the identical endowment. To earn profit from trading, you need to buy assets at a lower price and sell these at a higher price.

For example, suppose you buy an asset for 100 ECU, and then the price of the asset increases to 120 ECU. If you sell the asset, you will earn 120 (selling price) - 100 (purchase price) = 20 ECU profit. In contrast, suppose you buy an asset for 100 ECU, and then the price of the asset decreases to 80 ECU. If you sell the asset, you will make 80 (selling price) - 100 (purchase price) = 20 ECU loss.

If you want to buy assets, you need to submit the highest price at which you are willing to buy one asset and the maximum number of assets you wish to buy. This is called a buy order.

If you want to sell assets, you need to submit the lowest price at which you are willing to sell one asset and the maximum number of assets you wish to sell. This is called a sell order.

In practice, the price you actually pay for an asset may be lower than the maximum price you are willing to pay. This is because the market price is set based on all the orders placed by market participants. If the market price

is greater than the maximum you are willing to pay, your order will not be processed.

The orders of all traders will be aggregated in the end of every period to determine the single price for all assets in each period. There are two ways to determine the market price. The implemented way to determine the market price depends on the buy/sell orders done by all the participants. We will explain each of these ways separately.

First way to determine the market price

The market price is the lowest price at which there is an equal number of assets offered for buying and selling.

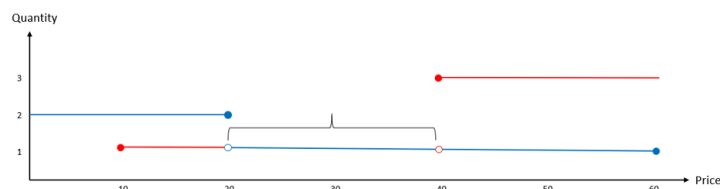
We illustrate how the market price is set through this first way by using the following example.

Consider the following buy/sell orders placed by four traders:

- Trader 1: One sell order, which can be executed at 10 ECU or higher
- Trader 2: Two sell orders, which can be executed at 40 ECU or higher
- Trader 3: One buy order, which can be executed at 60 ECU or lower
- Trader 4: One buy order, which can be executed at 20 ECU or lower

Figure 3.A.2 summarizes these orders.

Figure 3.A.2: Graphical example first way to determine the market price



Blue lines represent the quantity demanded and red lines represent the quantity supplied.

A seller is willing to sell at the price requested or higher. A buyer is willing to buy at the price specified or lower. As shown in Figure 3.A.2, there is only one asset supplied at 10 ECU or higher. If the price rises to 40 ECU, the number of assets supplied increases to three. On the other hand, only one asset is demanded at 60 ECU. If the price falls to 20 ECU, the quantity demanded increases to two. Therefore, the quantity demanded is equal to the quantity supplied at prices between 21 ECU and 39 ECU. The market price is set to the minimum price of this interval, i.e., 21 ECU.

Second way to determine the market price

If there is not a price at which the number of assets offered for buying is precisely the same as the number of assets offered for selling, and some of the assets offered for buying are at a lower price than the price at which assets are offered for selling, the market price is defined as follow. The market price is the lowest price at which there is a greater number of assets offered for selling than for buying.

We illustrate how the market price is set through this second way by using the following example.

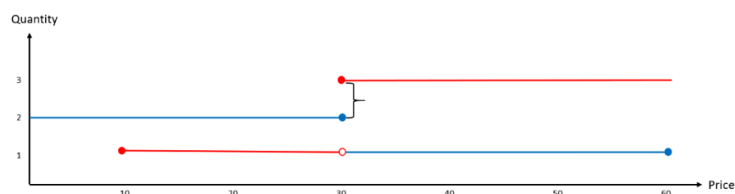
Consider the following buy/sell orders placed by five traders:

- Trader 1: One sell order, which can be executed at 10 ECU or higher
- Trader 2: One sell order, which can be executed at 30 ECU or higher
- Trader 3: One sell order, which can be executed at 30 ECU or higher
- Trader 4: One buy order, which can be executed at 60 ECU or lower

- Trader 5: One buy order, which can be executed at 30 ECU or lower

Figure 3.A.3 summarizes these orders.

Figure 3.A.3: Graphical example second way to determine the market price



Blue lines represent the quantity demanded and red lines represent the quantity supplied.

As shown in Figure 3.A.3, only one asset is supplied at 10 ECU or higher as in the previous example. If the price rises to 30 ECU, the number of assets that are supplied increases to three. However, there is only one asset demanded at 60 ECU or lower. If the price falls to 30 ECU, the quantity demanded increases to two. As a result, two transactions can be completed at 30 ECU. In this case, the market price is set to 30 ECU. The orders that will be fulfilled are determined as follows.

Priority is given to Trader 1, because he/she requested a price lower than the market price. In addition to the order of Trader 1, the order of either Trader 2 or Trader 3 will be fulfilled, since the traded quantity is two. The chosen order to trade between Trader 2 or Trader 3 is determined randomly by the computer.

Dividends

Other than predictions and trading, you can also earn money from dividends. The assets that you have purchased in one period are at your disposal at the next period. For example, if you happen to own 5 assets at the end of period 2, you own the same 5 assets at the beginning of period 3. **For every asset you**

own, you receive a dividend at the end of each of the 8 periods. The dividend is added automatically to your ECU account at the end of each period. After the dividend of period 8 has been paid, the market closes, and you will not receive any further dividends for the assets you own.

The computer randomly selects, with equal probability, the amount of the dividend each asset pays from a set of different possible values. This random selection is done at the end of each period. The different possible values of the dividends do not change within each market.

Example:

Suppose that each asset pays a **dividend of either 0, 10, 18, or 56 ECU, with equal probability.** This means that the **average dividend is 21 ECU.**

For example, if you own 5 assets at the end of period 2, and the **computer randomly chose a dividend of 10 ECU for this period.** Then, in period 3 you receive $50 \text{ ECU} = 5 \text{ (assets)} \times 10 \text{ ECU}$ as profit from dividends.

The **total profit from trading** assets consists of buying and selling them in the market **plus** the accumulated earnings from dividends.

Experimental interface

Figure 3.A.4 illustrates the interface of the second screen of each period. This image corresponds to what you will see in period 1. In such stage of the experiment, you can trade in the market, according to the rules stated in the instructions previously presented. The red numbers in Figure 1, are not part of the experimental interface. However, we include these numbers for illustrational purposes. Below, you will find the explanation of the information corresponding to each number. Please read them carefully. **Be aware that that the position of columns 2, 3, and 4 might vary in the experiment.**

Figure 3.A.4: Second screen of each period



1. This column shows the **trading period** corresponding to the information you will see in the other columns.
2. This column shows the **realized market prices until the period you are in**. If the selling and buying orders do not reach a realized market price, three dots (...) will appear. Note that since Figure 3.A.4 corresponds to period 1, no information is available because there have not been previous transactions in the market. Therefore, there is not realized market price to display yet.
3. This column shows the **average holding value of the asset**. This information is shown to facilitate your choices. It shows how one unit of the asset pays on average, if you hold it from the current period until the last period, i.e. period 8 of this market. These values are calculated as follows: *average dividend* \times *number of remaining periods*. As Figure 3.A.4 shows, you will observe the average holding value of all the periods in the market from the first period until the end along the entire market.

4. This column shows the **median of the predictions provided by all the participants** in the experiment.
5. This shows your earning separately. **First, how much you earned so far in the current market from your predictions.** Recall that for each prediction that lies within a fix interval of ± 25 around the actual realized market price, you earn 250 ECU. **Second, how much you earned in the current period from your trading.** **Third, how much you earned in the current period from dividends.**
6. This shows **how much money (ECU) you have at your disposal**, which is sum of your earnings from trading plus your earnings from dividends. You may buy assets up to this amount. Also, this shows the **number of assets you currently have**. You may sell a maximum of this number of assets.
7. This shows the **potential dividend values** that can be realized in the current market. Also, you can look at the **realized value of the last period's dividend**. Note that you will only observe the value of the last realized dividend after period 1.
8. Here is where you **enter the highest price you are willing to pay to buy an asset in the current period**. Recall that if the market price turns out to be greater than the highest you are willing to pay, your order will not be processed. Also, here is where you enter the highest number of assets you want to buy in this period. If you do not want to purchase any asset, enter 0.
9. Here is where you **enter the lowest price at which you would be prepared to sell an asset in the current period**. Recall that if the

market price turns out to be lower than your lowest selling price, your order will not be processed. Also, here is where you enter the number of assets you want to sell in this period. If you do not want to sell any of your assets, enter 0.

10. By clicking this button, you confirm your selling and buying orders and move to the next period.

3.B Trader types, cognitive abilities and socio-demographic variables

Table 3.B.1 presents the number of traders classified as feedback, passive, or speculators according to the CRT score. We do not reject the null hypothesis that distributions are the same across the four scores (χ^2 test, p -value = 0.591).

Table 3.B.1: Trader types and cognitive skills

CRT score	Feedback	Passive	Speculator
0	16 (19.05%)	8 (15.09%)	5 (16.13%)
1	24 (28.57%)	9 (16.98%)	10 (32.26%)
2	18 (21.43%)	16 (30.19%)	8 (25.81%)
3	26 (30.95%)	20 (37.74%)	8 (25.81%)

Note. For each trader type, each cell provides the number (fraction) of subjects with a given CRT score.

Table 3.B.2 shows the number of traders classified as either feedback, passive or speculators by gender. We find no gender difference in the distribution of types (χ^2 test, p -value = 0.244). Looking at Table 3.B.3, we do not find a statistically significant relationship (χ^2 test, p -value = 0.581) between the discipline in which subject majored (economics/ finance vs. other disciplines) and trader types.

Table 3.B.2: Trader types and gender

Gender	Feedback	Passive	Speculator
Male	60 (71.43%)	35 (66.04%)	17 (54.84%)
Female	24 (28.57%)	18 (33.96%)	14 (45.16%)

Note. For each trader type, each cell provides the number (fraction) of subjects of a given gender.

Table 3.B.3: Trader types and field of study

Major	Feedback	Passive	Speculator
Economics or finance	27 (32.14%)	17 (32.08%)	7 (22.58%)
Other disciplines	57 (67.86%)	36 (67.92%)	24 (77.42%)

Note. For each trader type, each cell provides the number (fraction) of subjects with a given major.

Finally, the analysis of variance (one-way ANOVA) shows that the mean age does not significantly differ across trader types ($p - value = 0.935$).

3.C Patterns of attention, cognitive abilities and socio-demographic variables

To analyze the relationship between patterns of attention, cognitive abilities and demographic variables, we run linear regressions taking the relative dwell times for each of the three sets of information presented in the experiment (realized prices, fundamentals and median forecasts) as dependent variable. Results are summarized in Table 3.C.1.

Model 1 shows that there is a significant positive correlation between relative dwell times in prices and CRT scores. Holding everything else constant, one unit increase in the CRT score increases the relative share of dwell time in realized prices by 6.4 percentage points. All remaining coefficients across the three models lack statistical significance at the 5% level.

Table 3.C.1: Relative dwell times, with CRT and demographics; regres

	Model 1: Dwells in prices		Model 2: Dwells in fundamentals		Model 3:
	Coefficient	Std. Error	Coefficient	Std. Error	Coeffi
CRT	0.064 *	(0.027)	-0.000	(0.040)	
Age	0.006	(0.010)	-0.014	(0.016)	
Female	-0.015	(0.065)	0.030	(0.086)	
Econ/finance	-0.002	(0.012)	-0.022	(0.015)	

Note. Binary variable *female* is set to 1 for females; binary variable *econ/finance* is set to 1 if subject Standard errors are clustered at the individual level. Asterisk indicates statistical significance at the

General conclusion

This thesis contributes to the behavioral and experimental economics literature on beliefs and ambiguity attitudes. In particular, this thesis proposes a new method to measure beliefs and ambiguity attitudes towards different sources of uncertainty and provides answers regarding which existing economic theories are more in line with ambiguous situations involving higher order ambiguity attitudes.

Chapter 1 develops a new method to completely estimate beliefs, utility function and weighting function – as a measure of ambiguity attitudes – for different sources of uncertainty. Such method is implemented experimentally to both different and equal sources of uncertainty under the context of the coordination and trust game. We study strategic uncertainty, social ambiguity, and betrayal aversion as sources of uncertainty. This chapter leads to two main results. First, in face of equal sources of uncertainty, beliefs on events are context-independent, but the transformation of beliefs through the weighing function is context-dependent. This let us conclude that the comparison of sources of uncertainty requires a complete measurement of the utility and weighting functions. This finding represents a contribution to several fields in economics which study decision-making processes involving uncertainty. Some of the fields that could implement this methodology into their research are game theory, health economics, environmental economics, transport economics, among

others. Our second result is that events that are not equally likely lead to an increase in the likelihood insensitivity parameter of the weighting function, which implies that the process of forming beliefs about unknown events is cognitively demanding.

Chapter 2 examines higher order ambiguity attitudes (aversion, prudence, and temperance) in a laboratory experiment in which subjects face two possible states of nature (a good one and a bad one). Precisely, it compares the effect of the ambiguity associated with the good versus the bad state of nature on subjects' higher order ambiguity preferences. In addition, in the case of ambiguity prudence, it evaluates the effect of news communication on ambiguity attitudes. This is done by comparing the cases in which ambiguity is presented as two harms versus one harm and one favor. This chapter brings two main contributions. First, it finds that empirical results are more in line with theoretical results when the ambiguity is introduced on the bad state of nature. Second, prudent behavior is only observed when ambiguity is presented in the form of one harm and one favor. Results from this chapter indirectly contribute to the theoretical literature by testing the empirical validity of theoretical predictions. Also, these results suggest an avenue for future research related to the effect of how ambiguous situations are communicated on ambiguity attitudes.

Chapter 3 takes a different perspective, instead of keeping the focus on ambiguity attitudes as the other chapters, it leads to a methodological and empirical contributions to the understating of dynamics of attention in decisions-making processes in economic contexts. This is accomplished by studying the coherence between patterns of trading, represented in models of trader types, and their underlying cognitive mechanisms of sampling information (analyzed through eye-tracking data). In an asset market experiment, we classify subjects' trading and forecast decisions into three models of trader types: feedback,

passive and speculators. Our findings are heterogeneous: while we find the expected relationship between feedback traders and their patterns of attention, our results only partially support passive trading behavior with its expected main source of information, and reject the expected patterns of attention of feedback traders. These results represent a promising avenue for future research in which the implementation of physiological measurements allows to go beyond the observable behavior to investigate to a greater extent agents' decisions in markets.

Naturally, the three chapters comprised in this thesis have both limitations and potential extensions for future research. The following are some of the limitations and possible extensions of each chapter.

One of the treatments implemented in Chapter 1 is the *nature* treatment. In this treatment, the outcome of the lottery is determined by nature, which is a randomly equally likely selection between the three possible outcomes (Left, Right, or Middle) made by the computer. Since ambiguous situations are characterized by containing unknown objective probabilities of the possible events (Knight, 1921), the fact that we announce that the computer selects one of the outcomes with equal probability, moves the treatment from ambiguity to risk. The reason why we announce these probabilities is because we require to perform an internal validity test for our method. Such test involves testing the null hypothesis of equally likely events for the nature treatment, which our method successfully satisfies. Replicating well known results and successfully passing validity tests provide support for our method (Abdellaoui et al., 2008). An interesting extension of Chapter 1 would be to replicate the experiment including a variation of the nature treatment, in which the probabilities of the possible events are unknown. This would permit to perform a comparison

between the treatments involving other sources of ambiguity and the nature treatment, where the nature treatment contains pure ambiguity.

To study higher order ambiguity attitudes, in Chapter 2, we conduct a context-free preferences laboratory experiment using a simple model with a good and a bad state of nature. Our results indicate that the way news are communicated in ambiguous situations is not neutral. In particular, subjects are ambiguity averse and temperate when the probability capturing ambiguity is presented on the bad state of nature. Regarding prudence, the probability capturing ambiguity on the bad state increases prudence only when the probability is presented as one harm and one favor. Therefore, It would be interesting to extend this study into specific context situations, which would shed light on the most effective way to influence higher order ambiguity attitudes through the communication of news. Context that could be explored include, but are not limited to, climate change and antibiotics overuse. For instance, study the efficiency of different communication strategies of public policies towards low-carbon transitions, in which the focus of ambiguity is presented on bad states, such the probability of natural disasters, versus communication strategies that announce a probability related to a good state such as air quality improvement.

Lastly, in Chapter 3, we implement two independent asset markets in which subjects trade during 8 periods. One limitation of this chapter concerns the number of periods in the markets. We set this number of periods because we had a constrain regarding the size of the screen. To analyze eye-movement data, we define Areas of Interest (AOIs), centered on each of the sources of information (prices, fundamentals, and medians of forecasts). Following previous research (e.g. [Halevy and Chou, 2014](#); [Polonio et al., 2015](#); [Peshkovskaya et al., 2017](#)), we study patterns of attention through the analysis of dwell times. In this context of analysis, it is important to keep a sufficiently large space between

the AOIs and to avoid overlapping between them. A valuable extension of this work would be to increase the number of periods in each of the markets by modifying the experimental interface. This could be achieved by displaying only the information regarding the two most recent periods, instead of displaying the information concerning all the previous periods in the market. This extension would allow to provide results based on a higher number of observations.

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Abstract

This thesis studies beliefs, ambiguity attitudes, and dynamics of attention and their role on decision-making processes in economic contexts. Chapter 1 proposes a new method to measure beliefs and ambiguity attitudes (determined by beliefs transformation) towards different sources of uncertainty. This method is implemented experimentally to equal and different sources and contexts of uncertainty. Findings support that, in face of equal sources of uncertainty, beliefs on events are context-independent, but the transformation of beliefs is context-dependent. To further understand ambiguity attitudes, Chapter 2 studies higher order ambiguity attitudes by comparing changes in higher order ambiguity attitudes when ambiguity is presented on the good versus the bad state of nature. Results shed light on which existing economic theories are more in line with particular ambiguous situations and the direction in which decisions vary according to how ambiguity is communicated. Finally, Chapter 3 investigates trading decisions in asset markets and their underlying cognitive mechanisms represented in sampling information (analyzed through eye-tracking). Findings reveal that behavioral trading patterns are not always coherent with their expected dynamics of attention.

Keywords: Experimental economics, uncertainty, beliefs, ambiguity attitudes, markets, sampling information.

Résumé

Cette thèse étudie les croyances, les attitudes face à l'ambiguïté et la dynamique de l'attention dans les processus de prise de décision dans des contextes économiques. Le chapitre 1 propose une nouvelle méthode pour mesurer les croyances et les attitudes face à l'ambiguïté (déterminées par la transformation des croyances) à l'égard de différentes sources d'incertitude. Cette méthode est appliquée expérimentalement à des sources et contextes d'incertitude égaux et différents. Les résultats confirment que, face à des sources d'incertitude égales, les croyances sur les événements sont indépendantes du contexte, mais que la transformation des croyances dépend du contexte. Pour mieux comprendre les attitudes face à l'ambiguïté, le chapitre 2 étudie les attitudes face à l'ambiguïté d'ordre supérieur en comparant les changements d'attitudes face à l'ambiguïté d'ordre supérieur lorsque l'ambiguïté est présentée sur le bon ou le mauvais état de la nature. Les résultats identifient les théories économiques existantes qui correspondent le mieux à des situations ambiguës particulières, et la direction dans laquelle les décisions varient en fonction de la manière dont l'ambiguïté est communiquée. Enfin, le chapitre 3 étudie les décisions de négociation sur les marchés d'actifs et leurs mécanismes cognitifs sous-jacents représentés dans les processus d'échantillonnage de l'information (analysées par eye-tracking). Les résultats révèlent que les modèles comportementaux de décision financière ne sont pas toujours cohérents avec la dynamique de l'attention attendue.

Mots Clés : Économie expérimentale, incertitude, croyances, attitudes face à l'ambiguïté, marchés, échantillonnage de l'information.