Essays on Experimental Analysis of Decision-Making under Risk and Ambiguity

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I, Julen Carlos Ortiz de Zarate Pina, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

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Abstract

This thesis contributes to the experimental literature on decision-making under risk and ambiguity. In chapters 1 and 2, I study how environments of increased uncertainty, which I model as increased uncertainty about the probability of an event occurring (i.e., ambiguity), affect the decision-making process, in two settings: in chapter 1, I focus on how this increased uncertainty influences preferences over the timing of resolution of uncertainty. The results of the experiment show that in a lottery choice problem, as the ex-ante likelihood of the good outcome occurring goes up, participants turn from wanting to receive partial information before the resolution of uncertainty to being averse to it. This result has important theoretical and applied implications. In chapter 2, I analyse how social identity (e.g., political ideas, gender, ethnicity) and the stereotypical decisions made by people in the same social group are used as a reference point by decision-makers when making uncertain decisions. I find that increased uncertainty makes participants in the experiment more likely to choose the same decision as the majority of participants that belong to their social group, especially participants who do not feel a strong identification with the group. In chapter 3, my co-authors and I look at how a global social and economic shock (namely, the COVID-19 pandemic) affects risk preferences in a sample of students and professional traders. We find no significant effect of the crisis on these preferences. This result gives support to standard economic theory, which considers these preferences to be stable. We also study if the crisis affects personality traits that are economically relevant, such as trust or locus of control. We find that some of these traits do change during the pandemic. The effect, however, is heterogeneous across samples of traders and students.

Impact statement

This thesis studies the relevance of uncertainty in different experimental frameworks. Knowledge derived from this work can be applied by public policy makers, academics and firms especially interested in the link between information and uncertainty.

The first two chapters focus on ambiguity which, within economics, is a phenomenon linked to uncertainty about the probability of an event occurring. It has long been established in the literature that subjects are usually averse to this type of uncertainty in most cases. There have been many theoretical attempts to reconcile this empirical regularity with standard economic theory.

Chapter 1 studies the plausibility of some of the most commonly used theories from a new perspective, namely, how preferences about the timing and number of periods over which uncertainty is resolved differ between an ambiguous environment, and a risky one (that is, one in which probabilities are known). We find that under ambiguity, unlike under risk, the likelihood of an event occurring significantly affects the willingness to learn partial information. The models we study cannot explain these results. Therefore, our work can inform new attempts to model attitudes towards ambiguity. Additionally, when developing information campaigns, in which there is significant uncertainty about the probability of an outcome (for instance, in health-related or environmental topics) understanding attitudes towards this information can help better evaluate their impact and, as a result, improve the welfare of society.

Chapter 2 looks at ambiguity from a different perspective. It studies how subjects behave in an uncertain environment in which the stereotypical (or modal) decision of social groups can be used as an anchor or reference point for individuals that identify with these groups. In an experiment in which we generate social groups according to political beliefs, we find that increased uncertainty leads to a higher alignment with the modal decision of the group subjects are assigned to. Uncertainty, therefore, leads to more polarising decisions. The experimental framework lets us find a causal interpretation of increased uncertainty on polarisation. Further studies would be required to evaluate the external validity of these results. However, the public policy implications of this effect of uncertainty on polarisations are many, and if this thesis is correct, it could help develop mechanisms to prevent issues that are arising in recent years, relating to extremism and polarisation of society.

Chapter 3 focuses on the effect that an unexpected and global shock like the COVID-19 pandemic has had on deep economic variables, such as, risk and trust. We use a sample of professional traders and students and observe that these key variables have not changed significantly after the shock has happened. Therefore, when evaluating economic policies aimed at recovering from the shock, the effect of risk or a decrease in trust could be disregarded, as we would not expect it to have been affected by the crisis. Additionally, this result would give empirical backing to the common assumption in the literature that these deep variables are stable for individuals.

To Itziar Pina Landeta, my mother

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Mila esker guztoi!

Introduction

Uncertainty is ubiquitous in social and economic decisions, and has only become more prevalent in the last few years, as economic and climate crises, and recently a worldwide pandemic are accelerating changes in society. Each chapter of this thesis studies how this uncertainty shapes human decision-making processes through a different perspective.

Chapter 1, titled *Preferences over the timing of uncertainty under risk and ambiguity: an experiment*, focuses on analysing how subjects' preferences over when they want to learn the outcome of an uncertain event changes between risk (i.e.if they probability of every outcome is known) or ambiguity (that is, if the probability is unknown). I also look at how preferences over receiving partial information about the outcome are differently affected by the two environments. This question has been extensively studied from a theoretical and empirical perspective in the risk domain, but the empirical evidence for the ambiguity case is still scarce. Recent theoretical work, however, has studied the implications of different ambiguity models on these preferences. My aim in this chapter is, thus, twofold: I first observe differences between preferences under risk and ambiguity regarding these preferences, and then, I try to study how well some of the most commonly used ambiguity models perform in terms of their explanatory power. Results from an online experiment with a sample of UCL students shows that the models I consider cannot explain many of the choices made by participants. This is due to a decrease in the percentage of participants that want to learn any partial information as the likelihood of the good outcome of the decision goes up. This trend is also uncorrelated to the participants' aversion towards ambiguity. None of the models I study can explain this dominant behaviour, and they can approximately only explain 20% of the behaviour of participants. Future research projects could focus on developing dynamic ambiguity models that can capture both ambiguity attitudes and preferences over the timing of resolution of uncertainty.

Chapter 2 (*Uncertainty is polarising: Social identity and decision-making under ambiguity*) studies a specific type of reference point that decision-makers can have as the uncertainty surrounding a decision increases. This reference point is the modal or stereotypical decision of subjects they identify with. These social groups are defined by a group of individuals with a common characteristic (e.g., gender, political affiliation) and that have a sense of belonging to the group. Many sociological studies have studied the importance of these groups when individuals form their own sense of self. Taking these studies into account, I write a very simple theoretical model of social identity and decision-making under uncertainty, and reach two conclusions: i) that subjects that feel a closer identification with their social group take the modal decision of the group more often, and ii) that uncertainty makes even those with a lower identification with the group take the decision of their own group more frequently. An on-line experiment on Amazon MTurk shows that these two hypotheses hold in my experiment. These results contribute to a better understanding of how individuals deal with uncertainty. They can also contribute to a better understanding on the factors that polarise individuals and lead them to make decision conditioned by the social groups they feel they belong to.

Finally, in chapter 3, titled *Risk preferences, Trust and Noncognitive Skills at the Time of COVID-19: An Experiment with Professional Traders and Students*, my co-authors and I analyse the effect that COVID-19 has had on deep economic variables like risk aversion and trust. We test this assumption making use of a unique longitudinal dataset on these variables from a sample of professional traders and students before the beginning of the pandemic and at its peak. We find no significant effect of this shock on these two variables. This result gives support to standard economic theory, which assumes that these variables are stable.

In every chapter of this thesis I look at the issue of uncertainty from a different perspective, but the methodology is experimental throughout. Experiments, being carefully designed environments, allow to establish causal relationship between variables, which is hard to pin down in observational studies, especially when it comes to individual decision-making. Future studies should extend these experiments to other environments or subject samples and test the empirical validity of the results of this work.

Chapter 1

Preferences over the timing of uncertainty under risk and ambiguity: an experiment

Abstract

This chapter empirically analyses two types of preferences over the timing of resolution of uncertainty: preferences between early and late resolution and preferences between one-shot and gradual resolution of lotteries under risk and ambiguity. In an on-line experiment with students, we find significant differences between treatments: under risk, a majority of participants show a strict preference against gradual resolution of uncertainty, for low, medium and high ex-ante probabilities of receiving the prize of the lottery. Under ambiguity, most participants show a preference for gradual resolution of uncertainty for lotteries with a low-likelihood of winning, and an aversion towards it for medium and high likelihoods. Additionally, in both treatments we find subjects show strict preferences more frequently in the one-shot vs. gradual resolution dimension than in the early vs. late resolution dimension. Results from the experiment contribute to the literature about the empirical validity of ambiguity models, as different models prescribe different preferences over the timing of the resolution of uncertainty.

1.1 Introduction

Under expected utility theory, receiving interim information about the outcome of a decision after it has been made (namely, non-instrumental information) should always be weakly preferred to not receiving it, as decision-makers are assumed to account for any further information they may receive in the future when making the decision (in other words, they satisfy the reduction of compound lotteries axiom). Additionally, standard theory also assumes that the time in which they learn about the outcome of a decision should not matter when making the decision either (i.e. they satisfy the time neutrality axiom, as defined by Segal, 1990).

In this work, we study the empirical validity of these axioms in an ambiguous setting, that is, in a setting in which the exact probability of states of the world is unknown. We do this by designing and implementing an experiment in which we compare preferences related to the axioms (and their deviations) between subjects assigned to making decisions in an environment in which probabilities are known, and one in which they are not. Additionally, we study the theoretical implications of deviations from the axioms on the empirical validity of several ambiguity models.

Deviations from the above mentioned axioms can have significant economic implications. For instance, subjects in a laboratory experiment have been shown to be more risk averse when they receive more frequent feedback about their performance, therefore, leading them to reach suboptimal levels of stock investments (Gneezy and Potters, 1997), even after controlling for the possibility of dynamic investment (Bellemare, 2005). Kocher et al. (2014) also showed, in an experimental setting, that feelings of hope and anticipation incentivised participants to take part in the national lottery in the Netherlands, and to delay as much as possible the resolution of that lottery.

Beyond this laboratory evidence, learning about preferences over non-instrumental information can also help to isolate the non-pecuniary cost of this information from the total effect of instrumental information. One frequent example of such information mechanisms are genetic tests of diseases, which are becoming ever more commonplace. These tests provide information about genetic mutations that have been found to be correlated with an increased chance of developing certain diseases (Evans et al., 2001). Some of these diseases (such as multiple endocrine neoplasia type 2) are almost always preventable if the associated mutations are detected. The probability of suffering other diseases can also be expected to increase given certain mutations, but no effective treatment exists to prevent their development (for instance, Alzheimer's disease), and other diseases lie somewhere in between (e.g. breast and ovarian cancer). This last example is paradigmatic of the interrelation between the instrumental and non-instrumental value of information[1]. The results of such a test are partly instrumental as they can incentivise surgical interventions to reduce the risk of developing this disease; however, this information can also be non-instrumental as successful prevention of the disease is not guaranteed, and as a result, learning about the increased risk can create negative anticipatory feelings due to the increased risk of developing the disease. In these cases understanding preferences over non-instrumental information is essential to perform a welfare analysis of the value of these tests to individuals.

There is an increasing experimental literature on preferences over non-instrumental information (Ahlbrecht and Weber, 1997; Lovallo and Kahneman, 2000; Budescu and Fischer, 2001; Zimmermann, 2015; Masatlioglu et al., 2017; Nielsen, 2020). All of these papers have focused on cases in which the ex-ante and interim probabilities of outcomes are perfectly known or *risky*. In real life, however, learning the exact probabilities of outcomes is in many cases impossible. Following on the example of genetic tests above, there exist competing studies that report different probabilities of developing a disease given a mutation (Chen and Parmigiani, 2007), and idiosyncratic variables, such as lifestyle and additional mutations, can increase the uncertainty about the real probability of suffering the disease. The same can be said about other phenomena that have deep and widespread economic and social effects, such as the recent Covid-19 pandemic or climate change. The limited, evolving and often conflicting understanding of these events generates ambiguity

[1] Lerman et al. (1996) offered a free test of genetic mutations to a sample of men and women with a family history of genetically determined breast-ovarian cancer. Only 43% of the participants in the study asked to learn the results of the test.

about the future state.

In a recent policy paper, Berger et al. (2020) discuss the three sources of uncertainty that an imperfect understanding of a crisis like the pandemic are related to: uncertainty within models, across models and about models. The first type of uncertainty is the one that is considered in risky problems. For instance, quantitative models make assumptions about random shocks with known distributions that lead to estimates of the probability of an event occurring. Uncertainty across models (e.g. conflicting evidence) and about models (for instance, missing variables, incorrect specification of models) are instead related to unmeasurable uncertainty or ambiguity. Receiving more information from new studies may increase this unmeasurable uncertainty[2].

Given the ubiquity of non-neutral attitudes towards ambiguity (Trautmann and de Kuilen, 2015), it is important to understand how the availability of uncertain or ambiguous information affects decision-making in these situations, and other decision-making processes. In this chapter, we perform an experimental analysis in which we study the two types of preferences over non-instrumental information mentioned above: preferences over early or late resolution of uncertainty, and preferences over one-shot or gradual resolution of uncertainty. We construct two between-subject treatments: risk and ambiguity. In the risk treatment, participants are shown lotteries in which ex-ante and interim probabilities (when further information is provided) of winning the prize are known; in the ambiguity treatment, on the other hand, the exact ex-ante and interim probabilities of winning the lottery are unknown. Within each treatment subjects have to make 20 pairwise choices. These pairwise choices are composed of two lotteries that may differ in two aspects: they can be lotteries that are resolved in one stage (one-shot lotteries), or lotteries resolved over two periods (gradually resolved lotteries); if they are one-shot lotteries, they can also be resolved either early or late. Comparisons along the former aspect allow to study if subjects have preferences about learning partial non-instrumental information before the lottery is resolved, or instead show aversion towards learning this

[2]For instance, in a meta-analysis of 172 observational studies Chu et al. (2020) find that the reduction in the risk of being infected by the SARS-CoV-2 virus by using a mask ranges from 6% to 80%, depending on the study.

partial information. Comparisons along the latter aspect can show preferences over early or late resolution of uncertainty. The lotteries we compare, on the other hand, both have the same ex-ante probability of winning so they only differ in how the information is learnt. Gradually resolved lotteries share the same variance as well, so none are more informative than others.

We consider two additional within-subject treatments: across pairwise choices we vary the ex-ante likelihood or probability of winning the lottery. We do this to test whether different likelihoods of the good outcome occurring affect preferences, especially in the ambiguity treatment, as it has already been established that the likelihood of an event occurring can lead to changing attitudes towards ambiguity (Dimmock et al., 2013, 2016, Bouchouicha et al., 2017). In the risk treatment we also consider positively and negatively skewed lotteries. Masatlioglu et al., 2017 show that i) more participants have a preference to resolve the lottery early than late as the probability of winning the prize goes up, ii) preference for positively skewed lotteries over negatively skewed lotteries is greater for higher probability of the desired outcome. We include this additional within-subject treatment to test preferences between one-shot and gradually resolved (positively and negatively skewed) lotteries at different probabilities of winning the lottery.

Finally, following the theoretical work linking ambiguity models and preferences over the timing of resolution of uncertainty (Strzalecki, 2013, Li, 2020), we also reach conclusions about the empirical validity of several ambiguity models (maxmin model, multiplier model, Choquet utility model).

Our results show that there exist significant difference in preferences over gradual resolution of uncertainty between risk and ambiguity treatments. Under risk, we find no significant effect of the ex-ante likelihood of the lottery affecting these preferences. Under ambiguity, however, there is a shift from a majority of participants liking gradual resolution at low likelihoods of winning the lottery, to most of them becoming averse to it for higher levels of likelihood. This attitude is orthogonal to attitudes towards ambiguity, and as a result, none of the models we study can explain this behaviour. It can, however, help develop new ambiguity models that can better explain this empirical evidence.

Related literature

Our work is most closely related to three strands of the literature: empirical papers on preferences over the timing of resolution under risk, experimental analysis of ambiguity models, and a recent strand of the literature on ambiguous signals.

Ahlbrecht and Weber (1997), and Lovallo and Kahneman (2000) first studied how anticipation about the outcome of a hypothetical lottery, and the implications of its structure (specifically its skewness and whether it reports gains or losses) affect preferences over one-shot or gradual resolution of uncertainty, between positively and negatively skewed lotteries and with different ex-ante probabilities of winning. In incentivised experiments, Abdellaoui et al. (2010) showed that subjects become more risk loving as the outcome of a lottery is delayed and Kocher et al. (2014) that a large minority of participants in an experiment had a strict preference to receive a ticket to a real state-run lottery whose draw is performed later rather an early. With respect to learning partial information, Eliaz and Schotter (2010) find that in risky choices, participants in an experiment choose to pay for non-instrumental information. They relate this to the 'confidence effect', that is, participants want to become more confident that they made the right decision by acquiring this additional information. Zimmermann (2015), on the other hand, observed that approximately half of the participants in his experiment preferred to receive information in one period, whilst the other half had a preference for gradual resolution of uncertainty throughout a whole week. Falk and Zimmermann (2016) considered a decision in the domain of losses and concluded that if a distracting activity is available before learning the outcome, subjects show a preference to delay learning about the outcome. Masatlioglu et al. (2017) find that subjects usually have a preference for positively skewed risky lotteries, or lotteries that are more informative in the good state, than negatively skewed lotteries, and this preference becomes stronger the higher is the ex-ante probability of winning the lottery. Finally, most recently, Nielsen (2020) studied differences in preferences in the timing of the resolution of uncertainty if the outcome of the lottery has already been resolved and if it is still has to be resolved. She found, using an interesting experimental approach where no constraints were set on the choice of lotteries, that in the former case there is a preference for early resolution of uncertainty and in the latter case there is a preference for later resolution of uncertainty.

These empirical papers stem from theoretical work pioneered by Kreps and Porteus (1978). They first considered the issue of non-indifference towards the timing of information axiomatically. Their work was further refined by Grant et al. (1998, 2000). Dillenberger (2010) linked a preference for one-shot resolution of uncertainty to the certainty effect, as shown by the Allais paradox (1953). Palacios-Huerta (1999) provided a first behavioural foundation to the aversion to partial information by linking it to disappointment aversion, as described by Gul (1991). Koszegi and Rabin (2009) similarly explain that partial information will be avoided by assuming loss aversion in a consumption model with an endogenous reference point. Hoy et al. (2015) show that ambiguity aversion (characterised as a 'dilation' of priors[3]) could explain the low take-up rate of genetic tests. Ely et al. (2015) go against the previous papers and propose that suspense (modelled as shifts in the prior about the outcome of an event) can actually lead to a preference for partial information.

Our work also relates to the growing literature on empirical tests of ambiguity models. Halevy (2007) analysed the validity of subjective expected utility, maxmin and the smooth model, by analysing preferences over compound lotteries and ambiguous lotteries. Conte and Hey (2013) estimated parametric versions of the subjective expected utility model, the smooth model, the rank dependent expected utility and the α-maxmin model. Baillon et al. (2015) concluded that prospect theory best explains ambiguity attitudes, in an experiment with positive and negative ambiguous lotteries[4]. As far we are aware, ours is the first paper to check the empirical validity of ambiguity models by studying preferences over the timing of the resolution of ambiguous lotteries.

Lastly, there exists a recent branch of the ambiguity literature that studies attitudes

[3] Dilation of priors is defined as the extension of the set of possible priors after receiving a signal (Seidenfeld, Wasserman, 1993).

[4] Other papers that evaluate ambiguity models are Andersen et al. (2009), Hayashi and Wada (2010), Abdellaoui et al. (2011), Ahn et al. (2014), Hey et al. (2014), Chew et al. (2017), Cubitt et al. (2020).

towards ambiguous information. Epstein and Halevy (2020) experimentally test the martingale property of Bayesian updating in an environment in which the likelihood of the outcome of a lottery is ambiguous and subjects also have ambiguity about the extent of the informativeness of the signal, by eliciting conditional and unconditional probability equivalents of the lotteries. Liang (2021) considers an experiment where the prior about the outcome of a lottery is risky and the informativeness (whether the signal is true or misleading) is uncertain, or vice versa. It also elicits certainty equivalents of conditional and unconditional lotteries. Kellner et al. (2020) look at how ambiguous information leads to changes in beliefs about the state of the world[5]. The approach of these three papers is very different to ours, as they do not study the aversion to gradual resolution of uncertainty. The first two papers elicit conditional certainty or probability equivalents, thus, already doing away with the aversive nature that may be related to receiving the partial information, and in which we are most interested. In Kellner et al. (2020) subjects always receive partial information, so the authors do not study the possibility of aversion towards gradual resolution of uncertainty either. Shishkin and Ortoleva (2021) is the paper closest to ours in its motivation. They study the value of information in an experiment in which they allow for "dilation" of priors, which is a common feature of models like maxmin and the smooth models, under certain conditions. They consider risky and ambiguous priors over the outcome of the lottery and ambiguous information about the trustworthiness of the signal. Their experiment differs from ours in three key aspects: i) we compare risky lotteries with risky information to ambiguous lotteries with ambiguous information; ii) in the ambiguity treatment of our experiment, we consider the case in which the prior is ambiguous and the partial information (or signal) that is received enforces a dilation of the priors. This allows to pin down the predictions of standard models like maxmin under ambiguous priors, and study their empirical validity. iii) We also analyse different likelihood levels of priors to check for variations in preferences over partial information under ambiguity.

In the next section, we discuss our experimental design. In section 1.3 we show

[5]De Filippis et al. (2021) also study belief updating under ambiguity in a social environment.

the connection between some theoretical models of ambiguity aversion and the decisions that participants have to make in the experiment. Section 1.4 shows the results of the experiment, which are discussed in section 1.5, and section 1.6 concludes.

1.2 Design of the experiment and implementation

The experiment consists of two between-subject treatments (risk and ambiguity).

In each of the treatments subjects are asked to make 20 pairwise choices between lotteries. These lotteries can be of two types: simple lotteries and compound lotteries. Each type of lottery is used to analyse preferences over two classes of choices: simple lotteries represent choices in which all uncertainty is resolved in one period (one-shot resolution); compound lotteries represent choices in which uncertainty is resolved over two periods (gradual resolution).

1.2.1 Composition of lotteries

In the risk treatment, simple lotteries have two elements: an urn that contains one hundred balls, numbered from 1 to 100, and a subset of these balls, which determine the winning numbers of the lottery.

The first stage of the compound lottery has the same urn as the simple lottery, with balls numbered from 1 to 100. In the first period one ball is drawn from this urn. The content of the urn in the second period depends on the value of this drawn ball. If the value of the ball drawn in the first period is lower or equal to a pre-determined value that we call *threshold value*, then the second stage urn is composed of all balls from the top urn with value equal or lower to the *threshold value*, including the drawn ball. If the ball has a value larger than the *threshold value*, then the second stage urn is composed of all balls with value greater than it. The ball drawn from the second urn determines the prize of the lottery. If the drawn ball coincides with one of the winning numbers, then, the participant wins the lottery prize, otherwise she wins nothing. This is an intuitive and novel way of generating compound lotteries that can easily be understood by subjects in the experiment. Additionally, varying the threshold value and the set of winning numbers, lotteries with same variances but changing skewness can be easily generated.

In the ambiguity treatment, simple lotteries are also formed by an urn, but this urn is composed of two hundred balls. One hundred balls have a value between 1 and 100, whereas the value of the other hundred balls is unknown to both the experimenter and the participant. The value of these 100 balls is achieved using Stecher et al. (2011)'s mechanism at the beginning of the experiment[6], and neither the experimenter nor the participant learns about the content of the urn until the end of the experiment[7]. This algorithm is designed to generate distributions with no finite moments. This approach, in conjuction with the fact that the experimenter cannot observe the content of the urn until the end of experiment, prevents ambiguity being understood by participants as the experimenter being more knowledgeable about the distribution than themselves (Fox, Tversky, 1995), as past observations of the distribution are not informative about future ones.

Compound ambiguous lotteries are generated similarly to compound risky lotteries. We first determine the *threshold value*, which varies from lottery to lottery. The value of the ball drawn in the first period determines the content of the second urn. If the value of the ball drawn is smaller or equal to the *threshold value*, then the second urn is composed of all balls with value smaller or equal to the threshold value, including the ball drawn. If the value drawn is higher than the threshold value, then the second urn is composed of all balls with value larger than the threshold value.

1.2.2 Choice of lotteries

In both treatments we consider 4 different categories of compound and simple lotteries: 3 lotteries vary in probability or likelihood. Probabilities of winning the prize are either 10%, 50% and 90%. Risky compound lotteries of these categories all have

[6]In our experiment there is no possibility of hedging between choices, but we still follow the prescribed incentive compatible mechanism proposed by Baillon et al. (2014).

[7]Participants are informed about this fact at the beginning of the experiment.

the same variance, that is, the dispersion from the ex-ante probability to the interim probability from receiving the partial information is always the same. This allows us to compare choices between different categories while keeping the informativeness of lotteries constant. One drawback from maintaining informativeness constant for all three probabilites is that changes from the ex-ante probabilities to the interim probabilities are relatively small. This is due to the fact that changes in interim probabilities for very low (10%) and very high (90%) ex-ante probabilities are very constrained from below and above respectively, which limits the set of lotteries that preserve the ex-ante probability and variance. As a way to check whether higher informativeness has a differential effect in preferences, we include an additional set of lotteries, with 50% ex-ante probability, which allows for higher variance in the interim probabilities from the ex-ante probability.

Additionally, in order to study if differences in skewness also affect decision-making, we include one positively and one negatively skewed lottery for each of the four categories.

As mentioned above, participants make 20 pairwise choices between lotteries. These lotteries are completely characterised by the set of winning numbers (for all lotteries) and the threshold value (if the lottery is a compound lottery). The amount of winning numbers pins down the ex-ante probability/likelihood of winning. The number of those winning numbers and the threshold together determine the interim probability of winning, after one of the possible information sets (ball is below or above threshold) has been realised. Different combinations of these two elements lead to positively skewed or negatively skewed lotteries in the risk treatment.

Table 1.1 shows these two variables, and the characteristic of each lottery.

The 20 pairwise choices elicit preferences over early, gradual and late resolution of uncertainty, for different ex-ante probabilities/likelihoods and skewness by combining the 12 lotteries described in table 1.1. As can be seen in table 1.2, for each probability/likelihood level there are 5 pairwise choices: the first choice is between early and late resolution of uncertainty, the second and third ones between early resolution and gradual resolution with a positive and negative skew respectively, and the fourth and fifth ones between late resolution and gradual resolution with a positive and negative skew respectively.

Lottery #	Set of winning numbers	Threshold value	Description:
1	1-5; 96-100	-	Simple lottery (10%)
2	1-24; 46-71	-	Simple lottery (50%, low variance)
3	16-40; 61-85	-	Simple lottery (50%, high variance)
4	8-97	-	Simple lottery (90%)
5	1-5; 96-100	37	Compound lottery (10 %), positively skewed
6	1-7; 98-100	56	Compound lottery (10 %), negatively skewed
7	1-24; 46-71	45	Compound lottery (50 %), low variance positively skewed
8	25-45; 72-100	45	Compound lottery (50 %), low variance negatively skewed
9	1-15; 41-60; 86-100	20	Compound lottery (50 %), high variance positively skewed
10	16-40; 61-85	80	Compound lottery (50 %), high variance negatively skewed
11	8-97	56	Compound lottery (90 %), positively skewed
12	6-95	37	Compound lottery (90 %), negatively skewed

Table 1.1: Lotteries in the Experiment

Due to the admittedly complicated nature of computing interim probabilities of winning these lotteries, we compute these probabilities for the participants and show them these probabilities below the lotteries (see figure 1.4 and Appendix for examples). We also show them the probability of reaching each information set. In the case of the ambiguity treatment we show the lowest and highest probability of the ex-ante probability and the interim probabilities (for cases in which the ball drawn is lower than the threshold and when it is higher) of winning the lottery, as well as the lowest and highest probability of any given information set occurring.

Additionally, all gradually-resolved lotteries lead to the same updating of probabilities under multiple prior models (maxmin, maxmax, α-maxmin) for the two most common Bayesian updating rules in the literature (Gilboa and Marinacci, 2016): *maximum likelihood updating*[8] and *full-Bayesian updating*[9]. The first rule establishes that decision-makers only update the priors that maximise the likelihood of the interim event happening. In our experiment this event is whether the first ball drawn has a number above or below the threshold. The second rule updates all priors considered. Under multiple prior models, decision-makers either consider the prior that minimises their utility (in the maxmin model), maximises it (in the maxmax model), or a convex combination of

[8]Formally, the updated probability, for realised event A under *maximum likelihood updating* is : $C_A^{ML} = \left\{ P(\cdot|A) | P \in \arg\max_{Q \in C} Q(A) \right\}$, where C is a set of priors over the state of the world and Q is a subset thereof, that represents the marginal prior probabilities of event A.

[9]Formally, the updated probability under *full-Bayesian updating* for realised event A, and given a prior P about the state of the world in the set of priors C is : $P_A^{FB} = \{P(\cdot|A) | P \in C\}$.

Pairwise choice #	Choice X	Choice Y
1	Early resolution of lottery 1	Late resolution of lottery 1
2	Early resolution of lottery 1	Lottery 5
3	Early resolution of lottery 1	Lottery 6
4	Lottery 5	Late resolution of lottery 1
5	Lottery 6	Late resolution of lottery 1
6	Early resolution of lottery 2	Late resolution of lottery 2
7	Early resolution of lottery 2	Lottery 7
8	Early resolution of lottery 2	Lottery 8
9	Lottery 7	Late resolution of lottery 2
10	Lottery 8	Late resolution of lottery 2
11	Early resolution of lottery 3	Late resolution of lottery 3
12	Early resolution of lottery 3	Lottery 9
13	Early resolution of lottery 3	Lottery 10
14	Lottery 9	Late resolution of lottery 3
15	Lottery 10	Late resolution of lottery 3
16	Early resolution of lottery 4	Late resolution of lottery 4
17	Early resolution of lottery 4	Lottery 11
18	Early resolution of lottery 4	Lottery 12
19	Lottery 11	Late resolution of lottery 4
20	Lottery 12	Late resolution of lottery 4

Table 1.2: Choices in the Experiment

these two (in the α-maxmin). The priors that minimise (or maximise) utility in this case are the priors that assume the lowest (highest) number of winning numbers among the 100 balls with unknown number. Out of all these priors the maximum likelihood rule establishes that only those priors with the highest number of balls that are below (above) the threshold will be considered, if participants are told that the first ball drawn is indeed below (above) the threshold. Out of all these priors, the prior that will minimise (maximise) the interim probability is the one that has the highest number of balls below or above the threshold (depending on the event), but at the same time considers all these balls as loser (winner) numbers. The posterior generated this way will coincide with the full-Bayesian updating posterior, as in this case again, the lowest (highest) interim probability of winning is the one in which the highest possible number of balls are below or above the urn, and at the same time they are all losing (winning) numbers. Therefore, in this experiment choices cannot be affected by the updating rule, if participants consider multiple priors and we assume that the satisfy one of the most common Bayesian updating rules.

1.2.3 Timing of experiment

Table 1.2 shows that the same lottery can be chosen to be resolved early or late. The aim of this pairwise choice is to analyse how the timing of the resolution of uncertainty affects decision-making. In order to effectively test this, the timing of when decisions are made and resolved is explained in detail to participants in the instructions of the experiment. Participants are also told that lotteries resolved early will be played right after all 20 pairwise choices have been shown to participants and that lotteries resolved late will be resolved 30 minutes after all choices have been made[10]. The first part of the gradually resolved lotteries is resolved at the same time as the lotteries resolved early, and the second part at the same time as the lotteries resolved late. We also tell participants that even if they choose to resolve a lottery early, and that lottery is played for money,

[10]We follow standard waiting time of 30 minutes to determine a sufficient time distance between early and late resolution, following the work by Masatlioglu (2017) and Nielsen (2020).

they will stil have to wait 30 minutes for the experiment to conclude. This rules out the time cost of taking part in the experiment causing any strict preferences for early resolution over either gradual or late resolution. As part of the instructions, participants are also told that, during the 30 minutes between the times in which lotteries can be resolved, they will either be constantly reminded by the prize they won (if an early-resolved lottery is played) or lottery that will be played in 30 minutes (if a gradually resolved or late-resolved lottery is played). They are reminded about this through a small box on the lower right-hand side of their screen[11].

After the instructions, they have to answer a set of questions to show they have understood how lotteries are formed and how they are resolved. Then, participants are shown the 20 pairwise choices in four different orders (see Appendix)[12].

One of the pairwise choices is then randomly selected and one of the three decisions from the selected pairwise choice is also randomly chosen to be played for money by the computer. This method has been determined to be incentive-compatible under the standard assumption of monotonic utility over monetary prizes (Azrieli et al., 2018).

Depending on the choice made by the participants in the randomly selected decision the lottery will be either played by the computer and the outcome shown to participants (if chosen lottery is resolved early), partly resolved and the second part of the lottery shown to participants (if chosen lottery is resolved gradually), or no lottery will be resolved (if chosen lottery is resolved late). In the case of gradually resolved lotteries in the ambiguity treatment, they are not told about the exact value of the drawn value, to maintain participants agnostic about the content of the urn, and prevent updating of beliefs about the numbers on the unknown balls. During the following 30 minutes participants have to complete the slider (real effort) task (Gill and Prowse, 2012). This task is part of a separate project, which aims to look at how differences in endowment, increased or decreased chance of having high future earnings as compared to an ex-ante exogenous

[11]In an on-line experiment, the possibility of being distracted by external stimuli is increased as we cannot control the environment to the same extent as in a lab experiment. We, therefore, choose to make this information more salient to participants at all times, so that the feeling of unresolved uncertainty is felt more strongly throught the experiment.

[12]This is done to control for possible order effects.

probability, and the level of uncertainty about the environment motivates or discourages effort. There are 10 rounds (with two practice rounds) of 90 seconds in this section of the experiment. If participants complete this before the 30 minutes are over, they are taken to a waiting screen that shows for how much longer they will have to wait before they can complete the experiment and the same information they have had during this interval.

After 30 minutes have passed, participants whose selected lotteries had still not been played learn the outcome of the lottery. We then perform some control tasks: risk aversion elicitation is done using the BRET method (Crosetto and Filippin, 2013). We measure ambiguity aversion using the standard two-urn choice problem of Ellsberg. However, as we want to elicit ambiguity aversion for different likelihoods of winning the prize, we use a risky urn that contains 10 balls numbered from 1 to 10, and an ambiguous urn that also contains 10 balls but where any ball can take any value between 1 and 10. The winning numbers in each of the three decision problems are: 1, 1 to 5 and 1 to 9. This is a standard method used to elicit ambiguity aversion with changing likelihoods of winning (Trautmann, de Kuilen, 2015). We again follow Baillon et al. (2014) and generate the ambiguous urn, which is the same for all three decision problems at the beginning of the experiment. However, due to the risk of suspicion from participants (Hey et al., 2010; Abdellaoui et al., 2015) and possibility of hedging of ambiguity, we chose to pay for all choices in this case. Lastly, we perform a common ratio effect test. This is done to study if a (negative) certainty effect is correlated with preferences over gradual and one-shot resolution of uncertainty, as prescribed by Dillenberger (2010). We also evaluate psychological characteristics of participants with two measures: Big-five personality traits (Rammstedt and John, 2007) and positive and negative affect (Watson et al., 1988).

1.2.4 Elicitation of strict preferences

As we discussed in section 1.1, standard expected utility theory establishes that the timing and structure of non-instrumental information should not affect preferences. Therefore, indifference between the choices participants face in the experiment would be

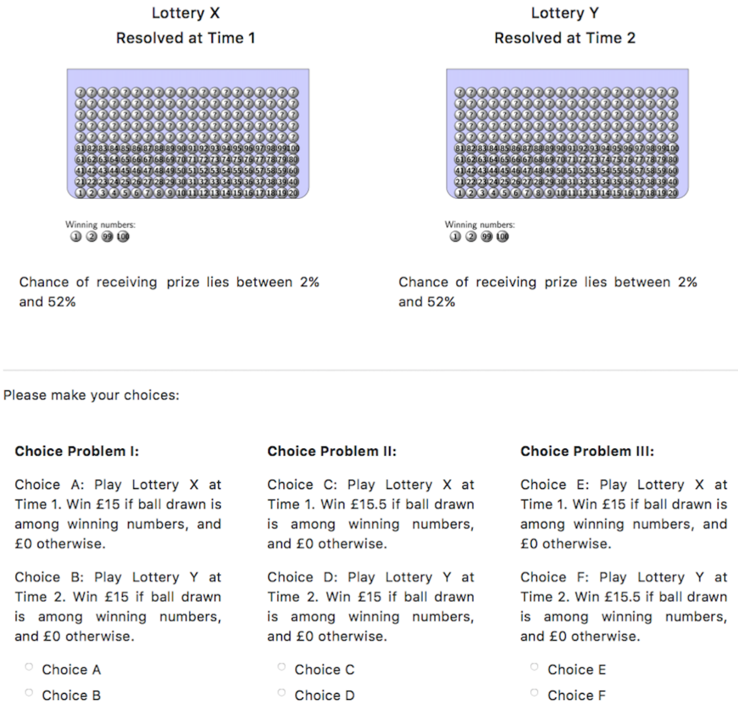


Figure 1.1: Example of Pairwise Choices and Decisions

compatible with standard models, as neither the independence axiom, nor the reduction of compound lotteries would be violated. Establishing a method to separate strict preferences from preferences that are compatible with indifference is, as a result, necessary to draw conclusions about the validity of the standard and alternative models. We follow the strict preference elicitation method developed by Epstein and Halevy (2019). For each of the 20 pairwise choices, we ask participants to make three decisions, as can be seen in figure 1.1. In the first one, the prize of the two lotteries is the same (£15), in the second one choice X has a higher prize (£15.5) than Y (£15), and the opposite happens in the third decision. Assuming monotonicity of preferences, if a participant has a strict preference for one of the two lotteries, they would choose that lottery in all three decision problems; if, instead, they only have a weak preference for one of the lotteries, then they would choose that lottery in the first decision problem, and the lottery that gives the highest prize in the second and third lotteries[13].

[13]Participants may still have a strict preference over one of the lotteries in this case, if the difference certainty equivalents of the lotteries is smaller than £0.5. Therefore, strict preferences using this method

This preference elicitation method has several advantages: firstly, as we assume that participants do not necessarily satisfy the axioms of (subjective) expected utility (e.g. ambiguity neutrality, reduction of compound lotteries), it prevents issues with eliciting monetary certainty equivalent values of lotteries (Freeman et al. 2019); secondly, due to the high number of decision, and the increased cognitive load this leads to, having only three decisions for each pairwise choice simplifies the experiment compared to other methods of elicitation; thirdly, it simplifies the observation of non-monotonic choices, without imposing them. This is particularly important in an on-line experiment in which participant's attention is one of the main issues compared to lab experiments.

1.2.5 Implementation

The experiment was run on-line, using oTree (Chen et al., 2016; Holzmeister and Armin Pfurtscheller, 2016) to program it. 121 students from ELFE (Experimental Laboratory of Finance and Economics) at UCL participated in the experiment, and were randomly assigned to one of the two between-subject treatments: 61 participants were assigned to the ambiguity treatment and 60 participants were assigned to the risk treatment[14]. The experimental design and main hypotheses were pre-registered at AsPredicted[15]. The average payment was £25.5 (including £5 participation fee). This is in line with laboratory experiments performed at the ELFE lab.

1.3 Theoretical framework

We now discuss the theoretical predictions of different models of decision-making under risk and ambiguity about the choices over the lotteries we show to participants in the experiment.

We characterise each lottery f as a Savage act f: $\Omega \to X$, a mapping from the set of

can be interpreted as a lower bound.

[14]The UCL Research Ethics Committee approved the experiment with IRB: 12439/ 001.

[15]AsPredicted is a deposit for experimental designs funded by the Wharton School of the University of Pennsylvania and managed by the Wharton Credibility Lab.

states of the world Ω to the set of consequences X. In our experiment we can decompose the set of states of the world into two subsets, $\Omega = B \times S$, where $b \in \{1, ..., 100\}$, that is, the realised state within the subset B ($b \in B$) is the ball drawn from the urn that determines the outcome and S is the set of possible compositions of the ambiguous urn, that is, the set of probability distribution over the 100 unknown balls. $x \in \{0, 15, 15.5\}$ ($x \in X$) is the associated prize to the lottery which varies across decision problems, due to the strict preference elicitation method.

We define subsets of the set of the ball that determines the prize B as events or information structures: $E \subseteq B$. In simple or one-shot lotteries the set of events is unique, equivalent to the whole set B, and it is not partitioned further before the realisation of the state of the world; this is so because in these lotteries no further information about the value of the ball is learnt before its realisation. We denote this partition as $\pi_{\varnothing} = \{E_0\} = \{B\}$. In compound or gradually resolved lotteries instead the set of states is partitioned in two events. We denote this partition as $\pi_I = \{E_1, E_2\}$, where $E_1 = \{1, ..., th\}, E_2 = \{th + 1, ..., 100\}$ (where th is the threshold value as shown in table 1.2), that is, in compound lotteries participants learn if the true state of the world is below or equal to the threshold value, or above it, before they learn b.

1.3.1 Decision-making under risk

In the risk treatment, we determine the ex-ante probability of winning the lottery in every pairwise choice problem to be the same, that is, for every $b_i \in B$, we enforce that $\Pr(b_i){=}p_i$ and $\Pr(E_j){=}q_j$ and $\Pr(b_i|E_j){=}r_{i,j}$, such that $p_i{=}\sum_{j=1}^{2} q_j r_{i,j}$. In other words, if subjects satisfy the axiom of reduction of compound lotteries (which implies time neutrality as well (Segal, 1990), then participants should be indifferent between one-shot lotteries and gradually resolved lotteries, and between one-shot lotteries resolved early and late. We can also assume away the subset of states of the world that characterise the distribution of unknown balls as this is completely identified in this treatment (i.e., $\Omega = B$).

However, if the reduction of compound lotteries did not hold [16] we could observe that $f_{\pi_I} \succeq f_{\pi_\varnothing}$ or $f_{\pi_\varnothing} \succeq f_{\pi_I}$ (where f_{π_I} represents lotteries that are gradually resolved and $f_{\pi_\varnothing}$ lotteries that are resolved in one-shot).

1.3.2 Decision-making under ambiguity

In the experiment, we mainly use risky lotteries as a benchmark with which to compare decision-making under ambiguity. We elicit ambiguity generating an urn with 100 balls with unknown values, and 100 balls with a known value . Therefore, Pr(b)$\in$ $\{\frac{1}{200}, ..., \frac{101}{200}\}$, $\forall b \in B$. The exact ex-ante probability depends on the compositions of the urn, which is an element $s \in S$. DM have a set of beliefs about the composition of the urn. These beliefs have been modelled using different models in the literature. Within the framework of our experiment we can reach conclusions about the empirical validity of some of these models. In order to study the implications of each of these models, we consider a monotonic $u : X \to \mathbb{R}$ utility function, and simplify it to u(15)=1 and u(0)=0.

Maxmin utility model (MEU)

This model, first axiomised by Gilboa and Schmeidler (1989), is the most popular model in the literature, mainly due to its simplicity in rationalising the Ellsberg paradox (1961), which is the cornerstone of the literature on ambiguity aversion. It considers a set of priors over the ambiguous state of the world, in this case the composition of the urn, $C \subseteq \Delta(S)$.

The model sets the utility from act $f_{\pi_\varnothing}$ (where a lottery has prize 15) as:

$$V(f_{\pi_\varnothing}) = \min_{p \in C} \sum_{w \in W} p(w) = \min_{p \in C} Pr(win)$$

where $W \subseteq B$ is the set of winning numbers in lottery f.

From our set of lotteries, we can reach the following conclusion.

[16] Abdellaoui et al. (2015) show a compound-risk premium, which is increasing in the probability of winning lottery. Harrison et al. (2015) find evidence against reduction of compound lotteries.

Proposition 1 *If we assume MEU, all gradually lotteries in table 1.1 satisfy these two conditions:*

i) $V(f_{\pi_\varnothing}) \geq V(f_{E_1})$

ii) $V(f_{\pi_\varnothing}) \geq V(f_{E_2})$

where $V(f_{E_1})$ *is the value of the lottery after* E_1 *is realised, and similarly for* $V(f_{E_2})$*, with at least one inequality strict for all f in table 1.1.*

As $Pr(E_1) > 0$ and $Pr(E_2) > 0$ for all $P \in C$, from proposition 1 we conclude that participants have a strict aversion towards all gradually resolved lotteries.

Proposition 1 is implied by Proposition 3 in Li (2020), which states that if a DM has MEU preferences, then she has aversion towards receiving partial information, and this aversion is strict if the set of priors C is not π_1-rectangular, that is, if it is not rectangular with respect to the partition imposed by gradually resolved lotteries. Rectangularity of priors (Epstein and Schneider, 2003) implies that all combinations of conditional and marginal probabilities contained in the set of ex-ante priors are also included in the set of priors. In our case this does not hold. As an illustration, imagine a combination of conditional lotteries where the probability of obtaining the ball 1 is 1/(100+th) after event E_1 (that is, all balls with unknown value have a value below the threshold but different from 1); suppose also a marginal distribution where the probability of state E_1 is th/200 (that is all balls with unknown value have a value greater than the threshold). It is easy to check that a combination of these two leads to a prior that is lower than the lowest ex-ante probability of obtaining 1. Therefore, this set is not rectangular[17].

Therefore, in any event that results from the partition π_1 of the gradually resolved lottery, if participants satisfy MEU, the probability of winning the lottery will be lower than the ex-ante probability, and subjects will therefore have a strict preference for one-shot lotteries.

[17]Formally, a set of priors C is rectangular if $C = \{p \in \Delta(S) : p = \sum_E p^E(\cdot|E)q(E)\ \forall p^E(\cdot), q(E) \in C\}$ where $p^E(\cdot)$ represents the conditional probability after event E and q represents the marginal probability of state E.

Choquet expected utility

Choquet expected utility (Schmeidler, 1989) is a representation of preferences in which expected utility is computed using a capacity instead of probabilities. That is, a utility function $V : f \to \mathbb{R}$ is Choquet expected utility if:

$$V(f) = \sum_{\omega \in \Omega} u(f(\omega))v(\omega)$$

where v is a capacity; that is, it is a mapping from the sigma-algebra Σ of states Ω to the interval between 0 and 1 ($v : \Sigma \to [0, 1]$) that satisfies the following conditions:

i) $v(\varnothing) = 0$ and $v(\Omega) = 1$

ii) $E' \subseteq E$ implies that $v(E') \leq v(E)$

Choquet expected utilities can represent ambiguity-averse or ambiguity-seeking attitudes depending on the shape of the capacity v. If v is convex (that is, if $v(E \cup F) + v(E \cap F) \geq v(E) + v(F)$, for any two events E and F in Σ) then they represent ambiguity-averse attitudes and ambiguity-seeking if v is concave (that is, if $v(E \cup F) + v(E \cap F) \leq v(E) + v(F)$).

Choquet expected utilities are a special case of MEU when v is convex (Gilboa and Marinacci (2016)). Therefore, the same results apply as for MEU when the DM is ambiguity averse, i.e., she has a strict preference for the one-shot lotteries over gradually resolved lotteries. Similarly if v is concave, then Choquet expected utility represents an ambiguity-seeking decision-maker's preferences and as a result gradually resolved lotteries will be preferred to one-shot lotteries.

Multiplier preferences

Multiplier preferences (Hansen and Sargent, 2001) are most commonly used in macroeconomic models. They are characterised by the following utility function:

$$\text{U(f)}=\min_{p \in C} \left[\sum_{w \in W} p(w) + \theta R(p||q) \right]$$

where p is a prior from the set of priors C, as we defined for the MEU model, q is a reference probability measure, R represents the relative entropy of two probabilities measure and θ the degree of ambiguity aversion, and W is defined as above.

Li (2020) uses a model where the reduction axiom is relaxed, and concludes that if decision-makers have the multiplier preferences, then they are indifferent between one-shot and gradually resolved lotteries. This result uses the proof by Strzalecki (2011) about multiplier preferences satisfying Savage's Sure-Thing Principle.

Early vs. late resolution of uncertainty under ambiguity

Strzalecki (2013) using a recursive dynamic model over the timing of resolution of uncertaintiy shows that the only model out of the main models studied in the literature (maxmin, second-order expected utility, smooth model, multiplier model and its generalisation the variational model), only MEU is compatible with indifference to the timing of resolution of uncertainty.

In the next section we analyse the data obtained from the experiment and link the results to the theoretical predictions discussed in this section.

1.4 Results

In this section we discuss the main results of the experiment. We first focus on comparing one-shot and gradually resolved lotteries across treatments (both between and within subjects). We then analyse preferences between early and late resolution of uncertainty. Lastly, we discuss how strong the preferences expressed in the previous two subsections are.

1.4.1 One-shot vs. gradual resolution of uncertainty

We first analyse the prevalence of preferences between one-shot or gradual resolution of uncertainty in our sample across (between-subject and within subject) treatments. When comparing decisions we exclude observations that do not satisfy the monotonicity axiom[18], but there are no significant qualitative or quantitative differences if we include

[18]These represent at most 11% of the sample.

them. Figure 1.2 compares the percentages of participants that show a preference for one-shot (either early or late) for positively skewed lotteries[19] [20].

By looking at the figure we can see there is a significant difference in behaviour between treatments. In the risk treatment the percentage of participants that prefer early resolution over gradual resolution remains relatively constant as the ex-ante probability of winning grows, whereas in the ambiguity treatment there is a upward trend, such that approximately only a third of participants choose to resolve the lottery early when the likelihood of winning is low (10%) and 80% choose it when the likelihood of winning is high (90%). Table 1.3 shows the p-values of McNemar tests on matched choices between early and late resolution of uncertainty for each participant and each pairwise combination of probabilities or likelihoods for risk and ambiguity[21]. They confirm the results from figure 1.2. The shift from early to gradual resolution of uncertainty as probability increases is not significant under risk, but it is significant under ambiguity.

We also use Page's nonparametric test for ordered alternatives (Abdellaoui et al. (2015)) to test for the existence of a trend in the preference for gradual resolution of uncertainty. The trend is highly significant for ambiguity, both when comparing early and gradual resolution (p-values 0.0001 and 0.0035, for positively and negatively skewed lotteries, respectively) and late and gradual resolution (p-values 0.0077 and 0.0009, for positively and negatively skewed lotteries, respectively)[22]. No such trend exists, however, under risk[23].

From figure 1.2 we can also notice that there are some differences regarding the choice of early vs. gradual resolution and late vs. gradual resolution of uncertainty. Under

[19]In the ambiguity treatment, skewness can differ depending on the beliefs of participants, but for illustrative purposes we use this term for the corresponding lottery of the positively skewed lottery in the risk treatment, and similarly for the negatively skewed lotteries.

[20]Corresponding graphs for negatively skewed lotteries are in the Appendix.

[21]Corresponding tables for negatively skewed and pairwise comparisons with late resolution of uncertainty can be found in the Appendix.

[22]We do not include the 50% high variance probability treatment in the test as it is not directly comparable to the other treatments, due to differences in the informativeness of the additional information.

[23]P-values for choice between early or gradual resolution of uncertainty are 0.3832 and 0.1493, for positively and negatively skewed lotteries. P-values for choice between late or gradual resolution of uncertainty are 0.4379 and 0.3832.

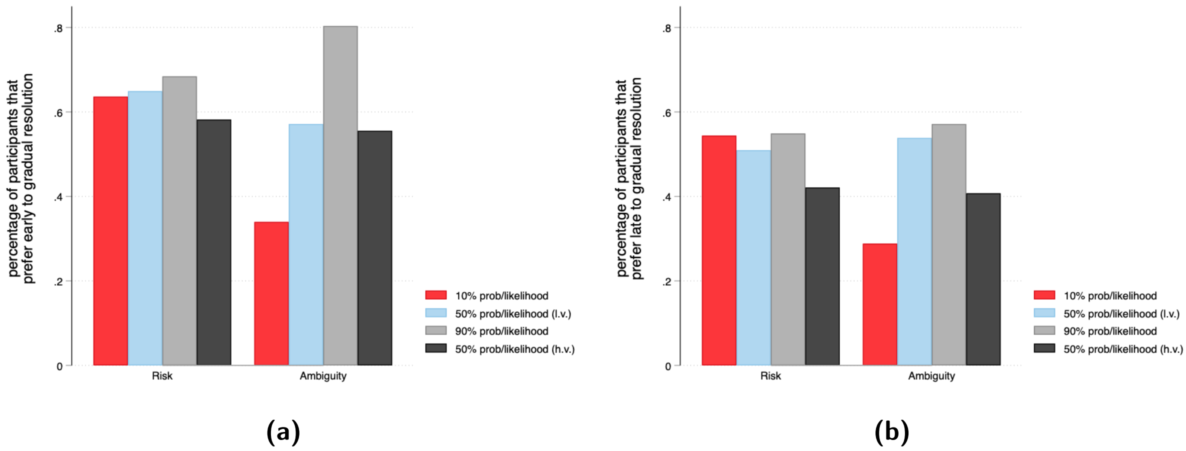


Figure 1.2: Percentages of Preferences of Early/Late Resolution over Gradual Resolution

Note: Figure (a) shows the percentage of participants that prefer early resolution of uncertainty over gradual resolution. Figure (b) shows the the percentage of participants that prefer early resolution of uncertainty over gradual resolution. In both cases we consider the positively skewed lotteries. "l.v." stands for low variance and "h.v." means high variance.

ambiguity, the only significant difference is when comparing the pairwise choices that contain 90% likelihood positively skewed lotteries (p-value of McNemar test 0.0047). This, however, does not extend to the choices that contain the negatively skewed lotteries (p-value 0.1967). More importantly, under risk, there is a significant shift of choices from early resolution over gradual resolution to late resolution against gradual resolution for the 50% probability high-variance lottery, for the positively and negatively skewed lotteries (p-values 0.0184 and 0.0325, respectively). In both treatments, there is a significant minority (25% and 21% of the sample, respectively) that shifts from choosing one-shot early lottery to the gradually resolved lottery when faced with the alternative of late resolution. This means that when there is a very large change in probability provided by the additional information, in situations in which participants have to wait, they are willing to receive extra information. However, most participants do not change their preference and can be consistently identified as averse to gradual resolution, or instead gradual resolution loving.

Result 1: *There is a significant differences in attitudes towards the gradual resolution*

	10% likelihood	50% likelihood (l.v.)	90% likelihood	50% likelihood (h.v.)
Risk treatment - Positively skewed lotteries				
10% likelihood	-	1.000	0.8388	0.3173
50% likelihood (l.v.)	-	-	0.5930	1.000
90% likelihood	-	-	-	0.3323
Ambiguity treatment - Positively skewed lotteries				
10% likelihood	-	0.0146**	0.0000***	0.049**
50% likelihood (l.v.)	-	-	0.0192**	0.5485
90% likelihood	-	-	-	0.0029***

Note: Each cell shows the p-values of McNemar test for matched choices between early and gradual resolution of uncertainty under risk for different probabilities.
*10% significance level, **5% significance level, ***1% significance level.

Table 1.3: Test of Significant Shifts Between Early and Gradual Resolution of Uncertainty

of uncertainty between risk and ambiguity. Under ambiguity, the dominance of this type of resolution is inversely related to the likelihood of winning the lottery. No such trend can be observed under risk.

1.4.2 Early vs. late resolution of uncertainty

We now study preferences between early and late resolution of uncertainty for both treatments. Figure 1.3 shows the percentage of participants that prefer early resolution of uncertainty to late resolution for the two between-subject treatments and the 4 different within-subject treatments. We can see that, contrary to the previous analysis, there is no significant difference between treatments. A large majority of participants (approximately between 70% and 85%, depending on treatment) prefer early resolution of uncertainty over late resolution. Slightly fewer participants have a preference for early resolution of uncertainty under ambiguity. However, this difference is not significant for any within-subject treatment [24].

Result 2: *Across all between and within treatments, a large majority of participants prefer to learn the outcome of the lottery early rather than late.*

[24] P-values of Fisher exact test: 0.599 (10% probability/likelihood), 0.502 (50% probability/likelihood, low variance), 0.813 (50% probability/likelihood, high variance), 0.316 (90% probability/likelihood).

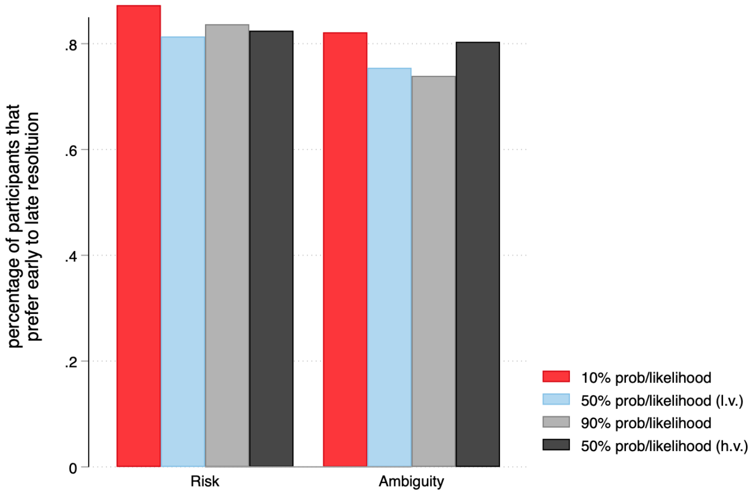


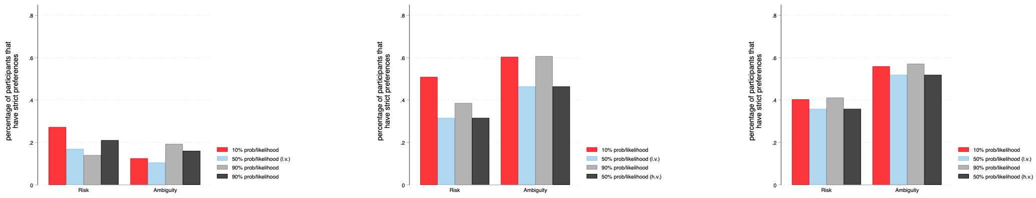
Figure 1.3: Percentage of Participants that Prefer Early Resolution of Uncertainty over Late Resolution

Note: "l.v." stands for low variance and "h.v." means high variance.

1.4.3 Strict preferences

As we mentioned in the Introduction and section 1.2 indifference between early, late or gradual resolution of uncertainty is compatible with expected utility theory. In order to study if there are deviations from the model we, therefore, also have to take into account if there are strict preference for early or late resolution of uncertainty.

Figure 1.4 shows the percentage of participants that show a strict preference when asked to choose between early or late resolution of uncertainty (Figure (a)), early or gradual resolution of uncertainty (Figure (b)), and late or gradual resolution of uncertainty (Figure(c)). The main takeaway is that there is a big difference in strict preferences between choices that involve the pure time dimension (those in Figure (a)), and those that also involve gradual resolution of uncertainty (Figures (b) and (c)). Between 11% and 27% of participants have a strict preference between early and late resolution of uncertainty. However, between 32% and 61% have a strict preference between early and gradual resolution of uncertainty, and 40% and 57% between late and gradual resolution of uncertainty (see Appendix for details). The shift from weak to strict preferences is significant at 1% for all pairwise comparisons in the ambiguity treatment, and 5% for all comparisons in the risk treatment, except for one, which is significant at 1% (see Appendix).



(a) (b) (c)

Figure 1.4: Percentage of Participants with Strict Preferences Across Treatments

Note: Figure (a) shows the percentage of participants that have a strict preference between early and late resolution of uncertainty. Figure (b) shows the the percentage of participants that have a strict preference between early and gradual resolution of uncertainty. Figure (c) shows the the percentage of participants that have a strict preference between late and gradual resolution of uncertainty. In comparisons that include gradually resolved lotteries we consider the positively skewed lotteries. "l.v." stands for low variance and "h.v." means high variance.

It can also be noted that in choices that include gradually resolved lotteries the percentage of participants that have strict preferences is overall lower in the risk treatment than in the ambiguity treatment, although in most cases the difference is not statistically significant, or only marginally significant at 10% (see Appendix).

Result 3: *Approximately half of the sample show a strict preference for or against gradual resolution of uncertainty for all within-subject treatments. Preferences over early or late resolution of uncertainty are much weaker and no more than 20% of the sample has a strict preference over them.*

1.5 Discussion

The results above show that there are significant deviations from the (subjective) expected utility and its predictions about preferences over the timing of uncertainty, both under risk and ambiguity.

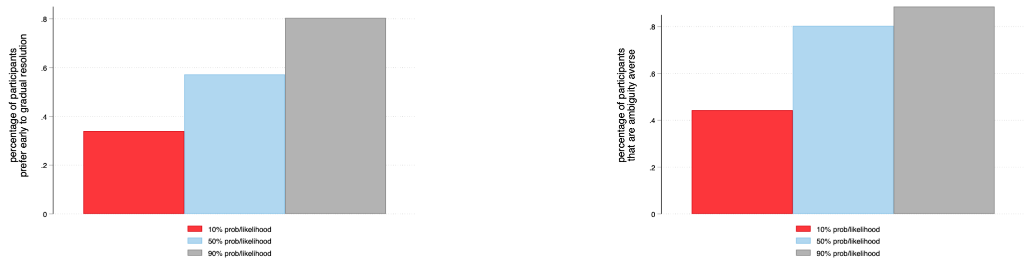
Firstly, at least a third of participants in the experiment have a strict preference over solving uncertainty gradually in both treatments[25]. This is in line with the results from other studies like Nielsen (2020), which find around 40% of participants having a strict preference over the number of periods over which the lottery is resolved. Results also show that there seems to be a difference (albeit only marginally significant) that the strength of preferences is stronger under ambiguity than under risk. We can therefore conclude that a large proportion of the sample (generally more than half in the ambiguity treatment) show preferences consistent with aversion to information that shifts the ex-ante probability or likelihood or a liking for it. There is a significant difference between treatments, however, in terms of the distribution of these preferences. Under risk, this distribution remains quite constant across within-subject treatments, that is, as the probability of winning the lottery goes up there is no significant change in the preferences, and neither is there between more informative and less informative lotteries. This result is in opposition to the main result by Abdellaoui et al. (2015), which finds an upward trend in the preference for simple lotteries as the probability of winning the lottery increases. There are two important differences between our design and theirs, however, that could have influenced the outcome: firstly, they do not take the time aspect into account, that is, compound lotteries are compared to simple lotteries, but they are all solved at the same time. Their elicitation method is also different as they rely on a multiple-price list to estimate a certainty equivalent of lotteries, whereas we have turned to the three decision method developed by Epstein and Halevy (2019).

Secondly, preferences over when lotteries are resolved play a much smaller role in the decision-making process than the number of periods in which the lottery is resolved (no more than 20% of the sample shows a strict preference over early or late resolution of uncertainty). It is possible that the 30 minute interval between both periods is not perceived by subjects to be long enough to generate strict preferences. Additionally, to be the best of our knowledge, this is the first experiment performed on-line that looks

[25]Notice that because of the strict preference elicitation method this can be considered only a lower bound on strict preferences

into preferences over the timing of information. This may have affected preferences, as the environment and exposure to the outcome of the lottery can significantly affect these preferences (Falk and Zimmermann, 2016). When looking at the distribution of weak preferences, we see that a large majority of participants prefer to learn the outcome of the lottery early rather than late. This result is very different to the result obtained by Nielsen (2020), which states that very few participants choose early resolution of uncertainty. However, there is a big difference in the experimental design, as their design allows for all possible combinations of early gradual or late resolution of uncertainty, and therefore, does not directly compare early and late resolution of uncertainty.

In the ambiguity treatment, we observe a trend across likelihoods of winning. This could be explained in terms commonly used in the ambiguity literature as optimism or pessimism towards the composition of the urn. For low likelihoods of winning, participants are more optimistic about the content of the urn and, therefore, are more willing to learn the event before the final outcome as this increases their chances of winning in both events. As the likelihood of winning becomes larger, however, they become more pessimistic and learning about the event before the final outcome lowers the probability of winning. This argument is close to the intuition first used by Ellsberg (2011) about how ambiguity aversion changes across different likelihood choices. This result has been empirically observed in the past, and is also consistent with the results we obtain from the control task where we test ambiguity aversion for different likelihoods events, as can be seen in figure 1.5. However, these two phenomena seem to be uncorrelated. A Fisher exact test of the correlation between ambiguity aversion and preferences for either early or gradual or late or gradual shows there is no significant correlation in any of the 16 pairwise tests. One caveat is worthing mentioning. Ambiguity aversion is tested using an urn with 10 balls, whereas for the other lotteries we assume an urn with 200 balls. Some theoretical papers (Einhorn and Hogarth, 1985; Rode et al., 1999) explain ambiguity aversion in such a way that it could be interpreted that more complex ambiguity problems may affect ambiguity preferences. In an experimental setting, however, Pulford and Colman (2008) show that this does not seem to alter these preferences. Therefore,



(a) **(b)**

Figure 1.5: Preferences over Gradual Resolution of Uncertainty and Ambiguity Aversion

Note: Figure (a) shows percentage of participants in the ambiguity with a preference for early resolution of uncertainty over gradual resolution. Figure (b) shows percentage of participants in the ambiguity treatment with behaviour compatible with ambiguity aversion

these two similar trends seem to be orthogonal to each other.

Theoretical implications

As we discussed in section 1.3, different models have different prescriptions for preferences over the timing of resolution of uncertainty. With respect to risky choices, we find that the sample is quite evenly split between participants that prefer one-shot resolution of uncertainty and those that prefer gradual resolution of uncertainty. We can state, however, that a non-negligible percentage of participants have a behaviour that is not consistent with standard economic models. We found no significant correlations between these choices and measures like the big-five personality traits and positive and negative affect, that could provide some psychological underpinnings to the observed behaviour, and link it loss aversion, disappointment aversion or having a preference for suspense or suprise, as proposed by the main papers that provide theoretical explanations for these preferences.

We now turn to study evidence for or against the ambiguity models discussed in section 1.3.

Results from this section show that under MEU participants should always choose one-shot lotteries over gradually resolved lotteries, and have a strict preference over them.

However, we find that only 3 (out of 61) participants show a behaviour compatible with this result. The Choquet model establishes the same result for situations in which participants are ambiguity averse, and that they should have a strict preference for gradual resolution of uncertainty when they are ambiguity-seeking. Only 5 participants satisfy this condition. Finally, the multiplier model establishes that participants should be indifferent between one-shot and gradual resolution of uncertainty. 4 participants satisfy this condition. These three models can, thus, barely account for 20% of the observed choices.

The main reason behind the poor behaviour of these models is that neither the multiplier or MEU model can account for the changing preferences as the likelihood of winning changes. The Choquet model is more flexible as it allows for ambiguity averse and ambiguity seeking attitudes (although the capacity is supposed to be constant for all likelihood levels). But even allowing for changes in the capacity, the Choquet model cannot capture the changes preferences either, as these are not correlated with ambiguity attitudes. A more realistic model would have to capture the two dimensions (changing ambiguity aversion, changing gradual resolution aversion) at the same time.

1.6 Conclusion

This chapter has focused on studying differences in preferences over the timing of the resolution of uncertainty in situations in which probabilities are known, and those in which they are not known. We find significant deviations from the standard economic model in both cases.

The results can have significant implications in our understanding of these preferences. We find that when the additional information is available about the outcome of the lottery a majority of participants choose to learn it if the ex-ante likelihood of the good outcome is low, but they want to avoid it if the ex-ante likelihood of the good outcome is high. This could, for instance, explain why the take-up of genetic tests is generally low, as the ex-ante probability of having the mutations related to developing these diseases is generally low.

These results could also help to develop information campaigns around individual behaviour related to health or public goods like environmental protection. As we discussed in the Introduction, most information provision has two components (instrumental and non-instrumental). Noticing that under certain circumstances this information may be chosen to be avoided, and as result its instrumental value be neglected, can help design more efficient information mechanisms or better evaluate its welfare-improving value.

There are also gaps in our understanding of the results that would be interesting to look into in future projects. For instance, we still need to understand what makes some subjects more averse to gradual resolution of uncertainty than others, and how to link their behaviour to the alternative explanations provided by the literature. On the theory side, it would be interesting to develop a model that can explain the changes in ambiguity aversion as the likelihood of the good outcome changes, but also how preferences over gradual resolution of uncertainty change as this likelihood varies.

Appendix to Chapter 1

A.1 Proofs

Proof of proposition 1

From the main text we know that $V(f_{\pi_\varnothing}) = \min_{p\in C} \sum_{w\in W} p(w)$, and that the minimum probability, without further information, of obtaining one of the winning numbers is $\frac{1}{200}$. Therefore,

$$V(f_{\pi_\varnothing}) = \frac{|W|}{200}$$

where $W \subset B$ is the set of winning numbers in lottery f, and $|W|$ is the cardinality of W.

We can define the utility after E_1 is realised in a similar fashion to $f_{\pi_\varnothing}$.

$$V(f_{\pi_{E_1}}) = \frac{|W_{E_1}|}{100 + th}$$

where $W_{E_1} \subset E_1$ is the set of winning numbers in lottery f after E_1 has occurred, $|W_{E_1}|$ is its cardinality and th is the threshold value in lottery f. The expression above states that lowest probability of winning the lottery after E_1 has occurred is when the numerator is minimised (there is only one ball per winning number in the urn) and the denominator is maximised (all 100 balls with unknown value have value equal or lower than the threshold).

It is easy to see that:

$$V(f_{\pi_\varnothing}) = \frac{|W|}{200} \geq \frac{|W_{E_1}|}{100 + th} = V(f_{\pi_{E_1}}) \iff \frac{|W_{E_1}|}{|W|} \geq \frac{1}{2} + \frac{th}{200}$$

and that this holds for all $|W_{E_1}|$, $|W|$ and th in compound lotteries described in table 1.1, with strict inequality for all cases but one (lottery 9) where the both sides of the inequality are equal to each other.

Similarly to the case of E_1, we can see that the utility of lottery f after E_2 is realised is:

$$V(f_{\pi_{E_2}}) = \frac{|W_{E_2}|}{200 - th}$$

Therefore,

$$V(f_{\pi_\varnothing}) = \frac{|W|}{200} > \frac{|W_{E_2}|}{200 - th} = V(f_{\pi_{E_2}}) \Longleftrightarrow \frac{|W_{E_2}|}{|W|} > 1 - \frac{th}{200}$$

and this also holds for all $|W_{E_2}|$, $|W|$ and th in compound lotteries described in table 1.1.

A.2 Order of lotteries

The following table shows the four different orders of lotteries used to control for order effects. The numbers used represent number of choice problems as shown in table 1.2.

Order #	List of choices in order shown
1	[1, 20, 6, 15, 2, 19, 7, 14, 3, 18, 8, 13, 4, 17, 9, 12, 5, 16, 10, 11]
2	[16, 5, 11, 10, 17, 4, 12, 9, 18, 3, 13, 8, 19, 2, 14, 7, 20, 1, 15, 6]
3	[11, 20, 1, 10, 12, 19, 2, 9, 13, 18, 3, 8, 14, 17, 4, 7, 15, 16, 5, 6]
4	[6, 5, 16, 15, 7, 4, 17, 14, 8, 3, 18, 13, 9, 2, 19, 12, 10, 1, 20, 11]

A.3 Experimental instructions

The Experiment

This experiment consists of 3 parts. Each part consists of a set of instructions detailing what is expected of you during that part of the experiment. In the first two parts, this will include a quiz to test your understanding of the questions. You will not be paid according to the answers of the quiz and the exact questions that appear in the quiz will never be asked as part of the choice problems of the experiment. After the instructions and the quiz, you will have to consider some choice problems where you will be paid according to your choices. You will be reminded when the instructions and the quiz have concluded and the choice problems are about to begin. This same sequence of instructions, quiz, and choice problems will occur for the first 2 parts of the experiment.

You will be able to revise the instructions at each page by clicking on buttons at the bottom of the page.

Part 1 - Instructions: Lotteries

(Risk treatment)

In this part of the experiment you will be asked to make choices between different lotteries.

A lottery is a game of chance where the prize depends on the number on a ball drawn from an urn.

-Types of lotteries

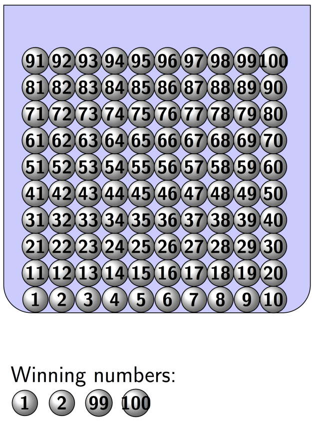
During the experiment you will see two different types of lotteries: 1.) *one-stage* lotteries and 2.) *two-stage* lotteries.

1.) One-stage lottery

A one-stage lottery is a lottery that is resolved after drawing **one** ball from an urn that contains 100 balls.

Below you can see what a one-stage lottery looks like:

Lotteries are composed of two elements, the urn and the winning numbers:



The urn: The urn with 100 balls in total is generated by the computer. Each of the balls have a known number from 1 to 100. None of those balls can have the same number.

The winning numbers: To determine whether you win the lottery or not, one ball will be drawn from the urn. If the number on the ball coincides with one of the winning numbers, then you win the prize of the lottery, otherwise you win nothing. The winning numbers are given and may vary between lotteries.

The winning numbers also determine the chances of winning the prize of the lottery. In the example above there are four winning numbers. This means the chance of winning the prize is 4 divided by 100, which is 4%. These calculations will be provided to you with every lottery before you have to make your choice.

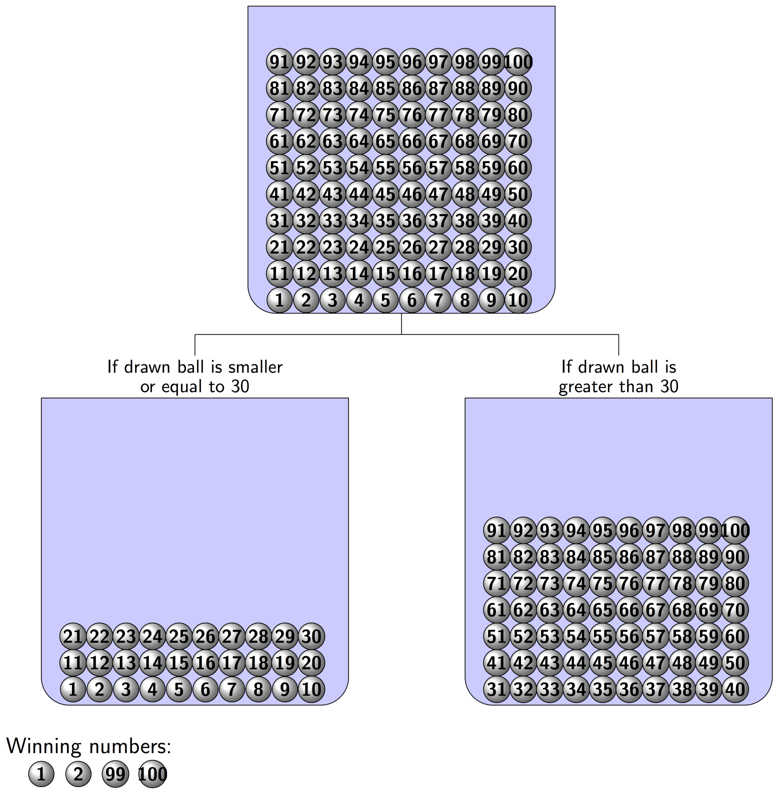
2.) Two-stage lottery

A two-stage lottery is a lottery that is resolved after two draws.

Below you can see what a two-stage lottery looks like:

Similarly to the one-stage lottery case, lotteries are composed of two elements, the (three) urns and the winning numbers:

The urns: The first urn for this lottery on top of the figure is created in exactly the same way as the one-stage lottery before. It is generated by the computer and contains 100 balls.



The content of the two urns on the bottom of the figure depends on a value that is pre-determined for each two-stage lottery. This value is called the threshold value. In the example above, the threshold value is 30. This value may be different for each two-stage lottery.

The leftmost urn contains all balls from the urn on top that have numbers smaller or equal to the threshold value. So, in the example above, all balls with a value equal or smaller than 30 are included in the leftmost urn. All remaining balls are included in the rightmost urn.

The winning numbers: As before, a set of winning numbers determines whether you win the lottery or not. Remember that in this type of lottery two balls are drawn. The first ball is drawn from the top urn. The number on this ball determines from which of the other two urns the second ball is drawn. If the number on the first ball is below the threshold value, the leftmost urn is used to draw the second ball. Otherwise, the rightmost urn is used to draw the second ball.

The chance that the second ball is drawn from either of the urns therefore depends on the threshold value. In the example above, the chance that the second ball is drawn from the leftmost urn is 30%, as there are 100 balls in total and 30 are equal or lower than 30. The chance that the second ball is drawn from the rightmost urn is 70%, as out of the 100 balls 70 are larger than 30, so the chance is 70 divided by 100, i.e., 70%.

The second ball determines the prize. If the number on the second ball coincides with one of the winning numbers, you win the prize. Otherwise, you win nothing. This is the same principle as in the one-stage lottery.

In contrast to the one-stage lottery, you learn some intermediate information about the chance of winning the prize after the first ball is drawn in two-stage lotteries. In the example above, the chance of winning the prize is 4% before the first ball is drawn. This is the same as in the one-stage lottery.

After the first ball is drawn this chance changes depending on the threshold value:

- If a ball lower or equal to 30 is drawn from the first urn, the chance of winning the prize is 2 over 30, i.e., 6.6%, as out of the 30 balls 2 are winning numbers.
- Similarly, if a ball with a number greater than 30 is drawn from the first urn, the chance of winning the prize is 2 over 70, i.e., 2.9%, because from the 70 balls in the urn, 2 are winning numbers.

You will be told about the chance of winning the prize before any ball and after the first ball is drawn at the time of making your choice.

•••••••••••••••••••

(Ambiguity treatment)

In this part of the experiment you will be asked to make choices between different lotteries.

A lottery is a game of chance where the prize depends on the number on a ball drawn from an urn.

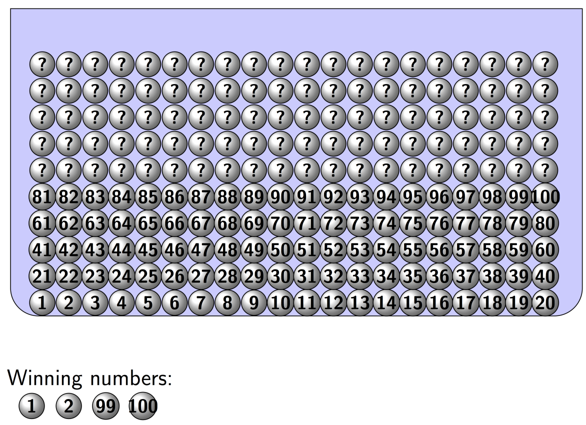
-Types of lotteries

During the experiment you will see two different types of lotteries: 1.) *one-stage* lotteries and 2.) *two-stage* lotteries.

1.) One-stage lottery

A one-stage lottery is a lottery that is resolved after drawing one ball from an urn that contains 200 balls.

Below you can see what a one-stage lottery looks like:



Lotteries are composed of two elements, the urn and the winning numbers:

> **The urn:** The urn with 200 balls in total is generated by the computer. Half of the balls have a known number from 1 to 100. None of those balls can have the same number.
>
> The other half of the balls have an unknown number. These are represented above with a '?' symbol. Each of these 100 balls can have any number between 1 and 100. This means that the same number can be on more than one of those balls. It could also mean that the same number is on all 100 balls or

that a number is on none of the balls. The numbers on these balls will be randomly determined by the computer before the first choice problem is shown to you. Neither you nor the experimenter will know the numbers written on these balls until the end of the experiment today. Due to this procedure it is also impossible for the experimenter to guess what the numbers on the balls may be from previous sessions of this experiment.

The winning numbers: To determine whether you win the lottery or not, one ball will be drawn from the urn. If the number on the ball coincides with one of the winning numbers, then you win the prize of the lottery, otherwise you win nothing. The winning numbers are given and may vary between lotteries.

The winning numbers also determine the chances of winning the prize. In the example above there are four winning numbers. Among the 100 balls whose number we can observe four are winning. This means the chance of winning the prize is at least 4 divided by 200 which is 2%. If none of the balls whose numbers we cannot observe have any of the winning numbers, the chance of winning the prize is still 2%. If all of the balls whose number we cannot observe shows any of the winning numbers the chance of winning the prize is 104 divided by 200 which is 52%. So, the chance of winning the prize depends on the number of balls with the ''?' that have the winning numbers. This number can be anywhere between 0 and 100 which means the chance to win the prize will lie between 2% and 52%. These calculations will be provided to you with every lottery before you have to make your choice.

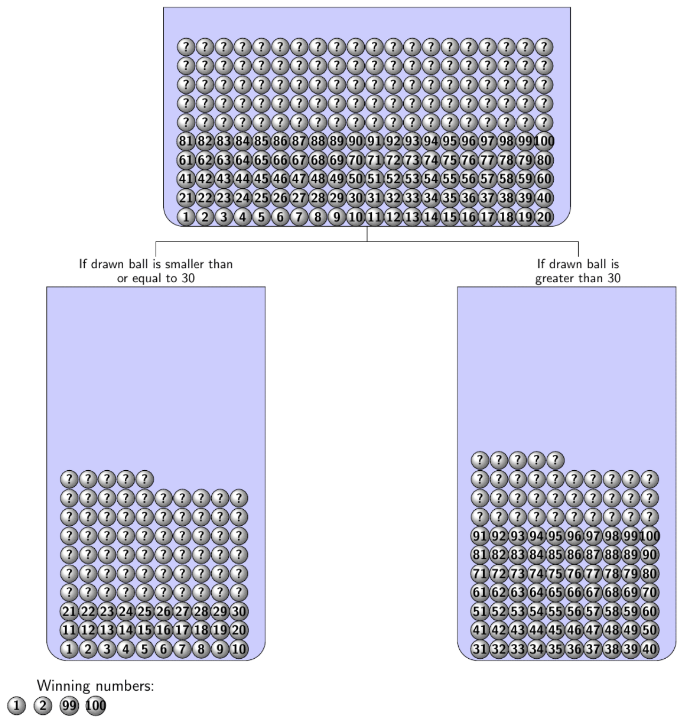
2.) Two-stage lottery

A two-stage lottery is a lottery that is resolved after two draws.

Below you can see what a two-stage lottery looks like:

(Note: In the actual experiment, the figure below was animated, and the 100 balls with unknown number moved back and forth between the two lower urns. We used this so that participants would have a graphical representation of the uncertainty about the content of these two urns. The animated version of the figure can be found at `https:`

//elfeexpjulenstatic.s3.amazonaws.com/example_compound_blue_amb.gif.)



Similarly to the one-stage lottery case, lotteries are composed of two elements, the (three) urns and the winning numbers:

> **The urns:** The first urn for this lottery on top of the figure is created in exactly the same way as the one-stage lottery before. It is generated by the computer and contains 200 balls. Again, neither you nor the experimenter will be able to observe the numbers written on the 100 balls with the '?' symbol until the end of the experiment.
>
> The content of the two urns on the bottom of the figure depends on a value that is pre-determined for each two-stage lottery. This value is called the threshold value. In the example above, the threshold value is 30. This value may be different for each two-stage lottery.
>
> The leftmost urn contains all balls from the urn on top that have numbers smaller or equal to the threshold value. So, in the example above, all balls with a value equal or smaller than 30 are included in the leftmost urn. This

includes the 30 balls that we know have a number smaller or equal to this threshold value and also all balls with the '?' sign that have such a number. All remaining balls are included in the rightmost urn. Those are balls with values we know are larger than 30 and also those with the sign '?' that have a value larger than 30.

The winning numbers: As before, a set of winning numbers determines the prize of the lottery. Remember that in this type of lottery two balls are drawn. The first ball is drawn from the top urn. The number on this ball determines from which of the other two urns the second ball is drawn. If the number on the first ball is below the threshold value, the leftmost urn is used to draw the second ball. Otherwise, the rightmost urn is used to draw the second ball.

The chance that the second ball is drawn from either of the urns therefore depends on the threshold value. If none of the balls with a '?' symbol in the first urn in the example have a number smaller than or equal to 30, the chance that the second ball is drawn from the leftmost urn is 30 divided 100, i.e., 15%. If all of the balls with a '?' symbol have a number smaller than or equal to 30 the chance is 130 divided by 200, i.e., 65%. Since any number of balls with a '?' symbol can have a number smaller than or equal to 30, the chance that the second ball is drawn from the leftmost urn is therefore between 15% and 65%. Similarly, the chance that the second ball is drawn from the rightmost urn is between 35% and 85%.

The second ball determines the prize. If the number on the second ball coincides with one of the winning numbers, you win the prize. Otherwise, you win nothing. This is the same principle as in the one-stage lottery.

In contrast to the one-stage lottery, you learn some intermediate information about the chance of winning the prize after the first ball is drawn in two-stage lotteries. In the example above, the chance of winning the prize lies between 2% and 52% before the first ball is drawn. This is the same as in the one-stage lottery.

After the first ball is drawn this chance changes depending on the threshold value:

- If a ball lower or equal to 30 is drawn from the first urn, the lowest chance of winning the prize is now 1.5%. This is the case when all the balls with the '?' symbol in the first urn are smaller than or equal to 30 but none of them have the numbers 1 or 2 on them. The chance of winning the prize is then 2 divided by 130 which is 1.5%. The highest chance of winning is 78.5% which is the case if all balls with a '?' symbol from the first urn are smaller than or equal to 30 and show either a 1 or a 2 as 102 divided by 130 is 78.5%. The overall chance of winning is therefore between 1.5% and 78.5% if the first ball shows a number smaller than or equal to 30.
- Similarly, if a ball with a number greater than 30 is drawn from the first urn, the chance of winning the prize lies between 1.1% (if all balls with the '?' symbol are greater than 30, but different from 99 and 100) and 60% (if all balls with the '?' symbol are greater than 30 and have numbers 99 or 100).

You will be told about the highest and lowest chance of winning the prize before any ball and after the first ball is drawn at the time of making your choice.

Part 1- Instructions: Choice tasks

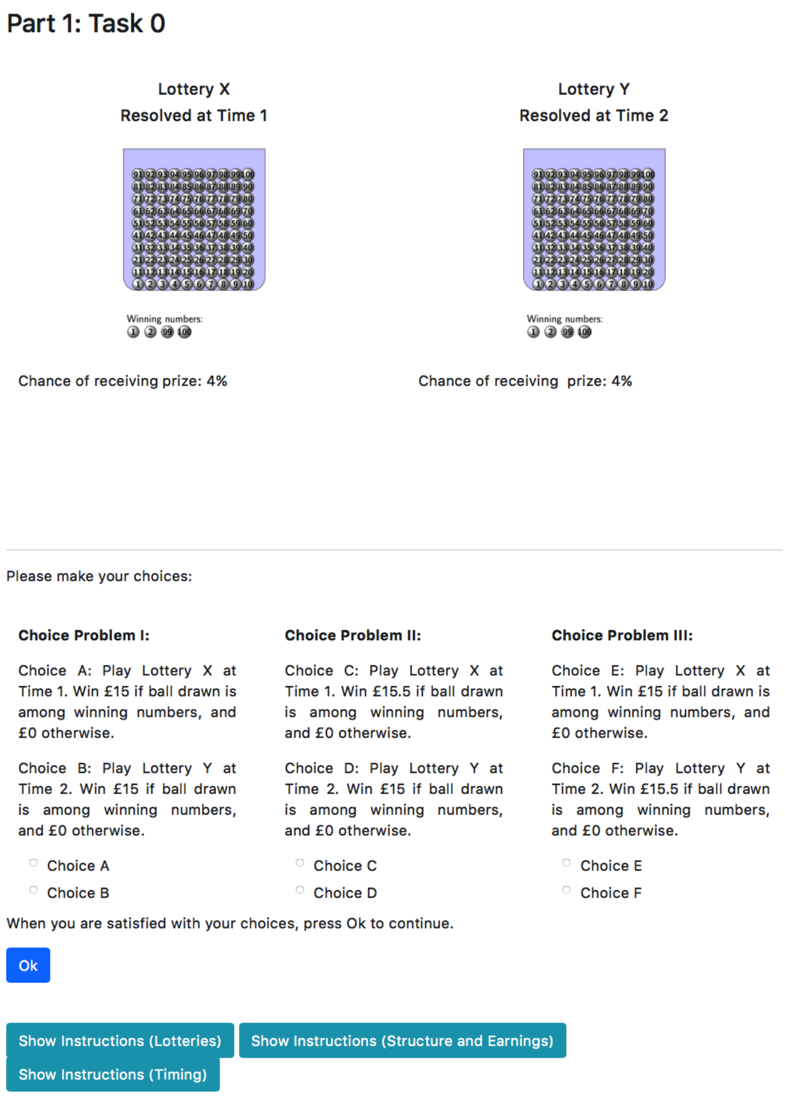
In the first part of the experiment, you will have to complete 20 choice tasks. Here is an example of how each task will look:

In each of them, we will show you two lotteries.

You will have to decide which one of the two lotteries you prefer. The two lotteries may differ in three aspects:

1.) Whether they are one-stage or two-stage lotteries

If the lottery is a one-stage lottery, you will learn whether you won the prize or nothing after one ball is drawn. If the lottery is a two-stage lottery, you will

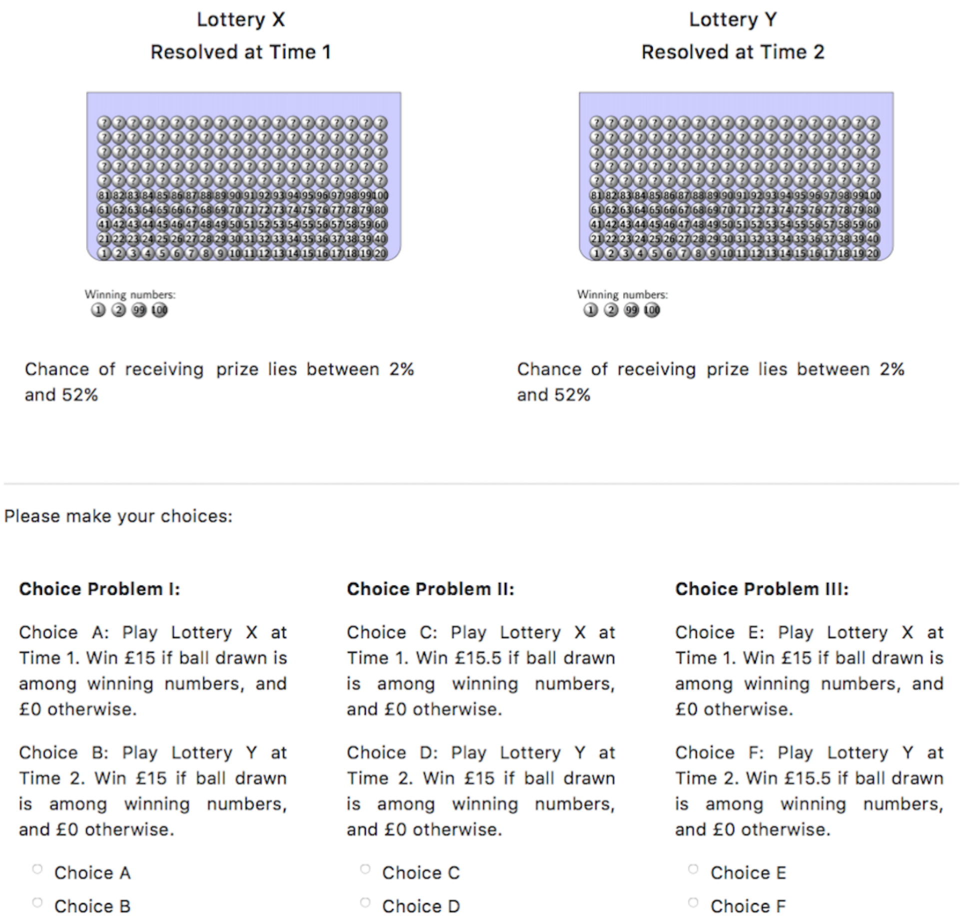


(Risk Treatment)

learn whether you won the lottery only after the second ball is drawn. However, as we mentioned above, you will learn some extra information about the chance of winning the prize after the first ball is drawn in two-stage lotteries.

2.) The time when a lottery is resolved

A lottery is resolved when the ball that determines the prize is drawn. One-stage lotteries may be resolved at Time 1 or Time 2. This means that you will learn whether you won the prize earlier (if the lottery is resolved at Time 1) or later (if the lottery is resolved at Time 2). Two-stage lotteries are always



(Ambiguity Treatment)

resolved at Time 2, as the first ball is drawn in Time 1 and the second one is drawn at Time 2. Time 1 happens right after you have made all your choices. Time 2 happens 30 minutes after you have made all your choices. You can see when the lotteries are resolved under the name of each lottery.

For instance, if you choose a lottery that is resolved at Time 1 you will learn whether you won the prize or not right after you have made all your choices and the lottery that will be played for payment is determined (more on this later). If, instead, you choose a lottery that is resolved at Time 2 you will only learn whether you won the prize 30 minutes after that.

3.) The prize of the lottery

In each task you will have to choose three times between the two different lotteries. We will call each of these three choices a choice problem to distinguish them from the 20 choice tasks.

In each of the choice problems the prizes will be different:

• In the first choice problem, the prize is £15 in both lotteries, i.e., you will earn £15 if the ball that determines the prize is equal to one of the winning balls. Otherwise, you will earn £0.

• In the second choice problem, the prize is £15.5 in the first lottery and £15 in the second lottery.

• In the third choice problem, the prize is £15 in the first and £15.5 in the second lottery.

Within each choice task the two lotteries will coincide in two aspects:

1.) The chance of winning the prize before any ball is drawn.

Both lotteries will have the same chance of winning the prize before any ball is drawn. You will be informed about the chance of winning the prize in every choice task. In two-stage lotteries, you will also learn what the chance of winning the prize are after the first ball has been drawn depending on whether the first ball drawn has a number below or above the threshold value.

2.) The set of winning numbers.

The winning numbers which would give you the prize are the same in both lotteries.

Please be aware that there are no right or wrong answers to any of the choice problems. We are trying to learn about your preferences so you should always choose what you personally prefer.

Also keep in mind that your choices will be relevant for your payment today. Therefore, your choices should only be guided by your own preferences.

Part 1 Earnings

One of the 20 choice tasks will be randomly selected by the computer, and one of the 3 choice problems from that choice task will also be selected by the computer. All of these tasks and problems will be equally likely to be chosen by the computer. The lottery you have chosen from the choice problem picked by the computer will be played for payment, and depending on the outcome of this lottery you will either win or lose the prize and this will be added to your final payment.

Part 1- Instruction: Timing of experiment

(Risk treatment)

1.) Quiz

After you have finished reading these instructions you will have to take a short quiz on the content of these instructions. The aim of the quiz is to make sure you have correctly understood the instructions.

2.) Choice tasks

Once you have correctly completed all the questions in the quiz you will be asked to make the choices in the 20 choice tasks we have discussed before.

As only one choice task and one choice problem will be played for payment, and all are equally likely to be chosen, you should consider each of them in isolation when making the decision. That is, you should consider each of the choice problems as if they were the ones that are going to be played.

3.) Drawing of lotteries to be played for payment

After you have made all decisions in the choice tasks, the computer will randomly draw the choice task and choice problem that will be played for payment. The lottery you choose in that specific choice problem will be played for real and determines the prize that will be added to your payment. So, for instance, if numbers 4 and 3 are drawn, the lottery you chose in the fourth choice task in the third choice problem, is the one that will be played for real.

4.) Drawing of ball in Time 1

After learning about the lottery that will be played for payment, one ball will be drawn by the computer. If the chosen lottery is a one-stage lottery resolved at Time 1 you will learn whether you won the lottery immediately. If it is a two-stage lottery you will learn whether the number on that ball is larger or smaller than the threshold, and whether the urn from which the second ball that determines the payment is drawn is the leftmost or the rightmost urn. In this case, the exact number of the first ball will be revealed at the end of the experiment to you and the experimenter, at the same time as the number of the second ball.

If the lottery that will be played is a one-stage lottery to be resolved at Time 2 you will simply see this lottery again.

5.) Part 2 Task

In the second part of the experiment you will perform a different task. We will give you the details of this task after the drawing of the ball in Time 1. This task will be completely unrelated to the decisions or outcome of the choice task. However,**while you are performing the task, and until the drawing of the second ball at Time 2 you will be informed of the prize you won after Time 1, if the lottery played was a one-stage lottery resolved at Time 1. You will also be reminded about the lottery that will be played in Time 2 if the lottery chosen to be played for real is a one-stage lottery to be resolved at Time 2, or a two-stage lottery.** This information will be shown in a box in the lower right corner of the screen for the duration of the second task.

This task will have to be performed even if the lottery chosen has been completely resolved at Time 1.

6.) Drawing of ball in Time 2

Exactly 30 minutes after the drawing of the ball in Time 1, the computer will draw a ball from the lottery that was chosen to be played. This ball will be drawn from the single urn if the lottery chosen to be played is a one-stage lottery resolved at Time 2, or from the urn that was selected in Time 1 if the two-stage lottery is played. If the lottery was already resolved at Time 1, you will be reminded of the prize you won.

7.) Final part of the experiment

After the Time 2 drawing of the ball, you will be asked to make some more choices. These choices will be unrelated to the choice task. After you have completed these tasks, you will have to fill in a short survey, and the experiment will conclude.

• • • • • • • • • • • • • • • • • •

(Ambiguity treatment)

1.) Quiz After you have finished reading these instructions you will have to take a short quiz on the content of these instructions. The aim of the quiz is to make sure you have correctly understood the instructions.

2.) Generating urn Right before we show you the first choice task, the content of the urn will be randomly generated by the computer, following the process we discussed before. Remember that the whole content of the urn will not be shown to you or the experimenter until the end of the experiment.

3.) Choice tasks Once you have correctly completed all the questions in the quiz , and the urns have been generated, you will be asked to make the choices in the 20 choice tasks we have discussed before.

As only one choice task and one choice problem will be played for payment, and all are equally likely to be chosen, you should consider each of them in isolation when making the decision. That is, you should consider each of the choice problems as if they were the ones that are going to be played.

4.) Drawing of lotteries to be played for payment After you have made all decisions in the choice tasks, the computer will randomly draw the choice task and choice problem that will be played for payment. The lottery you choose in that specific choice problem will be played for real and determines the prize that will be added to your payment. So, for instance, if numbers 4 and 3 are drawn, the lottery you chose in the fourth choice task in the third choice problem, is the one that will be played for real.

5.) Drawing of ball in Time 1 After learning about the lottery that will be played for payment, one ball will be drawn by the computer. If the chosen lottery is a one-stage lottery resolved at Time 1 you will learn whether you won the lottery immediately. If it is a two-stage lottery you will learn whether the number on that ball is larger or smaller than the threshold, and whether the urn from which the second ball that determines the payment is drawn is the leftmost or the rightmost urn. In this case, the exact number of the first ball will be revealed at the end of the experiment to you and the experimenter, at the same time as the number of the second ball.

If the lottery that will be played is a one-stage lottery to be resolved at Time 2 you will simply see this lottery again.

6.) Part 2 Task In the second part of the experiment you will perform a different task. We will give you the details of this task after the drawing of the ball in Time 1. This task will be completely unrelated to the decisions or outcome of the choice task. However, **while you are performing the task, and until the drawing of the second ball at Time 2 you will be informed of the prize you won after Time 1, if the lottery played was a one-stage lottery resolved at Time 1. You will also be reminded about the lottery that will be played in Time 2 if the lottery chosen to be played for real is a one-stage lottery to be resolved at Time 2, or a two-stage lottery.** This information will be shown in a box in the lower right corner of the screen for the duration of the second task.

This task will have to be performed even if the lottery chosen has been completely resolved at Time 1.

7.) Drawing of ball in Time 2

Exactly 30 minutes after the drawing of the ball in Time 1, the computer will draw a ball from the lottery that was chosen to be played. This ball will be drawn from the single urn if the lottery chosen to be played is a one-stage lottery resolved at Time 2, or from the urn that was selected in Time 1 if the two-stage lottery is played. If the lottery was already resolved at Time 1, you will be reminded of the prize you won.

8.) Final part of the experiment

After the Time 2 drawing of the ball, you will be asked to make some more choices. These choices will be unrelated to the choice task. After you have completed these tasks, you will have to fill in a short survey, and the experiment will conclude.

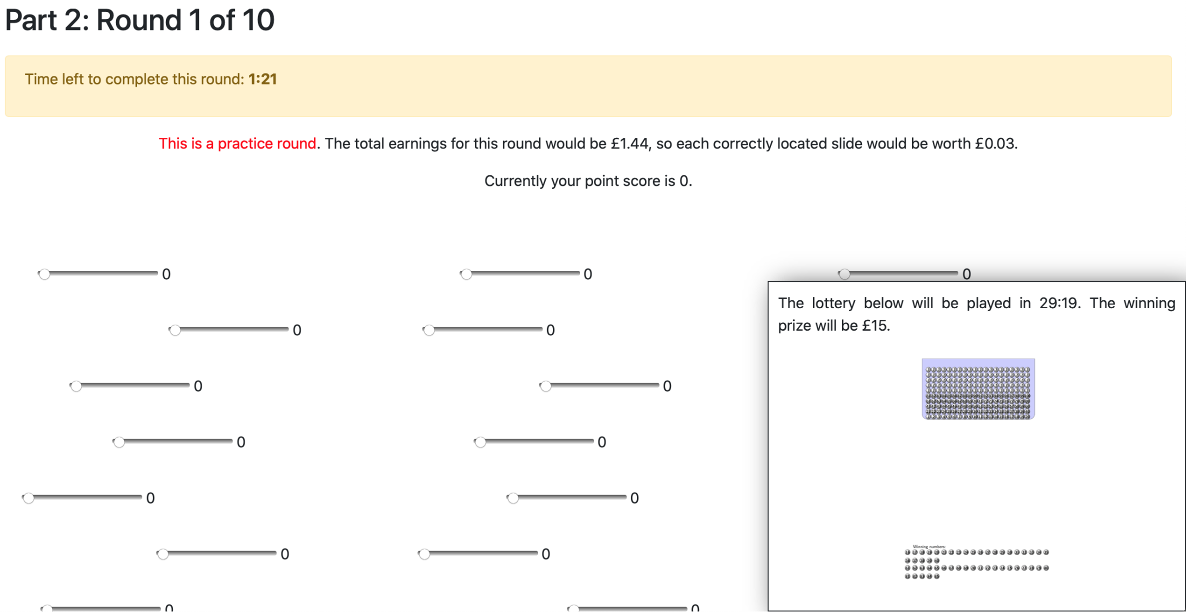


Figure A.1: Example of Slider Task in Ambiguity Treatment

Note: The lottery to be played at time 2 is also shown.

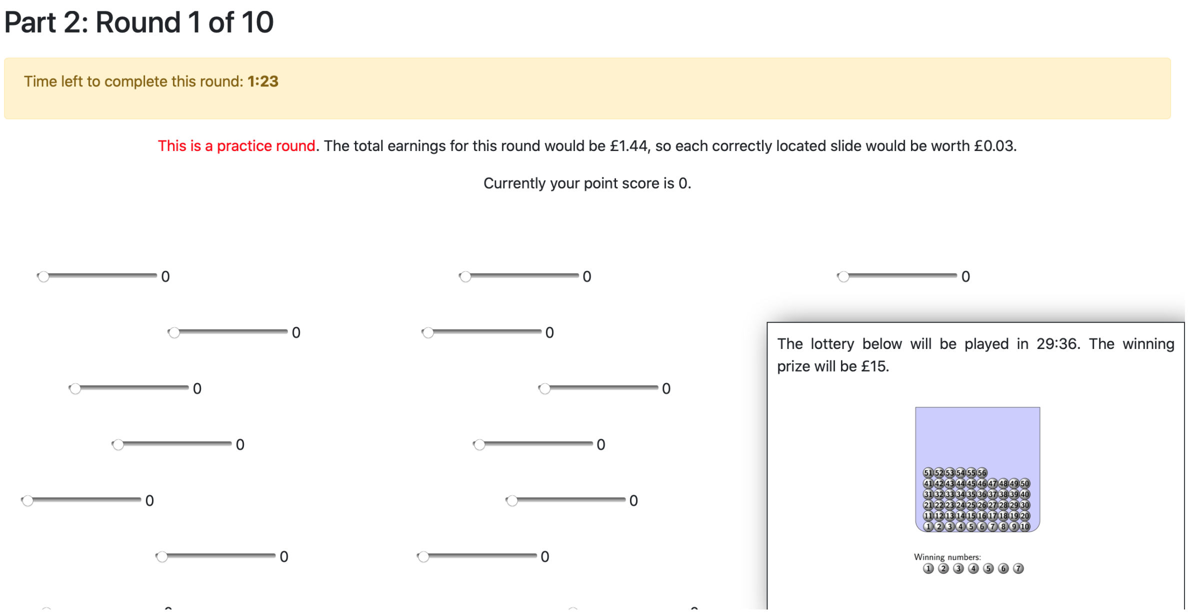


Figure A.2: Example of Slider Task in Risk Treatment

Note: The lottery to be displayed at time 2 is also shown.

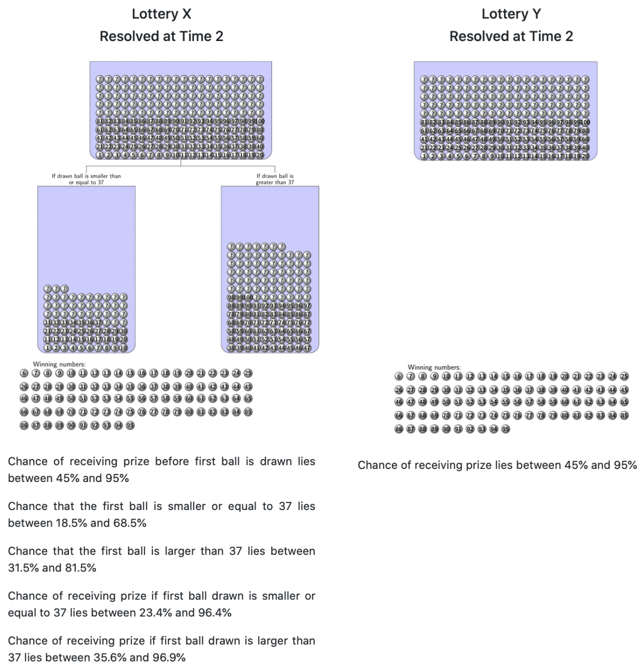


Figure A.3: Example of Lottery Choices in Risk Treatment

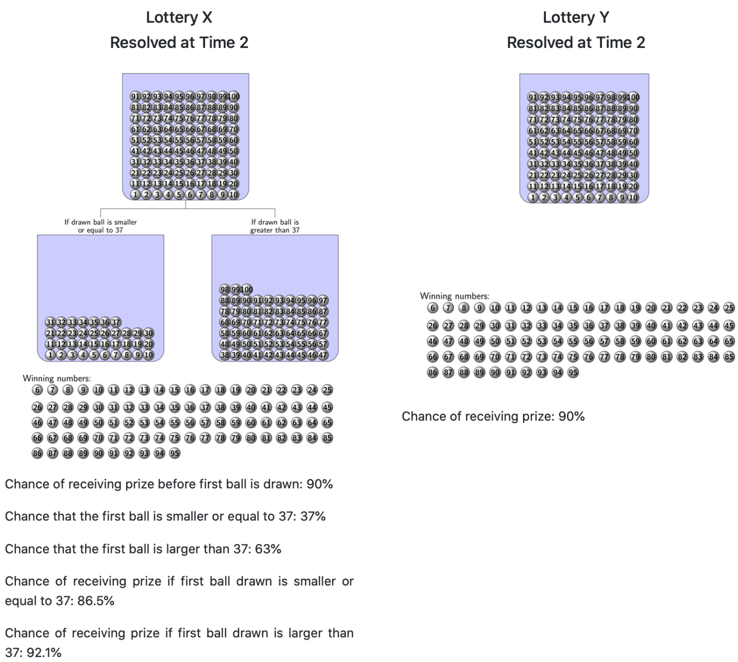
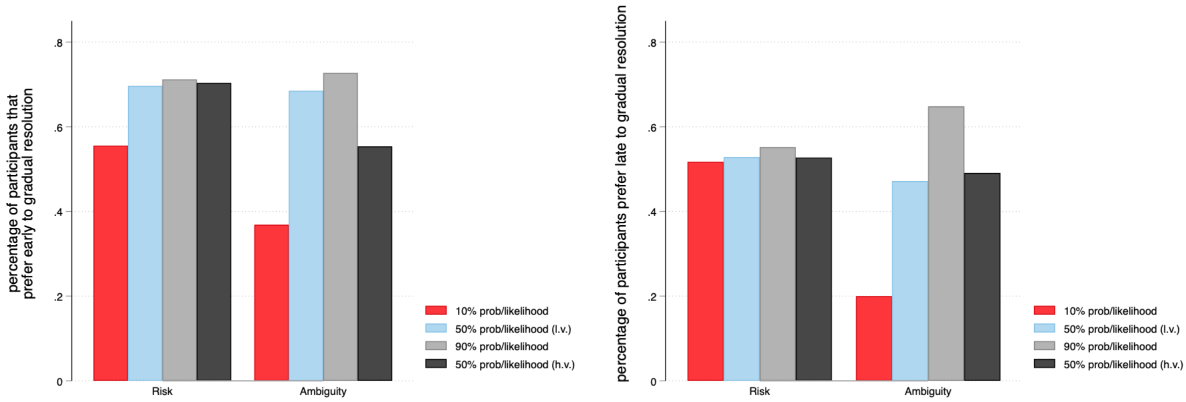


Figure A.4: Example of Lottery Choices in Risk Treatment

A.4 Additional empirical tests



(a) **(b)**

Figure A.5: Percentages of preferences of early/late resolution over gradual resolution (negatively skewed lotteries)

Note: Figure (a) shows the percentage of participants that prefer early resolution of uncertainty over gradual resolution for negatively skewed lotteries. Figure (b) shows the the percentage of participants that prefer early resolution of uncertainty over gradual resolution. In both cases we consider the positively skewed lotteries. “l.v.” stands for low variance and ‘h.v.” means high variance.

	10% likelihood	50% likelihood (l.v.)	90% likelihood	50% l likelihood (h.v.)
Risk treatment - Negatively skewed lotteries				
	10% likelihood	50% likelihood (l.v.)	90% likelihood	50% likelihood (h.v.)
10% likelihood	-	0.8273	0.6831	0.3173
50% likelihood (l.v.)	-	-	0.5930	0.8084
90% likelihood	-	-	-	0.2253
Ambiguity treatment - Negatively skewed lotteries				
10% likelihood	-	0.0001***	0.0010***	0.0076***
50% likelihood (l.v.)	-	-	0.8185	0.1083
90% likelihood	-	-	-	0.1797

Note: Each cell shows the p-values of McNemar test for matched choices between early and gradual resolution of uncertainty for different probabilities/likelihoods. *10% significance level, **5% significance level, ***1% significance level.

Table A.1: Test of shifts between early and gradual resolution of uncertainty II

	10% likelihood	50% likelihood (l.v.)	90% likelihood	50% likelihood (h.v.)
Risk treatment - Positively skewed lotteries				
10% likelihood	-	0.6171	1	0.1025
50% likelihood (l.v.)	-	-	0.3711	0.2971
90% likelihood	-	-	-	0.1083
Ambiguity treatment - Positively skewed lotteries				
10% likelihood	-	0.0046***	0.0077***	0.0896*
50% likelihood (l.v.)	-	-	0.3458	0.1967
90% likelihood	-	-	-	0.0389**

Note: Each cell shows the p-values of McNemar test for matched choices between late and gradual resolution of uncertainty under risk for different probabilities/likelihoods. *10% significance level, **5% significance level, ***1% significance level.

Table A.2: Test of shifts between early and gradual resolution of uncertainty III

	10% likelihood	50% likelihood (l.v.)	90% likelihood	50% likelihood (h.v.)
Risk treatment - Negatively skewed lotteries				
10% likelihood	-	1	0.6547	0.8273
50% likelihood (l.v.)	-	-	0.7963	0.8084
90% likelihood	-	-	-	1
Ambiguity treatment - Negatively skewed lotteries				
10% likelihood	-	0.0028***	0.0001***	0.0082***
50% likelihood (l.v.)	-	-	1	0.0455**
90% likelihood	-	-	-	0.1573

Note: Each cell shows the p-values of McNemar test for matched choices between late and gradual resolution of uncertainty under ambiguity for different likelihoods (negatively skewed lotteries). *10% significance level, **5% significance level, ***1% significance level.

Table A.3: Test of shifts between early and gradual resolution of uncertainty IV

Early vs. late choices problems			
Early vs. late (10%)	0.27		
Early vs. late (50% l.v.)	0.17		
Early vs. late (90%)	0.14		
Early vs. late (50% h.v.)	0.21		
Positively skewed gradually resolved lotteries			
Early vs. gradual (10%)	0.51	Late vs. gradual (10%)	0.40
Early vs. gradual (50% l.v.)	0.32	Late vs. gradual (50% l.v.)	0.35
Early vs. gradual (90%)	0.38	Late vs. gradual (90%)	0.41
Early vs. gradual (50% h.v.)	0.36	Late vs. gradual (50% h.v.)	0.44
Negatively skewed gradually resolved lotteries			
Early vs. gradual (10%)	0.44	Late vs. gradual (10%)	0.47
Early vs. gradual (50% l.v.)	0.34	Late vs. gradual (50% l.v.)	0.36
Early vs. gradual (90%)	0.47	Late vs. gradual (90%)	0.43
Early vs. gradual (50% h.v.)	0.5	Late vs. gradual (50% h.v.)	0.49

Table A.4: Percentage of participants with strict preferences by probability in the risk treatment

Early vs. late choices problems			
Early vs. late (10%)	0.13		
Early vs. late (50% l.v.)	0.11		
Early vs. late (90%)	0.19		
Early vs. late (50% h.v.)	0.16		
Positively skewed gradually resolved lotteries			
Early vs. gradual (10%)	0.60	Late vs. gradual (10%)	0.55
Early vs. gradual (50% l.v.)	0.46	Late vs. gradual (50% l.v.)	0.51
Early vs. gradual (90%)	0.61	Late vs. gradual (90%)	0.57
Early vs. gradual (50% h.v.)	0.52	Late vs. gradual (50% h.v.)	0.52
Negatively skewed gradually resolved lotteries			
Early vs. gradual (10%)	0.63	Late vs. gradual (10%)	0.51
Early vs. gradual (50% l.v.)	0.51	Late vs. gradual (50% l.v.)	0.47
Early vs. gradual (90%)	0.65	Late vs. gradual (90%)	0.56
Early vs. gradual (50% h.v.)	0.57	Late vs. gradual (50% h.v.)	0.55

Table A.5: Percentage of participants with strict preferences by probability in the ambiguity treatment.

Prob/likelihood	(1) p-value positive skew/early vs. gradual	(2) p-value negative skew/early vs. gradual	(3) p-value positive skew/late vs. gradual	(4) p-value negative skew/late vs. gradual
Risk treatment				
10%	0.0029***	0.0330**	0.0290**	0.0719*
50% (l.v.)	0.0389**	0.0253**	0.0116**	0.0593*
90%	0.0047***	0.0001***	0.0016***	0.0006***
50% (h.v.)	0.0201**	0.0002***	0.0186**	0.0011**
Ambiguity treatment				
10%	0.0000***	0.0000***	0.0000***	0.0000***
50% (l.v.)	0.0001***	0.0000***	0.0000***	0.0001***
90%	0.0000***	0.0000***	0.0003***	0.0011***
50% (h.v.)	0.0001***	0.0002***	0.0001***	0.0003***

Note: Each column (1)-(4) shows p-value of McNemar test of shift in strict preferences from early vs. late choices to early/late vs gradual lotteries, for positively and negatively skewed lotteries and same ex-ante probability/likelihood. *10% significance level, **5% significance level, ***1% significance level.

Table A.6: Test of changes in strict preferences between early/late and early-late/gradual choices

Prob/likelihood	(1) Early vs. late	(2) Early vs. gradual (positive)	(3) Early vs. gradual (negative)	(4) Late vs. gradual (positive)	(5) Late vs. gradual (negative)
10%	0.060*	0.340	0.058*	0.099*	0.708
50% (l.v.)	0.421	0.125	0.082*	0.117	0.324
90%	0.616	0.024**	0.061*	0.123	0.256
50% (h.v.)	0. 0.630	0.124	0.566	0.450	0.703

Note: Each column (1)-(4) shows the exact p-value of the Fisher test of difference in percentage across treatments of participants that have a strict preference over each lottery comparison. *10% significance level, **5% significance level, ***1% significance level.

Table A.7: Test of differences in strict preferences between risk and ambiguity treatment

Chapter 2

Uncertainty is polarising: Social identity and decision-making under ambiguity

Abstract

In this chapter, I analyse how social identity affects decision-making under uncertainty. In a theoretical model, I link identity to regret, and find the conditions under which aligning with a social group that the individual identifies with will happen more often under ambiguity than under risk. I design and run a experiment that, improving on previous empirical work performed in Amazon Mturk, tests the hypotheses from the theoretical model, namely, that the effect of the social group's decision is stronger under ambiguity than under risk.

2.1 Introduction

How do individuals react to high uncertainty environments in society? Ellsberg's (1961) thought experiment introduced the idea that individuals tend to be ambiguity averse, that is, they prefer choices that have known probability distributions to choices in which this distribution is unknown, that is, choices under risk to choices of Knightian (1921) uncertainty or ambiguity. Ambiguity averse behaviour has been linked to decisions in financial markets such as home-bias or portfolio under-diversification (Garlappi et al, 2007; Dimmock et al, 2016), but little attention has been paid to how ambiguity aversion affects decision-making in more general environments.

In this chapter, I present a theoretical model and empirical evidence to support the idea that decisions that are most common (stereotypical) within social groups have a significant effect in influencing individuals when faced with ambiguous decision problems. The theoretical model explains this result by incorporating a social identity component to a reference-dependence ambiguity model similar to the one observed in Mihm (2016). Social identity is incorporated in the model as a weight on losses relative to the outcome of the reference group's stereotypical decision. The weight is larger the higher is the identification with the reference group. This modelling assumption has two alternative behavioural explanations: social regret and cognitive dissonance. Social regret is a cost associated to having taken a decision with a worse outcome than the one taken by the majority of a social group. This has been empirically proved (Cooper and Rege, 2011) to be a relevant motivator for individuals to align with the decision of a certain social group.

The alternative explanation is derived from the original interpretation of the influence of social identity introduced to economics by Akerlof and Kranton (2000). They argue that individuals derive utility from belonging to social groups, and following the prescriptions of those groups. A logical consequence of this assumption , which follows from Tajfel and Turner's (1979) pioneering work on social identity is that when they deviate from these prescriptions and take a decision with a worse outcome than the social group's their utility goes down. This occurs because their self-concept depends on the ability to take the right decision and of belonging to the social group. A cost of cognitive dissonance (Akerlof, 1982) is incurred when this two beliefs are contradicted by the outcome of their decision. This cost is naturally bigger when the sense of belonging or identification with that group is stronger. Deviating from the group's prescription, and choosing an ex-post inferior decisions, will harm the individual more, the more they care about belonging to that social group.

Using data from an online experiment with 180 participants, I show that facing a more uncertain decision-making problems has an effect on converging to a group's modal decision similar to that of having a very close identification with that social group. This result is consistent with the main conclusions of the theoretical model.

2.1.1 Related literature

This work can be related to three different strands of the literature: ambiguity aversion modelling and its empirical analysis, social identity and peer effects.

There has been extensive research on the axiomatic specification of ambiguity averse behaviour, starting with Schmeidler's Choquet expected utility model (1989), which considered the fact that the subjective probabilities assigned to each of the states of the world may not be additive. The more widely used maxmin expected utility model (MEU, Gilboa and Schmeidler, 1989), included an additional axiom that considered uncertainty aversion: a convex combination of two uncertain acts is strictly preferred to either of the acts on their own, and considered sets of priors of probabilities, instead of capacities, thus making it more tractable.

After MEU, other models have tried to account for ambiguity aversion by modifying some axioms: α - maxmin model (Castagnoli, Maccheroni, and Marinacci, 2003) (which gives weight α to more pessimistic beliefs, and weight $(1-\alpha)$ to more optimistic ones), the smooth model (Klibanoff, Marinacci, and Mukerji, 2005) (that separates information on the uncertain states, which is given by the probabilities, and the attitude towards that ambiguity, given by the shape of the utility function) and variational preferences

(Maccheroni, Marinacci, and Rustichini, 2006) that consider second-order beliefs over the first-order distribution of probabilites) [1]. Other models have tried to accommodate further empirical evidence on non-neutral attitudes towards ambiguity, such as the fact that being endowed with an ambiguous act, individuals show behaviour more consistent with ambiguity seeking than aversion (Roca et al., 2006). One such model is Mihm (2016), that relates this empirical regularity to reference dependence. Other models take a different perspective by considering source dependence, a behaviour first empirically shown by Tversky and Kahneman (1992) and Tversky and Fox (1995), further studied by Abdellaoui et al. (2011) and axiomatised by Nau (2006), Chew and Sagi (2008), and Ergin and Gul (2009). These papers study how different sources of ambiguity (e.g. financial markets of country of residence or foreign financial market) can alter ambiguity attitudes, and explain financial paradoxes like the home-bias.

The second strand of literature is the literature on social identity. Social identity in social psychology has been extensively studied[2], and the relation of identity, alignment with the group's behaviour and uncertainty has also been studied (Hogg, 2007). Within economics, after Akerlof and Kranton's (2000) seminal paper, social identity has been used to study topics as diverse as social preferences (Chen and Li, 2009), equilibrium levels of effort on coordination games (Chen and Chen (2011)), equilibria in non-cooperative games (Charness et al, 2007), redistribution preferences (Shayo, 2009; Klor and Shayo 2010), risk aversion and impatience (Benjamin and Choi, 2010) and shirking and free-riding behaviour (Eckel and Grossman; 2005). As far as I know, only one paper (Gioia, 2016) has considered decision theory and social identity together. They look at how different levels of identification generated in the lab affect decision-making under risk. However, they do not consider ambiguous decisions.

The last leg of the literature than can be related to this study is that of peer effects. Seminal theoretical papers on herd behaviour (Banerjee, 1992; Bikhchandani et al., 1992) have been followed by recent empirical papers that focus on the behaviour of others, in

[1] See Gilboa, Marinacci (2016) for an extensive literature.

[2] See Hogg (2016) for a survey on the field

contexts in which others share some bond (e.g. Bursztyn et al., 2014, for the effect of family ties on financial decisions) or alignment with a group randomly generated in the lab (Cooper and Rege, 2011). This last paper looks at decisions under risk and ambiguity, but from a pure peer effect perspective, that is, it does not take into account the behavioural implications of belonging to a social group which is opposed to another, as I do in this work. Additionally, in a recent paper, Dykstra, Exley and Niederle (2021) show that when subjects are more uncertain about what to choose they are more willing to give up agency, and let others choose for them. In this paper, I do not explicitly allow to give up agency in favour of the social group, but ambiguous choices may be harder to decide between and, therefore, the decision of the subject's social group may be used as a factor to make decision easier. This could also be related to the concept of cognitive uncertainty, first described by Enke and Graeber (2020).

In the following section, I introduce the theoretical model. Section 2.3 presents the design and implementation of the experiment. Section 2.4 discusses the results of the experiment. Section 2.5 concludes.

2.2 Model

In this section, I introduce a model that explains the mechanism by which social identity affects decision making at different levels of uncertainty. This model draws from Mihm's (2016) model of reference-dependence ambiguity, and introduces social identity as a term related to social regret.

Social regret can be understood as a psychological cost that reflects regret experienced in states of the world in which the most common decision taken by individuals in the social group (namely, the stereotypical decision of the group) leads to higher utility than the decision taken by the decision-maker. Cooper and Rege (2011) show experimentally that in situations in which decisions made by peers are announced, alignment with the peer's decision is best explained by behaviour compatible with social regret. I deviate from their approach by including social groups as opposed to just randomly chosen peers.

I, then, weight social regret differently depending on the perceived identification with the group. That is, social regret is higher when this cost is associated to a missed opportunity to align with the decision of a group the decision-maker identifies herself more with.

Social regret could alternatively be interpreted as a cognitive dissonance cost (Akerlof, 1982). The individual derives utility from a positive self-image associated to making the "right" decision, and utility from belonging to a social group. By deviating from the group's decision in states of the world that lead to an ex-post suboptimal outcome, the individual's utility is doubly affected. If he made the right decision the utility from positive self-image, would, however, be preserved[3].

I follow Akerlof and Kranton (2000) when modelling social identity. They consider that individuals belong to different social groups (e.g. ethnicity, gender) and obtain a sense of self through belonging to these groups; that is, an individual's identity is a function of the groups she belongs to. This interpretation of social identity follows directly from Tajfel and Turner's (1979) pioneering works on social psychology. I define a vector $Id^i \in \mathbb{R}^N$ as the identity vector of the decision-maker. Each element of the vector measures the weight that the decision-maker assigns to each of the N groups that the individual may identify herself with. For instance, one decision-maker may give a very high weight to her political ideas but a low one to her profession.

Similarly, I define the vector $Id^g(a)$ as the identity vector of the social group whose stereotypical decision action is a. This vector can be understood as the average of the identity vectors of people linked to that group. For example, a sports fan club may give a very weight to being supporters of a team but a low one to ethnicity, as will do many of its members. To be concrete, and to link the theory to the posterior design of the experiment, a group's stereotypical decision is the modal decision for that group, which is observable by the individual.

I modify a model of reference-dependent ambiguity (Mihm, 2006) in order to account for social regret. Mihm's model rationalises an empirical result by Roca et al. (2006) by

[3]This could alternatively understood as anticipated regret too, which is theorised to be linked to ambiguity aversion by Krähmer and Stone (2013).

which when endowed with an ambiguous act and faced with the prospect of exchanging this act for a risky one, individuals behave as ambiguity seeking, that is, they choose their endowment rather than the alternative. This goes against Ellsberg's (1961) thought experiment that led to the development of the MEU, but can be accomodated by considering this endowment as a reference point. Therefore, this model seems to be more realistic, while remaining tractable, which is one of the main advantages of the MEU model.

Within this frameworks, let us consider a set of states of the world Ω, with typical element ω and decision making problem over actions, where an actions f is a mapping from the set of states of the world to a set of consequences X (f: $\Omega \rightarrow X$), which in our model are monetary outcomes. I denote $\mathcal{F}$ as the set of possible actions. There exists a subset of actions $\mathcal{R} \in F$ that are stereotypical decisions taken by social groups that the DM gives positive weight to in her identity vector Id^i. $u : X \rightarrow \mathbb{R}$ is the DM's utility function over monetary outcomes. We also consider a set of priors over the states of the world $\Upsilon \subseteq \Delta(\Omega)$, where $\Delta(\Omega)$ is the set of all probability distributions of Ω. In a situation of risk, this set is a singleton as the probability of states of the world is determined and known. Under ambiguity, the set Υ may have more than one element.

As a result of the points made above, I denote the DM's utility for action $a \in \mathcal{F}$ as:

$$V(a) = \underset{v \in \Upsilon}{min} \sum_{r \in \mathcal{R}} \left(\sum_{\omega} \left[\max\{u(a(\omega)) - u(r(\omega)), 0\} + \frac{1}{D + ||Id^i - Id^g(r)||} \min\{u(a(\omega)) - u(r(\omega)), 0\} \right] v(\omega) \right) \tag{2.1}$$

where D is a measure of the individuality of the DM, that is, how much of the individual's identity is influenced by an idiosyncratic sense of self, and not by any group. We assume, for simplicity, that D>0 and $|| \cdot ||$ represents the Euclidean norm of the distance between both identity vectors.

Equation 2.1 characterises a subject's utility under ambiguity and with the social regret cost we discussed above. As can be seen, decision-makers evaluate the utility of action a in each state using the stereotypical decision of each group they identify themselves with as a reference point. We can, then, understand the utility in each state as characterised by loss aversion (Kahneman and Tversky, 1982) where the reference point is the decision of the group. As we have mentioned above, the weight given to the loss with respect to the gain is a function of the distance of the decision-maker from that particular group. The higher is the distance to the group, the smaller is the cost from choosing an action that gives a payoff lower than that chosen by the social group. The utility with respect to every stereotypical decision is added in each state, and then the sum over all states is performed, where each state is weighted by the probability assigned by the prior that minimises utility (as this is an extension of the MEU model).

2.2.1 Application to a 2(states of the world)×2(social groups) ×2(actions) case

In order to draw conclusions that will later be tested in the experiment, I restrict the model to the case in which we only have two states of the world (ω_1, ω_2) , two social groups (1,2) and two actions (a_1,a_2), which is the structure the experiment follows too.

Let us assume that the DM identifies more closely with the social group that has modal decision a_2 than with the group that has modal decision a_1 that is, $D+||Id-Id(a_2)||=\epsilon$ and $D+||Id-Id(a_1)||=\beta\epsilon$ where $\beta>1$ measures the relative distance that the DM perceives between the two groups. I normalise ϵ and set it equal to 1 so that β now measures the additional distance to the group with which the individual has a lower identification, or inversely, how much closer the individual is to the group she identifies most with. I, therefore, use β as an inverse measure of identification with the group that the DM is closer to.

The set of consequences X for each state and action is represented by the following matrix:

	ω_1	ω_2
a_1	b_{a_1}	w_{a_1}
a_2	w_{a_2}	b_{a_2}

where b_i and w_i stand for best and worst outcome for action i. I only consider nondegenerate results, so I restrict attention to cases in which $b_{a_1} > max\{w_{a_1}, w_{a_2}\}$ and $b_{a_2} > max\{w_{a_1}, w_{a_2}\}$.

I further assume that the DM's utility function over the set of consequences is CRRA with risk aversion parameter γ:

$$u(x_i) = \begin{cases} ln(x_i), & \text{if } \gamma = 1 \\ \dfrac{x_i^{1-\gamma}}{1-\gamma}, & \text{otherwise} \end{cases}$$

In order to compare differences in behaviour between risk and ambiguity, we can first consider a situation in which there exists an objective distribution over ω, and later extend our results to cases in which the distribution is unknown. I denote the objective distribution as $\Upsilon_1 = \{p_{\omega_1}, 1 - p_{\omega_1}\}$. By substituting these values into equation 2.1 we obtain the utility from each action:

$$V(a_1) = \frac{1}{1-\gamma}[p_{\omega_1}(b_{a_1}^{1-\gamma} - w_{a_2}^{1-\gamma}) + (1 - p_{\omega_1})(w_{a_1}^{1-\gamma} - b_{a_2}^{1-\gamma})]$$

$$V(a_2) = \frac{1}{1-\gamma}[p(x_1)(w_{a_2}^{1-\gamma} - b_{a_1}^{1-\gamma})\frac{1}{\beta} + (1 - p(x_1))(b_{a_2}^{1-\gamma} - w_{a_1}^{1-\gamma})]$$

And, therefore, DM will align with the with which she has a stronger identification (i.e., $V(a_2) \geq V(a_1)$) iff:

$$\frac{\frac{1}{1-\gamma}(b_{a_2}^{1-\gamma} - w_{a_1}^{1-\gamma})}{\frac{1}{1-\gamma}(b_{a_1}^{1-\gamma} - w_{a_2}^{1-\gamma})} \geq \frac{p_{\omega_1}\left(1 + \dfrac{1}{\beta}\right)}{2(1 - p_{\omega_1})} \tag{2.2}$$

I extend the comparison to situations of ambiguity, i.e., where the distribution over states of the world is unknown. Ghirardato and Marinacci (2002) show that ambiguity aversion is associated with a larger set of priors. I follow their approach and assume a set of prior distributions over states of the world $\Upsilon_2 = \{p_1, 1 - p_1 : p_1 \in [p_{\omega_1} - d, p_{\omega_1} + d]\}$, where d measures the level of ambiguity aversion and p_{ω_1} is the objective probability of state of the world ω_1, as defined before.

Modifying the utility maximisation problem to account for the set of probability distribution Υ_2, I conclude that $V(a_2) \geq V(a_1)$ iff:

$$\frac{\frac{1}{1-\gamma}(b_{a_2}^{1-\gamma} - w_{a_1}^{1-\gamma})}{\frac{1}{1-\gamma}(b_{a_1}^{1-\gamma} - w_{a_2}^{1-\gamma})} \geq \frac{p_{\omega_1}\left(1+\frac{1}{\beta}\right) - d\left[1-\frac{1}{\beta}\right]}{2(1-p_{\omega_1})} \tag{2.3}$$

It is easy to prove that the RHS of equation 2.3 is smaller than the RHS of equation 2.2 for all values d>0, which leads us to our proposition:

Proposition 1 *From the results of our model in equations 2.2 and 2.3 we can conclude that:*

a) In decision making processes under risk and ambiguity the stereotypical action of the social group closest to the DM will be chosen, keeping other parameters constant, for sufficiently high identification with this group (that is, for sufficiently high value of β).

b) In decision making processes under ambiguity the stereotypical action of the social group closest to the DM will be taken by more participants than under risk, keeping all parameters constant, including β.

It is relevant to note that all three elements of the model (reference dependent loss aversion, social identity and social regret) are required to obtain the results from proposition, as proved in the proposition below:

Proposition 2 *The three elements in the model, i.e., reference dependent loss aversion, social identity and social regret are necessary to obtain the results from proposotion 1.*

Imagine a model of reference dependence like Mihm's (2016), where the reference is simply the group the DM is closer to, that is:

$$V(a) = \underset{\upsilon \in \Upsilon}{min}\left(\sum_{\omega}\left[u(f(\omega)) - u(r(\omega))\right]\upsilon(\omega)\right)$$

equation 2.2 becomes:

$$\frac{\frac{1}{1-\gamma}(b_{a_2}^{1-\gamma} - w_{a_1}^{1-\gamma})}{\frac{1}{1-\gamma}(b_{a_1}^{1-\gamma} - w_{a_2}^{1-\gamma})} \geq \frac{p_{\omega_1}}{(1-p_{\omega_1})} \tag{2'}$$

It is straightforward to see that part a) of proposition 1 does not hold in this case.

Consider a case, instead in which we introduce social identity, by considering the distance to the groups as weight:

$$V(a) = \min_{v \in \Upsilon} \sum_{r} \frac{1}{D + ||Id - Id(r)||} \left(\sum_{\omega} \left[u(f(\omega)) - u(r(\omega)) \right] v(\omega) \right)$$

The resulting condition for a preference of action a_2 over a_1 is unchanged from equation 2'. Part a) of proposition 1 does not hold in this case either. We, therefore, require the asymmetric weighting of gains and losses provided by social regret to obtain the results from proposition 1.

From the model we can therefore observe two main conclusions: that in situations of risk, higher identification with the group leads to higher alignment with their modal decision, and that under ambiguity, for all levels of identification it is more likely that the DM will take her group's stereotypical decision. In the next section, I propose an experimental design to test these hypotheses.

2.3 Design of the experiment and implementation

In this section I discuss the design of the experiment and explain its implementation using the online recruitment tool Amazon Mechanical Turk.

2.3.1 Implementation

180 participants took part in the online experiment, recruited through Amazon Mechanical Turk. Participants were randomly assigned to either of the two treatments: risk treatment (known probability distribution of states of the world) and ambiguity treatment (unknown probability distribution of states of the world). 96 participants were assigned to the ambiguity treatment, and 84 to the risk treatment. The experiment was written using the Python-based oTree platform (Chen et al. (2016), Holzmeister and Armin

Pfurtscheller (2016)), and run between December 2017 and February 2018. The sample was limited to participants in the US and who had at least 95% of their previous jobs on Amazon Mechinal Turk (called "assignment" in the MTurk jargon) approved. This requirement has been proved to perform well in tasks in which obtaining high quality data by focused participants is required, and to work better than attention check questions, which is another standard way of achieving the same end when performing experiments in Amazon Turk (Peer et al., 2014). I only perform one additional of these attention check questions (ACQ), which is to ask individuals at the end of the experiment the social group they have been assigned to in the experiment. Only 5 participants failed to give the right answer (3 in the ambiguity treatment, 2 in the risk treatmetnt). Given the relevance in our theory of having a clear understanding of the group you were assigned to, I restrict the participant pool to the 175 participants that correctly answered the ACQ. Qualitative results that will be presented in the next section do not significantly change when including these participants.

Experiments in Amazon Mechanical Turk have many advantages while still being able to replicate results performed in the lab (Horton et al., 2011; Amir et al., 2012; Dreber et al., 2013). However, one disadvantage is that experiments that require participants to take decisions at the same time are hard to implement. In my experiment, I require that participants first define stereotypical decisions of each group, so that the results from the theoretical framework can be evaluated. I achieve this by having a sample of 32 participants, different from my final sample of 175 (experimental sample), that I will refer to as the pre-experimental sample. I follow the same procedure to select them as for the experimental sample. They take the same decisions as those in the experiment, but they generate the stereotypical (modal) decisions for each of the groups that participants in the experiment sample will observe.

Participants were paid a participation fee of $2, and they were randomly chosen to receive the payment from either part 2 or part 3 of the experiment. Random problem selection has been shown to be incentive compatible under the assumption of monotonic preferences (Azrieli, 2018). This payment was expressed in tokens at an exchange rate of

100 tokens=$1.

2.3.2 Design

The experiment consists of four different parts:

Part 1: Generating group identification

Tajfel et al. (1971) first introduced a methodology to generate group identification in the lab, in order to study in-group bias in redistribution tasks. Their methodology consisted on either randomly assigning participants according to whether they consistently overestimated or underestimated the number of dots in a picture or through "aesthetic preferences". This last methodology consists of individuals choosing paintings by two expressionist artists Paul Klee and Wassily Kandinsky, and being assigned to the group of participants that prefer one of the painter over the other. This experimental setting has become to be known as the "Minimal Group Paradigm", because it requires a trivial task to assign individuals to groups, and has been extensively used since then in the identity economics and psychology field (Tajfel et al., 1971; Grieve and Hogg, 1999; Reicher, 2004; Chen and Li, 2009; Chen and Chen, 2011; Gioia 2016). However, some other methodologies have also been used such as random assignment (Eckel and Grossman (2005), Charness et al. (2007)), selection by field of study (Klor and Shayo, 2010), or selection by race (Benjamin and Choi, 2010).

My initial approach was to consistently follow the seminal papers on social identity and use the minimal group paradigm. However, given the specific context in which the experiment is to be performed [4] I decided to run a pilot experiment and the results showed that a) very low identification with the group was achieved and b) there was very low variation in group identification, which would prevent me identifying what we expect to observe in the data.

Therefore, I follow the alternative method observed in the literature which is to use natural groups. Recent evidence (Pew Research Center, (2014,2017)) shows that political polarisation is very high and continues to increase in the US, and therefore, I decided to

[4] As far as I know, no identity economics research has been performed on Amazon Turk.

choose political parties as social groups in order to prevent issues encountered with the minimal group paradigm.

In this first part of the experiment participants are faced with an eleven question quiz, which contains the Ideological Consistency Scale questionnaire, and an additional question on terrorism and surveillance, in order to adapt the questionnaire, first written in 1994 to current issues (see Appendix). Depending on the answers to the questionnaire, individuals are assigned to either the group of "liberal"-leaning individuals, or "conservative"-leaning individuals.

Part 2: Eliciting risk aversion

One aspect that is very relevant in order to replicate the theoretical framework in the experiment is to achieve differentiated stereotypical decisions from the groups. I aim to achieve this by separating individuals in groups following the procedure discussed above and also separating them by level of risk aversion. I use the "bomb" risk elicitation method Crosseto and Filippin (2013). The main reason to choose this method over other common risk elicitation methods, such as Holt and Laury (2002) or Eckel and Grossman (2002, 2008) is that unlike the other two methods it does not require much cognitive effort, and it never leads to inconsistent results while still allowing to identify risk neutrality and risk loving attitudes. Additionally, since the main task of the experiment consists of choices between actions, a task with a completely different framing avoids any possible misunderstanding of the main task, and improves understanding of the fact that payments from this task and the next one are uncorrelated, thus, preventing wealth effects.

Part 3: Choosing between actions

In this main part of the experiment, participants are separated between treatments: risk and ambiguity.

- **Risk treatment:** For every of the five decisions they have to make, participants are told there exists a virtual box in which there are 5 red balls and 5 black balls, as in the standard Ellsberg's urn (1961) thought experiment, from which one ball will be drawn. In every decision, participants have to choose between the red ball or the black ball. The payoff of each action is state contingent. Payoffs for each decision can be seen in table 2.1.

I set 50:50 probabilities because in the model it is also assumed that the objective probabilities are the midpoint of the set of priors in the ambiguity treatment. To my knowledge no one has tried to estimate the set of priors of a decision-maker when assuming the MEU model, and therefore, it seems reasonable to assume that this midpoint lies at 50%, which also allows for the highest possible dispersion in the set of possibe priors. Additionally, Fischhoff and Bruine De Bruin (1999) justify that under symmetry of ignorance, individuals will often assign a 50%-50% chance to each event, even when they are given an option to express their ignorance.

- **Ambiguity treatment:** Participants in this treatment are told there exists a virtual box in which there are 10 balls (for all five decisions), either red or black, the proportion of which is unknown, again following Ellsberg's example. Participants are also informed that this proportion may change from choice to choice. As in the risk treatment, they are told one ball will be drawn from this box. Again the decision in each case is to choose between the red or the black ball, and payoffs are the same as in the risk treatment, and shown in table 2.1.

In both treatments participants are informed of the stereotypical decision taken by both groups for each decision by subjects in the pre-experimental sample, before they have to make their own decision (see Appendix for an example of decision problem).

In order to achieve maximal separation in stereotypical decisions, I separate both the pre-experimental sample and experimental sample in the social group ("liberal-leaning" and "conservative-leaning") but also by risk-aversion, as can be seen in figure 2.1. I define "less risk averse" participants as those with a risk aversion parameter γ below a established $\bar{\gamma}$, and "more risk averse" those that have a risk aversion parameter $\gamma > \bar{\gamma}$. I estimate a value of γ such that approximately half of the sample is at either side. In my pilot experiment this value is approximately 0.42, which in the "bomb" risk elicitation task is equivalent to taking approximately 37 boxes. This is very close to the median value

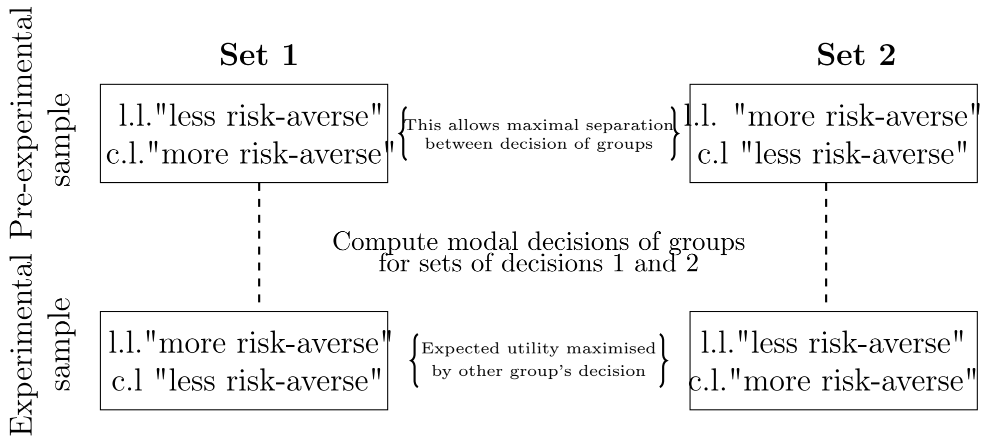


Figure 2.1: Experimental design for Part 3 of the experiment

Note: c.l. stands for "conservative-leaning" and l.l for "liberal-leaning"

	Set 1	
Decision #	Red	Black
1	(80,40)	(120,18)
2	(138,20)	(78,58)
3	(95,40)	(70,60)
4	(60,30)	(48,40)
5	(65,35)	(110,10)
	Set 2	
1	(48,40)	(84,15)
2	(110,15)	(60,45)
3	(120,35)	(90,55)
4	(70,25)	(50,40)
5	(75,60)	(110,35)

Note: Payoffs are in tokens.The first element of the vector represents the payoff if the chosen colour is randomly selected by the computer, and the second one the payoff if the other colour is selected by the computer

Table 2.1: Payoffs for each decision in Part 3 of the experiment

of 40 boxes obtained by Crosetto and Filippin (2013), in their "High Stakes" treatment[5].

Separating participants in both samples (pre-experimental and experimental) we can achieve two goals: a) because "more risk-averse" participants from one social group are

[5] It is slightly lower than the median 46 boxes opened in the baseline model.

shown the same lotteries as "less risk-averse" participants from the other social group in the pre-experimental sample, decisions from each group will differ sufficiently so that stereotypical decisions from each of the groups diverge, and b) by showing participants in the experimental sample the decision of their social group, but of the opposite group according to risk aversion, expected utility maximisation will be achieved by the stereotypical decision of the other group. Therefore, by observing alignment with the group, we will also observe deviations from expected utility theory.

Part 4: Survey

In the last part of the experiment participants are asked about some demographic information (age, marital status, education level, ethnicity) and most importantly about identification with the group they have been assigned to. I follow Grieve and Hogg (1999) and use a 10-item questionnaire to study the level of identification with the group participants were assigned to in the first part of the experiment (see Appendix for details).

2.4 Results

In this section I analyse the results obtained from the experiment described above. I, first, briefly discuss the results from the pre-experimental sample and, then, follow on to the main results of the study.

2.4.1 Pre-experimental sample results

In the previous section, I argued that the experimental method presented should maximise the distance between participants, by separating the individuals between decisions to make according to social group and risk aversion level. I achieve significant separation between the modal decisions of the groups. Only in two of the ten decision problems participants in the conservative group have both decisions as modal. A total of 13 participants in the experimental sample were assigned to those two decision problems where the modal decision was not unique. Because we want to analyse how the modal decision of the social group affects decision making, I exclude the 26 decisions in which this modal decision was not unique in the following analysis, although the qualitative results are not affected by including them.

2.4.2 Identification and decision-making under risk

I first analyse how decisions are affected by identification with the group under situations of risk. In order to obtain a measure of how much participants identify with the group, I consider 2 of the questions in the group identification questionnaire at the end of the experiment. One of the questions directly asks for the level of identification with the group (*"On a scale from 1 to 10 (10 being the highest), how much do you identify with this group?"*) that I denote as Identification Question (IQ) and the second one asks about the feeling of belonging to the group, which can be understood as a measures of the proximity to the group they have been assigned to (*"On a scale from 1 to 10 (10 being the highest), how much do you feel you belong to your group?"*), and I call Belonging Question (BQ).

With these two measures of group identity, I divide the sample between those with low, medium and high identification. Given that the measures can only take 10 different values, and because of the limitations of the subjective scale[6] I choose to divide the groups in this way, rather than consider the identification variable as continuous. When deciding on how to define these three groups I first consider visual evidence. In figure 2.2, the mean proportion of decisions that are the same as their group's for each of value of IQ and BQ is shown against identification. In general, although there are some outliers, it can be seen that the mean proportion of alignment with the group is much higher for very high levels of identification (i.e., 9 and 10) than for the other levels of identification. This holds for both measures. I therefore denote participants as having a high identification if they either chose 9 or 10 in the IQ and BQ. It is a bit more complicated to choose how to split the low and medium identification groups. Results are not really affected by this (see appendix) and so for simplicity I split the remaining sample in half, given

[6]Choosing between 4 or 5 for instance, may not reflect real differences on identification, but a different interpretation of the scale across participants.

the distribution of the values of each of the questions. So I denote as low identification participants those who responded with a value from 1 to 5, and if the responded with a value from 6 to 8 I call them medium identification participants.

Table 1 shows the results from regressing a variable that takes value 1 if the decision made by the participant was the same as the stereotypical decision of their group and zero otherwise on indicator variables for each of the identification groups, for the two measures I use for identification. These are pooled decisions in the risk treatment, and I cluster standard errors at the participant level. Columns (1) and (3) show the results of the regression of the dependent variable on identification level groups for BQ and IQ, respectively. We can see that both regressions show a significant difference in taking the group's stereotypical decision between high identification and low identification. There does not seem to be a significant difference between the high identification and medium level identification group. Columns (2) and (4) control for the group the participants have been assigned to (i.e., "conservative"-leaning or "liberal"-leaning), risk aversion levels, as measured by the bomb-risk elicitation task, and I also consider decision problem fixed effects, in order to control for the possible framing effect of every different payoff set. As can be seen, these controls do not significantly change our result that individuals with lower identification choose the group's stereotypical decision significantly less often than those with higher identification.

Result 1: Under risk, participants are more likely to take the stereotypical decision of the group if they have a higher identification with the social group that is closest to them.

It could be believed that this result is due to some type of reverse causality. That is, participants feel a high identification with others in their group or feel they belong because they have taken the same action as those in their assigned group more times. This, however, seems unlikely. Table B.1 in the appendix shows the correlations across all ten questions we use to study the identification with the group[7]. It can be seen that the two questions we use as our proxy for identification with the group (questions 4 and 9) are

[7]See appendix for the exact wording of these questions.

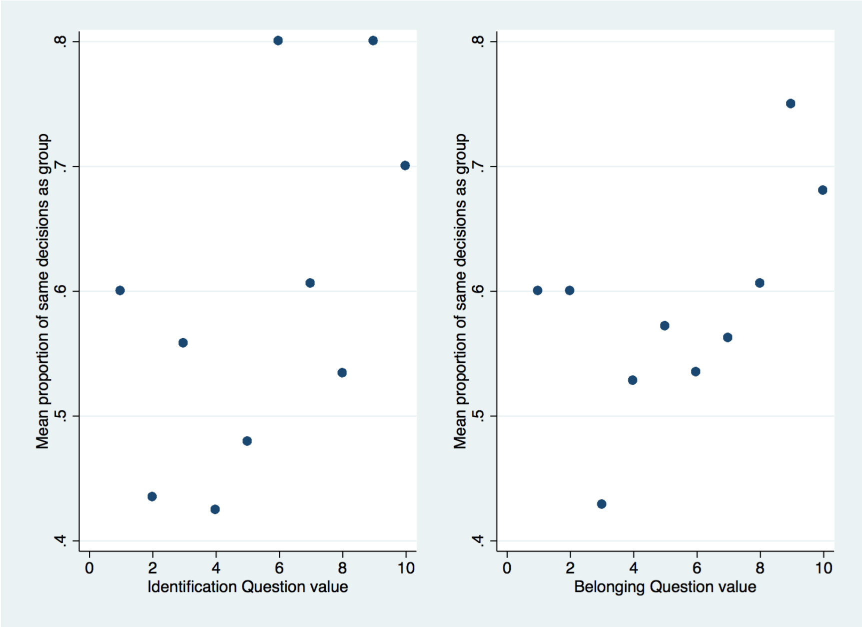


Figure 2.2: Plot of mean proportion of same decisions as the group, by level of identification according to the two measures of identity

	Belonging Question		Identification Question	
	(1)	(2)	(3)	(4)
Low Identity	-0.183**	-0.180**	-0.256***	-0.253***
	(0.077)	(0.074)	(0.084)	(0.081)
Medium Identity	-0.150*	-0.151*	-0.135*	-0.123
	(0.082)	(0.083)	(0.081)	(0.080)
Constant	0.723***	0.787***	0.756***	0.807***
	(0.064)	(0.11)	(0.069)	(0.101)
Controls				
Risk aversion		✓		✓
Group		✓		✓
Decision Fixed Effect		✓		✓
Observations	396	396	396	396

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Clustered standard errors at the participant level in parentheses.

Table 2.2: Regression of indicator variable (1 if same decision as modal group taken, 0 otherwise), on level of identification, and controls, under risk

very highly correlated (at 0.1% significance level) with all other questions, and specifically with questions that are unlikely to be affected by the choices in the experiment, such as question 2 (*"How similar do you think you are to those in your group in terms of your general attitudes and opinions"*)[8] or question 8 (*"How important is this group to you?"*)[9].

2.4.3 Identification and decision-making under ambiguity

I now study how increasing the uncertainty around the decision-making problem changes the preference to align with the stereotypical decision. I use a model in which I compare the ambiguity treatment and risk treatment groups according to the different identification levels defined in the previous subsection:

$$\begin{aligned} sameasgroup_{id} = \beta_0 + \beta_1 lowiden_i + \beta_2 mediumiden_i + \beta_3 treatment_i + \\ \beta_4 treatment_i * lowiden_i + \beta_5 treatment_i * mediumiden_i + \alpha' X + \epsilon_{id} \end{aligned} \tag{2.4}$$

where $sameasgroup_{it}$ is an indicator variable taking value 1 if decision d by participant i is the same as their group's stereotypical decision, $lowiden_i, medium_i$ are participant specific indicator variable, if they belong to any of the two identification level groups, and $treatmet_i$ is another indicator variable that takes value 1 if the participant is in the treatment group, and zero otherwise. I also include the interaction terms of the group identification level and the treatment variable, and consider the same control variables as in the previous subsection.

Table 2.3 shows the results from estimating the linear regression model above. Columns (1) and (3) show the results for the model without controls using the BQ and IQ for identification measures, respectively. In addition to result 1, we can also see that participants with low identification are significantly more likely to take the stereotypical decision under ambiguity than under risk. The effect of the treatment on either the medium or the high identification participants is not significantly different from zero, at a 5% significance

[8]Correlation with the belonging question is 0.77; correlation with the identification question is 0.72.
[9]Correlation with the belonging question is 0.78; correlation with the identification question is 0.83.

level. We cannot reject that the absolute value of the coefficients of the low identity and the interaction with the treatment are the same (p=0.35 and p=0.38, for belonging and identification questions, respectively). This means that the effect of lower identification on the decision-making process is counterbalanced by the increased uncertainty in the ambiguity treatment. Higher uncertainty makes lower identification participants take the group stereotypical decision as often as the high identification participants. This is consistent with the theoretical predictions from section 2.2.

Columns (2) and (4) include the same control variable as those explained in the previous subsection and additionally control for the interaction between assigned group and treatment, so that differences in perception of uncertainty between groups can be ruled out as causing the effect we observe. The qualitative results do not change from those in columns (1) and (3). We can still see that the effect of the treatment on low identification participants is positive and very significant. Additionally, under specification (2) we can also see that the medium identification participants are significantly less likely to take the group's stereotypical decision under risk than high identification ones. The treatment also has a positive effect on this probability for medium identification participants under specification (2). Again, we can also test for the equality of the absolute value of the low identification coefficients under treatment and control, which confirm that we cannot reject they are the same (p-value=0.14 and p-value=0.23, for belonging and identification questions, respectively). Using a non-parametric Mann-Whitney test of equality of distributions of both belonging and identification questions, we find no difference across treatments. P-values are 0.9323 and 0.9288 for each identity measure, respectively. This means that identification with the ambiguity treatment is not altered by the assigned treatment, but the treatment does affect decision-making in such a way that low identity participants make the same decision as participants in their assigned group as frequently as high identity participants. This is consistently lower under risk.

Result 2: Under ambiguity, low identification participants take the group stereotypical decision as often as those with higher identification. Additionally, the likelihood of high identification participants taking the stereotypical decision of their group is the

	Belonging Question		Identification Question	
	(1)	(2)	(3)	(4)
Low Identity	-0.183**	-0.182**	-0.256***	-0.253***
	(0.0770)	(0.0741)	(0.0841)	(0.0832)
Medium Identity	-0.150*	-0.162**	-0.135*	-0.132
	(0.0821)	(0.0817)	(0.0807)	(0.0813)
Ambiguity	-0.197*	-0.179*	-0.197*	-0.154
	(0.104)	(0.105)	(0.109)	(0.107)
Low Identity*Ambiguity	0.270**	0.309***	0.336***	0.354***
	(0.120)	(0.114)	(0.124)	(0.118)
Medium Identity*Ambiguity	0.235*	0.265**	0.140	0.152
	(0.124)	(0.121)	(0.127)	(0.123)
Constant	0.723***	0.772***	0.756***	0.783***
	(0.0639)	(0.0877)	(0.0691)	(0.0880)
Observations	849	849	849	849
Controls				
Risk aversion		✓		✓
Group		✓		✓
Decision Fixed Effect		✓		✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Clustered standard errors at the participant level in parentheses.

Table 2.3: Regression of indicator variable (1 if same decision as modal group taken, 0 otherwise), on level of identification, treatment group and controls.

same under risk and ambiguity decisions.

This result also reinforces the argument above against reverse causality. If there was indeed reverse causality and actually higher identification was a result of making the same decision more often, then the treatment variable and the interaction of this variable with the group indicator dummy variable should be insignificant.

2.5 Conclusion

This chapter presents evidence on the hypothesis that higher uncertainty about the outcome of a decision leads to higher alignment with the stereotypical decision of a social group. Incidentally, higher uncertainty alters decisions made by individuals with low identification with their social group, but not of those with high identification. This means that typical decisions made by a social group may be used as a reference point when the decision environment becomes more uncertain. This can have implications for modelling decision making under uncertainty, as social identity may be a key factor for decisions, especially when comparing different levels of uncertainty. Additionally, this may help explain the surge of identity politics in recent years; in more uncertain environments as the ones that arise after a financial crisis, associating social groups to particular political parties may raise votes to these parties among individuals belonging to these social groups, even if their identification with the group is weak. This is the first study, to the best of my knowledge, that links identity with decision making under uncertainty, but the positive results obtained lend to further analysis of this link (both theoretical and empirical) especially about the channels that explain this correlation between both concepts.

Appendix to Chapter 2

B.1 Additional empirical tests

The following tables show that dividing the groups differently does not affect results 1 and 2 from the main text of the chapter.

	Belonging Question		Identification Question	
	(1)	(2)	(3)	(4)
Low identity	-0.167**	-0.173**	-0.194**	-0.190**
	(0.0720)	(0.0692)	(0.0762)	(0.0763)
Ambiguity	-0.197*	-0.182*	-0.197*	-0.164
	(0.103)	(0.105)	(0.109)	(0.108)
Low Identity*Ambiguity	0.254**	0.286***	0.244**	0.258**
	(0.113)	(0.107)	(0.117)	(0.112)
Constant	0.723***	0.773***	0.756***	0.789***
	(0.0639)	(0.0868)	(0.0690)	(0.0888)
Observations	849	849	849	849
Controls				
Risk aversion		✓		✓
Group		✓		✓
Decision Fixed Effect		✓		✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Clustered standard errors at the participant level in parentheses. Low identification subject are those that chose a value between 1 and 8 in each questions. Comparison group is high identification group (those who answered with either 9 or 10).

Regression of indicator variable (1 if same decision as modal group taken, 0 otherwise), on level of identification, treatment group and controls.

	Belonging Question (1)	(2)	Identification Question (3)	(4)
Low identity	-0.123	-0.128	-0.235**	-0.231**
	(0.124)	(0.125)	(0.109)	(0.111)
Medium identity	-0.172**	-0.177**	-0.188**	-0.184**
	(0.0729)	(0.0706)	(0.0774)	(0.0773)
Ambiguity	-0.197*	-0.180*	-0.197*	-0.161
	(0.104)	(0.105)	(0.109)	(0.108)
Low Identity*Ambiguity	0.368**	0.444***	0.289*	0.344**
	(0.156)	(0.152)	(0.154)	(0.149)
Medium Identity*Ambiguity	0.242**	0.273**	0.236**	0.240**
	(0.114)	(0.108)	(0.119)	(0.113)
Constant	0.723***	0.783***	0.756***	0.791***
	(0.0639)	(0.0865)	(0.0691)	(0.0891)
Observations	849	849	849	849
Controls				
Risk aversion		✓		✓
Group		✓		✓
Decision Fixed Effect		✓		✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Clustered standard errors at the participant level in parentheses. Low identification subject are those that chose a value between 1 and 2 in each questions. Medium identification subject are those that chose a value between 3 and 8 in each questions. Comparison group is high identification group (those who answered with either 9 or 10).

Regression of indicator variable (1 if same decision as modal group taken, 0 otherwise), on level of identification, treatment group and controls.

	Belonging Question		Identification Question	
	(1)	(2)	(3)	(4)
Low identity	-0.206**	-0.199**	-0.217**	-0.214**
	(0.0957)	(0.0946)	(0.0905)	(0.0906)
Medium identity	-0.159**	-0.166**	-0.186**	-0.182**
	(0.0740)	(0.0723)	(0.0791)	(0.0795)
Ambiguity	-0.197*	-0.171	-0.197*	-0.161
	(0.104)	(0.105)	(0.109)	(0.108)
Low Identity*Ambiguity	0.370***	0.430***	0.286**	0.324**
	(0.136)	(0.131)	(0.136)	(0.130)
Medium Identity*Ambiguity	0.227*	0.254**	0.227*	0.234**
	(0.116)	(0.111)	(0.121)	(0.115)
Constant	0.723***	0.777***	0.756***	0.789***
	(0.0639)	(0.0882)	(0.0691)	(0.0889)
Observations	849	849	849	849
Controls				
Risk aversion		✓		✓
Group		✓		✓
Decision Fixed Effect		✓		✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Clustered standard errors at the participant level in parentheses. Low identification subject are those that chose a value between 1 and 3 in each questions. Medium identification subject are those that chose a value between 4 and 8 in each questions. Comparison group is high identification group (those who answered with either 9 or 10).

Regression of indicator variable (1 if same decision as modal group taken, 0 otherwise), on level of identification, treatment group and controls.

	Belonging Question (1)	(2)	Identification Question (3)	(4)
Low identity	-0.201**	-0.206**	-0.247***	-0.248***
	(0.0856)	(0.0806)	(0.0877)	(0.0868)
Medium identity	-0.150**	-0.155**	-0.165**	-0.160**
	(0.0759)	(0.0747)	(0.0797)	(0.0801)
Ambiguity	-0.197*	-0.176*	-0.197*	-0.159
	(0.104)	(0.105)	(0.109)	(0.108)
Low Identity*Ambiguity	0.278**	0.341***	0.313**	0.349***
	(0.131)	(0.124)	(0.130)	(0.124)
Medium Identity*Ambiguity	0.241**	0.261**	0.204*	0.207*
	(0.117)	(0.113)	(0.122)	(0.116)
Constant	0.723***	0.772***	0.756***	0.791***
	(0.0639)	(0.0873)	(0.0691)	(0.0887)
Observations	849	849	849	849
Controls				
Risk aversion		✓		✓
Group		✓		✓
Decision Fixed Effect		✓		✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Clustered standard errors at the participant level in parentheses. Low identification subject are those that chose a value between 1 and 4 in each questions. Medium identification subject are those that chose a value between 5 and 8 in each questions. Comparison group is high identification group (those who answered with either 9 or 10).

Regression of indicator variable (1 if same decision as modal group taken, 0 otherwise), on level of identification, treatment group and controls.

	Belonging Question		Identification Question	
	(1)	(2)	(3)	(4)
Low identity	-0.184**	-0.182**	-0.199**	-0.194**
	(0.0755)	(0.0731)	(0.0815)	(0.0810)
Medium identity	-0.135	-0.153*	-0.187**	-0.185**
	(0.0867)	(0.0871)	(0.0843)	(0.0856)
Ambiguity	-0.197*	-0.178*	-0.197*	-0.165
	(0.104)	(0.106)	(0.109)	(0.108)
Low identity*Ambiguity	0.271**	0.293***	0.232*	0.249**
	(0.117)	(0.111)	(0.122)	(0.117)
Medium identity*Ambiguity	0.221*	0.271**	0.288**	0.286**
	(0.133)	(0.129)	(0.131)	(0.126)
Constant	0.723***	0.769***	0.756***	0.790***
	(0.0639)	(0.0891)	(0.0691)	(0.0888)
Observations	849	849	849	849
Controls				
Risk aversion		✓		✓
Group		✓		✓
Decision Fixed Effect		✓		✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Clustered standard errors at the participant level in parentheses. Low identification subject are those that chose a value between 1 and 6 in each questions. Medium identification subject are those that chose a value between 7 and 8 in each questions. Comparison group is high identification group (those who answered with either 9 or 10).

Regression of indicator variable (1 if same decision as modal group taken, 0 otherwise), on level of identification, treatment group and controls.

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
Q1	1									
Q2	0.793^{***}	1								
Q3	0.687^{***}	0.670^{***}	1							
Q4	0.799^{***}	0.772^{***}	0.656^{***}	1						
Q5	0.696^{***}	0.677^{***}	0.682^{***}	0.810^{***}	1					
Q6	-0.351^{***}	-0.309^{***}	-0.111^{*}	-0.318^{***}	-0.138^{*}	1				
Q7	0.793^{***}	0.762^{***}	0.677^{***}	0.854^{***}	0.790^{***}	-0.325^{***}	1			
Q8	0.708^{***}	0.696^{***}	0.630^{***}	0.779^{***}	0.786^{***}	-0.211^{**}	0.732^{***}	1		
Q9	0.771^{***}	0.722^{***}	0.640^{***}	0.851^{***}	0.778^{***}	-0.297^{***}	0.838^{***}	0.825^{***}	1	
Q10	0.669^{***}	0.662^{***}	0.476^{***}	0.759^{***}	0.592^{***}	-0.421^{***}	0.755^{***}	0.639^{***}	0.728^{***}	1

* $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$

Table B.1: Correlations of the ten identity questions in the survey

B.2 Questionnaire to measure identification with the group

This 10-question form is used to evaluate identification with assigned social group and was drawn from Grieves and Hogg (1999).

We introduce the questionnaire with the following paragraph, which changes according to the group subject was assigned to:

*We would lastly want to ask you some questions about how you feel about the group you were assigned to, that is the <**liberal/conservative**>-leaning group, and specifically how you feel about other participants that have also been assigned to your group.*

The ten questions are the following:

	On a scale from 1 to 10 (10 being the highest)...
1	How much do you think you would like individuals in your group?
2	How similar do you think you are to those in your group in terms of your general attitudes and opinions?
3	How much would you like to know those in your group?
4	How much do you feel you belong to your group?
5	How much do you feel strong ties with your group?
6	How much do you feel your group may hold you back?
7	How pleased are you to belong to this group?
8	How important is this group to you?
9	How much do you identify with this group?
10	To what extent do you prefer to belong to your group than the other group?

B.3 Modified Ideological Consistency Scale

As discussed in the main text, I use a modified version of Ideological Consistency Scale to measure participants' ideology and assign them to social groups within the experiment.

I use the 10-item Ideological Consistency Scale developed by the Pew Research Centre (1994) and add an additional question to update it to current political concerns.

For each of the items participants are asked about which statement they agree with.

The 10 items are:

Item	Statement A	Statement B
1	Government is almost always wasteful and inefficient.	Government often does a better job than people give it credit for.
2	Government regulation of business usually does more harm than good.	Government regulation of business is necessary to protect the public interest.
3	Poor people have hard lives because government benefits don't go far enough to help them live decently.	Poor people today have it easy because they can get government benefits without doing anything in return.
4	The government today cannot afford to do much more to help the needy.	The government should do more to help needy Americans, even if it means going deeper into debt.
5	Racial discrimination is the main reason why many black people can't get ahead these days.	Blacks who cannot get ahead in this country are mostly responsible for their own condition.
6	Immigrants today strengthen our country because of their hard work and talents.	Immigrants today are a burden on our country because they take our jobs, housing and health care.
7	Good diplomacy is the best way to ensure peace.	The best way to ensure peace is through military strength.
8	Most corporations make a fair and reasonable amount of profit.	Business corporations make too much profit.
9	Stricter environmental laws and regulations cost too many jobs and hurt the economy.	Stricter environmental laws and regulations are worth the cost.
10	Homosexuality should be accepted by society.	Homosexuality should be discouraged by society.
11	Surveillance of communication technologies, like cell phones or the Internet, is positive if it prevents possible terrorist attacks.	Surveillance of communication technologies, like cell phones or the Internet, is a violation of fundamental rights to freedom and privacy.

B.4 Instructions of the experiment

Welcome

This is an experiment in the economics of decision-making. The instructions are simple, and if you follow them carefully and make good decisions you may earn a BONUS AMOUNT OF MONEY that will be announced to you at the end of the experiment, and paid through your chosen method. The currency in this experiment is called tokens. All payoffs are denominated in this currency.

There are three parts in the experiment:

- In Part I you will be asked to answer questions on your views on some political and social matters.
- In Part II you will play a game in which you will have to bet on the amount of money you may earn. More details will be provided later.
- In Part III you will have to choose between 5 pairs of lotteries (we will explain what this is later).

Your earning in the experiment will be determined as follows:

- After you have finished the experiment, the computer will randomly choose either your choice in Part II or one of the five choice problems in Part III. If after the random selection one choice of Part III is chosen the lottery you chose in that question will be played it, yielding your bonus earning. The amount of tokens that you receive will then be converted to US dollars using the rate 100 Tokens = $1.
- Your total earning will consist of the amounts above plus a $2 participation fee if you complete the experiment.

Part I - Instructions

There are 11 questions in this part. Most of these questions have been obtained from the Ideological Consistency Scale by the Pew Research Center.

You should answer the questions according to your beliefs.

Once you have made your choice you should click "Next" to go to the next question. Keep in mind that once you have clicked this button you will not be able to go back and change your decision.

For your convenience, these instructions will remain available to you on all subsequent screens of this section.

Part II Instructions

In the following, you will see a 10x10-matrix containing 100 boxes on your screen.

As soon as you start the task by hitting the 'Start' button, one of the boxes is collected per second, starting from the top-left corner. Once collected, the box is marked by a tick symbol. For each box collected you earn 1 token.

Behind one of the boxes hides a bomb that destroys everything that has been collected. The remaining 99 boxes are worth 1 tokens each. You do not know where the bomb is located. You only know that the bomb can be in any place with equal probability.

Your task is to choose when to stop the collecting process. You do so by hitting 'Stop' at any time. If you collect the box where the bomb is located, the bomb will explode and you will earn zero. If you stop before collecting the bomb, you gain the amount accumulated that far. You will not be told if you collected the bomb until the end of experiment.

For your convenience, these instructions will remain available to you on all subsequent screens of this section.

Part III Instructions

(Ambiguity treatment)

There are 5 questions in this part. In every question, you will be asked to choose between a red or a black ball. The computer will, for each question, randomly choose a ball from a set of balls that contains 10 red and black balls, where the proportion of red and black balls is unknown, and randomly chosen by the computer at the beginning of the section, for each of the 5 questions. This proportion may be different for each question. There may as few as 0 balls of either color, or as many as 10, and any quantity in between.

A set of more than 30 individuals participated previously in this experiment. The most common choice taken by participants in each of the groups will be displayed.

Also remember that there are only 10 balls. For example, if there are 3 red balls, there must be 7 black balls. In this case, the probability of the ball being red is 3/10=30% and the probability of it being black is 7/10=70

The possible payoff from each of the games will be shown on a table like this one:

Your choice	If the ball is red	If the ball is black
Red	30 tokens	10 tokens
Black	20 tokens	25 tokens

That is, if you choose the red ball and the ball randomly selected by the computer turns out to be red you will obtain 30 tokens, otherwise you will obtain 10 tokens. If, on the other hand, you choose the black ball and the ball randomly selected by the computer turns out be black you will obtain 25 tokens; otherwise, you will obtain 20.

Once you have made your choice you should click "Next" to go to the next question. Keep in mind that once you have clicked this button you will not be able to go back and change your decision.

Remember: THERE IS NO RIGHT OR WRONG ANSWER TO ANY OF THESE QUESTIONS. We only want to analyse your preferences.

For your convenience, these instructions will remain available to you on all subsequent screens of this section.

(Risk treatment)

There are 5 questions in this part. In every question, you will be asked to choose between a red or a black ball. The computer will, for each question, randomly choose a ball from a set of balls that contains 10 red and black balls, 5 of each color. This means that the probability of taking out a red ball is 1/2 and the probability of taking out a black ball is also 1/2 .

A set of more than 30 individuals participated previously in this experiment. The most common choice taken by participants in each of the groups will be displayed.

The possible payoff from each of the games will be shown on a table like this one:

Your choice	If the ball is red	If the ball is black
Red	30 tokens	10 tokens
Black	20 tokens	25 tokens

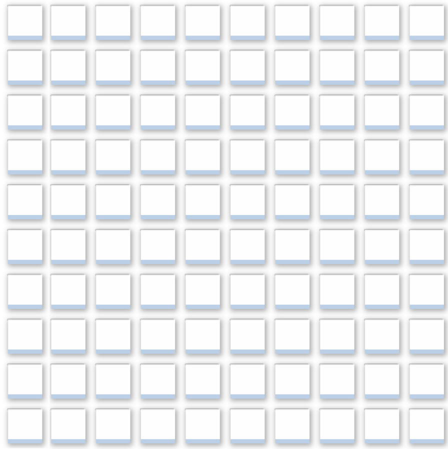
That is, if you choose the red ball and the ball randomly selected by the computer turns out to be red you will obtain 30 tokens, otherwise you will obtain 10 tokens. If, on the other hand, you choose the black ball and the ball randomly selected by the computer turns out be black you will obtain 25 tokens; otherwise, you will obtain 20.

Once you have made your choice you should click "Next" to go to the next question. Keep in mind that once you have clicked this button you will not be able to go back and change your decision.

Remember: THERE IS NO RIGHT OR WRONG ANSWER TO ANY OF THESE QUESTIONS. We only want to analyse your preferences.

For your convenience, these instructions will remain available to you on all subsequent screens of this section.

Part II



No. of boxes collected: 0
No. of boxes remaining: 100

Start Stop

Figure B.1: Example of risk elicitation task

Part III

This table shows the payoffs you will obtain for each possible choice you make.

Remember that the probability of taking out a red ball is 1/2, and the probability of taking out a black ball is 1/2, that is they are equally likely.

- The majority of participants in the **liberal-leaning** group chose the **red** ball.
- The majority of participants in the **conservative-leaning** group chose the **black** ball.

Your choice	If the ball is red	If the ball is black
Red	80 tokens	40 tokens
Black	18 tokens	120 tokens

Which color would you want to choose?

Next

Figure B.2: Example of decision problem in risk treatment

Part III

This table shows the payoffs you will obtain for each possible choice you make.

Remember that there may be as few as 0 balls of either color, or as many as 10, and any quantity in between, and that the computer has randomly chosen this quantity before the start of the game.

- The majority of participants in the **liberal-leaning group** chose the **red** ball.
- The majority of participants in the **conservative-leaning** group chose the **black** ball.

Your choice	If the ball is red	If the ball is black
Red	80 tokens	40 tokens
Black	18 tokens	120 tokens

Which color would you want to choose?

Next

Figure B.3: Example of decision problem in ambiguity treatment

Chapter 3

Risk preferences, Trust and Noncognitive Skills at the Time of COVID-19: An Experiment with Professional Traders and Students

(with Marco Angrisani, Marco Cipriani, Antonio Guarino and Ryan Kendall)

Abstract

We study the impact of COVID-19 on risk preferences and noncognitive skills by comparing experimental results gathered before and during the outbreak. Using a sample of professional traders, we find that risk preferences remain constant. Traders show a sharp decrease in Agreeableness and Locus of Control and a moderate decrease in Grit, whereas Trust, Conscientiousness and Self-Monitoring are unchanged. We contrast these results with those from a sample of undergraduates whose risk preferences and noncognitive skills remain constant (except Conscientiousness). Our findings support the view that risk preferences are stable; however, they provide evidence against the stability of noncognitive skills.

3.1 Introduction

In March 2020, following the outbreak of COVID-19, we have observed a sharp fall in asset prices and a sharp increase in risk premia across maturities and asset classes. Of course, such market turmoil is partially due to a change in market participants' assessment of future economic outcomes.[1] One may wonder, however, whether it is also due to a change in agents' risk tolerance. Assessing whether risk preferences are a stable individual characteristic or change over time, and whether they are affected by the business cycle or major economic or social events is of fundamental importance as risk preferences affect agents' saving, consumption, and investment decisions. An increase in risk aversion after a negative shock, for instance, could lead agents to lower consumption and investment in risky assets, thus depressing asset prices, exacerbating the economic downturn, and making recovery slower.[2] Despite the importance of understanding the stability of risk preference, research in this field is very limited.

Risk preferences are not the only individual trait important for economic outcomes. A large literature has shown that noncognitive skills play a key role in economic and social success (for a survey, see Almlund et al., 2011). Noncognitive skills are predictive of success in school (Van Eijck and De Graaf, 2004; Borghans et al., 2016), success in finding a job (Cobb-Clark and Tan, 2011), the amount of effort spent looking for a job (Caliendo et al., 2015), job performance (Rustichini et al., 2016), wages (Heckman et al., 2006; Fletcher, 2013), and long-term health (Roberts et al., 2007).

Typically, noncognitive skills are treated as stable characteristics that do not vary with the business cycle or other events. This traditional view argues that personality traits are considerably stable after they are formed in the early stages of life (McCrae and Costa, 1994). More recent empirical studies, however, cast some doubts on the stability of noncognitive skills showing that extremely frightening shocks to everyday life (Löckenhoff

[1]Investors' expectations at the time of the COVID-19 pandemic are studied by Giglio et al. (2020).

[2]While the standard approach in economics is to take preferences as fixed, time-varying risk aversion has also been used. For instance, in a well-known contribution, Campbell and Cochrane (1999) use a consumption-based asset pricing model with habit formation (which implies countercyclical risk-aversion) to solve famous puzzles (e.g., the equity premium puzzle) and to explain a variety of asset pricing phenomena, like the procyclicality of stock price changes or the countercyclicality of stock market volatility.

et al., 2009) or long lasting health conditions (Elkins et al., 2017) can significantly alter noncognitive skills. Given the role of these skills in determining economic outcomes, it is important to understand whether they are stable or whether they respond to economic shocks or other events.

To study the stability of risk preferences and noncognitive skills, we run an experiment with a sample of professional traders and a sample of students during the COVID-19 pandemic of 2020.[3] COVID-19 is arguably the biggest shock to developed economies since World War II. Because of the pandemic, economic activity has been disrupted to an extreme degree for a time of peace. At the time of the study, in April 2020, entire countries were under lockdown. Excess deaths in the first part of the year are estimated to be large, with health systems unable to cope with the peak of the pandemic. The IMF forecasts 2020 real GDP to decrease by 7.1% in the European Union and by 5.9% in the US. In April 2020, the unemployment rate reached 14.7% in the US and 6.7% in the European Union. Asset prices responded accordingly, with the NYSE depreciating by 19% between 24th February and 24th April and the FTSE-100 losing 20% of its value during the same period. The effect of the pandemic is not limited to the economy. Entire countries are under lockdown, schools have been closed, and mortality rates have climbed.

We compare the results of an experiment conducted with *the same* sample of participants before COVID-19 (in 2019) and at the time of COVID-19 (April 2020).[4] Before the pandemic, in 2019, we ran a laboratory experiment in which we elicited risk preferences using the methodology of Crosetto and Filippin (2013); we also asked participants to fill a series of questionnaires assessing their noncognitive skills. In particular, we asked questions to infer Agreeableness (which includes Trust), Conscientiousness, Locus of Control, Grit and Self-Monitoring. In April 2020, when the pandemic was at its peak in London, we invited the same participants to repeat these tasks and asked additional questions to gauge the extent to which COVID-19 affected them.

In addition to risk aversion, we focus on these five noncognitive skills in order to

[3]For a review of differences between students and financial professionals in economic experiments, see Fréchette (2015).

[4]According to the taxonomy of Harrison and List (2004), our study is an artefactual field experiment.

leverage our unique sample of professional traders, given that these skills are relevant for strategic decision making and trading activity.[5] For instance, Proto et al. (2019) study the relationship between Agreeableness and Conscientiousness and strategic behavior. Biais et al. (2005) find that Self-Monitoring enhances trading performance. The role of Grit and Locus of Control has been investigated in several studies, such as Caliendo et al. (2015).

We find that risk aversion has not changed during the pandemic for either trader or student participants. Before the pandemic, traders were less risk averse than students, and this has remained the case during the pandemic. Professional traders show a sharp decrease in Agreeableness and Locus of Control with a moderate decrease in Grit, while Trust, Conscientiousness and Self-Monitoring remain constant. In contrast, undergraduate students' noncognitive skills have remained constant, with the exception of Conscientiousness, which increased.

Our results on risk preferences suggest that the increases in risk premia observed during the pandemic are not due to changes in risk appetite. Our findings support the traditional view that risk preferences are not affected by economic or social circumstances. In contrast, the results on the noncognitive skills support the view that some of these traits may not be stable.

Moreover, we study if participants' response of risk aversion and noncognitive skills is related to participants' experience of the pandemic. Consistently with our main results, traders with a more negative experience of the pandemic are more likely to decrease their levels of Agreeableness, Grit, and Locus of Control. The response of risk aversion and the other non-cognitive skills, in contrast, is not related to the pandemic experience.

[5]Cognitive skills also play a key role in strategic decision making and trading activity. However, we do not study changes in cognitive skills because they are unlikely to be affected by a pandemic.

3.1.1 Related Literature

The COVID-19 pandemic has caused widespread social and economic disruption. Previous papers have studied the impact of both types of disruption on risk preferences.[6] Callen et al. (2014) show that exposure to violence and fear priming (recollection of the violence) affect risky decisions and, in particular, increase a preference for certainty. Cameron and Shah (2015) find that individuals who recently suffered a flood or earthquake in Indonesia exhibit higher risk aversion. Cassar et al. (2017) find an increase in risk aversion after a tsunami in rural Thailand. Cavatorta and Groom (2020) document changes in risk and time preferences as a result of counter-violence initiatives in the West Bank. All these studies are conducted in developing countries, and focus on extreme events. Although COVID-19 has been very disruptive by the standard of developed economies, it nevertheless does not compare to the ravaging of wars; this could explain the difference between these results and ours.

Three other papers close to ours are Cohn et al. (2015), König-Kersting and Trautmann (2018), and Guiso et al. (2018). These papers study how risk preferences change in the presence of an economic downturn. Cohn et al. (2015) use a laboratory experiment in which financial professionals are primed with a boom or a bust scenario in an artificial market. They find that those primed with a bust exhibit higher risk aversion. Note that the participants used in this study are financial professionals in general, whereas our professional sample is only made of people who directly trade or invest in the market (traders and portfolio managers). König-Kersting and Trautmann (2018) conduct a similar laboratory experiment using undergraduate subjects and find that students' risk preferences are not affected when primed with a boom or bust scenario. Finally, Guiso et al. (2018) use portfolio data and surveys to understand how clients of an Italian bank reacted to the 2008 crisis. They find an increase in risk aversion after 2008. Through a laboratory experiment, they support the view that these changes are mainly due to emotions. In the laboratory, some participants are asked to watch a 5-minute horror movie in order to

[6] Twenty-five percent of variation in risk preferences can be explained by genetic variation (Cesarini et al., 2010).

prime fearful emotions; these participants show higher risk aversion than those who did not watch the movie.[7]

As we have mentioned above, in the literature, personality traits are usually viewed as stable, at least after young adulthood (McCrae and Costa, 1994). Recent studies, however, show that personality traits may change with age. For instance, Conscientiousness and Agreeableness have been shown to change over an individual's lifetime (see Roberts et al. (2006) for a meta-analysis). Extreme physical or psychological trauma can also alter personality traits. Löckenhoff et al. (2009) show that suffering a frightening experience can decrease Agreeableness, whereas Elkins et al. (2017) show that long-term health conditions can decrease Locus of Control. Cobb-Clark and Schurer (2012, 2013) show very limited changes in noncognitive skills such as Locus of Control, Agreeableness, or Conscientiousness even for participants who experience many adverse events over a four-year time horizon.

Also related to our work are the few papers in the Social Capital literature that discuss the stability of Trust. Using survey data from the US and other countries, Stevenson and Wolfers (2011) show a procyclical trend in trust in national governments and financial institutions. Ananyev and Guriev (2019) exploit the differential effect of the 2009 financial crisis across Russian regions to study the effect of the crisis on societal trust; they find that a 1% drop in income reduces the level of trust by 0.5%. Guriev and Melnikov (2016) use weekly online searches for keywords related to social capital (e.g., blood donations, adoptions and charity) to estimate changes in social capital in Russia in 2014, which they attribute to changes in inflation and the escalation of the war against Ukraine.[8] Using longitudinal data, Algan et al. (2017) find a decrease in trust in institutions as a result

[7] A related question is tackled by Carvalho et al. (2016). Using a sample of low income households, they study whether changes in the availability of financial resources are related to changes in preferences, by measuring risk preferences before or after payday. They find no evidence that risk preferences are different before and after payday.

[8] Other related work includes Fisman et al. (2015) and Giuliano and Spilimbergo (2014). Fisman et al. (2015) study the behavior of undergraduate students in the dictator game. They find that after the 2008 financial crisis there were higher levels of selfishness and preferences for efficiency. Giuliano and Spilimbergo (2014) find that individuals who faced an economic shock as young adults show a greater preference for redistributive policies during their lifetime.

of the increase in unemployment during to the 2008 financial crisis in Europe, whereas this drop is much smaller for interpersonal trust. Owens and Cook (2013) find similar results for the US. Lindström and Giordano (2016), however, find a significant decrease in generalized trust in the UK at the time of the 2008 financial crisis.

The rest of the chapter is organized as follows. Section 3.2 explains the experiment. Section 3.3 describes the participant sample. Section 3.4 presents the results. Section 3.5 concludes. An Appendix contains additional results and the experimental instructions.

3.2 The Experiment

3.2.1 Setup

We ran our experiment twice, the first time between February and May 2019 and then again in April 2020. In 2019, we ran the experiment in the Experimental Laboratory for Finance and Economics (ELFE) in the Centre for Finance at the Department of Economics at University College London (UCL); in 2020, we ran the experiment online.

In 2019, we elicited participants' risk preferences and noncognitive skills (run with z-tree, see Fischbacher, 2007).[9] In April 2020, we invited *the same participants* to an online experiment (run with o-Tree, see Chen et al., 2016, and Holzmeister and Pfurtscheller, 2016) where we elicited risk preferences and noncognitive skills in the same manner as before. Furthermore, we asked participants to complete a questionnaire about the impact of COVID-19 on their lives.

In April 2020, the UK reported more than 100,000 cases of COVID-19 resulting in more than 15,000 deaths. London and the rest of the UK were locked down so that people were only allowed to leave their home for specific reasons and for a short time period. Universities were closed and teaching was exclusively remote. For most jobs, working from home had become the norm.We refer to the data gathered in 2019 as the "Pre-COVID" data and the data gathered in 2020 as the "COVID" data.

[9]These data are part of a larger experiment on trading activity by financial market professionals. We omit the citation to respect the anonymity of the review process.

In both sets of data, we measure risk preferences and five noncognitive skills: Agreeableness (which includes a measure of Trust), Conscientiousness, Locus of Control, Grit and Self-Monitoring.[10]

Our sample includes only those who participated in both experiments.

As part of a different experiment, we also collected data on the noncognitive skills of 34 other students; the data were collected in November-December 2019 and then again in April 2020.[11] We will not report the statistics from this additional sample in our main analysis but will discuss them at the end of Section 4.2.

3.2.2 Risk preferences

We measure risk preferences by using the "Bomb Risk Elicitation Task" (BRET, Crosetto and Filippin, 2013). In the BRET, participants are shown a screen with 100 boxes and are asked to "open a number of boxes" (between 1 and 99). Each box contains GBP 0.20; therefore, earnings increase linearly with the number of boxes chosen. Among the boxes, however, there is one that, if chosen, makes the participant lose all their earnings (in the original version by Crosetto and Filippin (2013) this box was described as a box containing a bomb; we used a more neutral description of an "empty box"). The decision about the number of boxes to collect is a decision under risk. A risk-neutral participant collects 50 boxes. A risk-averse participant collects less than 50 boxes and a risk-loving one more than 50. The more boxes a participant collects the higher their degree of risk-seeking preference. For example, a participant with constant relative risk aversion (CRRA) preferences would choose 45 boxes with a risk aversion coefficient of 0.18; 40 boxes with a coefficient of 0.33; 30 boxes with a coefficient of 0.57; 20 boxes with a coefficient of 0.75.[12]

[10] Trust is a facet of the Big-5 "Agreeableness" trait (John et al., 1991). In addition to these measures,we collected data on other traits that we do not include in our analysis because they do not have an immediate implication for economic decisions or outcomes (e.g., "Openness" and "Extroversion" of the Big-5). However, we discuss them in the Appendix.

[11] The data in November-December 2019 were collected as part of another study. We recontacted the same subjects in April 2020 for our study. We omit the citation to respect the anonymity of the review process.

[12] See Appendix C.6.

3.2.3 Noncognitive Skills

As we said, we measure five noncognitive skills: Agreeableness, Conscientiousness, Locus of Control, Grit, and Self-monitoring. For the first four measures, participants are asked to what extent they agree with a series of statements using a scale ranging from 1 (Disagree strongly) to 5 (Agree strongly). For Self-Monitoring, participants answer 18 true/false questions.

Agreeableness

We measure Agreeableness by using the two-item measure developed by Rammstedt and John (2007), consisting of the following two statements:

- *I am generally trusting.*
- *I tend to find fault with others.*

The second measure is reverse coded and Agreeableness is the average of the two measures. Higher values of this measure represent higher Agreeableness.

The first item is a measure of trust. It is similar to the trust measure used in the World Values Survey (WVS).[13] The same wording is used to measure trust in the US General Social Survey and The European Social Survey.[14] This measure has been used to study how trust is linked to financial decisions (Karlan, 2005), economic performance (Butler et al., 2016) and economic shocks (Ananyev and Guriev, 2019).

Conscientiousness

As with Agreeableness, we measure Conscientiousness by using the two-item measure from Rammstedt and John (2007), consisting of the following two statements:

- *I do a thorough job.*

[13] In the WVS, participants are asked: "Generally speaking, do you believe that most people can be trusted or that you can't be too careful in dealing with people?"

[14] A different approach to measure trust consists in asking participants to play the "Trust Game" (Berg et al., 1995). Behavior in this game, however, may depend on both beliefs and preferences (see Gale, 2005 and Sapienza et al., 2013).

- *I tend to be lazy.*

The second measure is reverse coded and Conscientiousness is the average of the two measures. Higher values of this measure represent higher Conscientiousness.

Locus of Control (LoC)

We measure Locus of Control (LoC from now on) by using the 7-item questionnaire developed by Cobb-Clark and Schurer (2013). Participants are asked to what extent they agree with some statements. Examples are:

- *What happens to me in the future mostly depends on me.*
- *I can do just about anything I really set my mind to do.*

We report all 7 statements in the Appendix. LoC is the average of these 7 measures, with higher values representing higher internal LoC.

Grit

We measure Grit using the 8-item questionnaire (GRIT-S) developed by Duckworth and Quinn (2009). We list two items here and report all eight items in the Appendix:

- *Setbacks don't discourage me.*
- *I finish whatever I begin.*

Grit is the average of these eight measures, with higher values representing higher Grit.

Self-Monitoring

We measure Self-Monitoring using the 18-item questionnaire developed by Snyder and Gangestad (1986). We list two items here and report all 18 items in the Appendix:

- *I find it hard to imitate the behaviour of other people.*

- *At parties and social gatherings, I do not attempt to do or say things that others will like.*

To calculate Self-Monitoring, we compute the proportion of times a participant's choice aligns with the higher Self-Monitoring answer. This measure takes a value between 0 and 1; a higher value represents higher Self-Monitoring.

3.2.4 Perceived impact of the pandemic

In the COVID experiment, we ask participants to answer a questionnaire about their experience of the pandemic, specifically: i) whether they or members of their household had been infected; ii) whether any relative or close friend had been infected; iii) the impact on their current financial situation; iv) their expectations about the impact on their financial situation in one year; v) the extent to which their quality of life has been affected by changes in daily activities; vi) how worried they were about the pandemic. Questions iii) to vi) are measured on a Likert scale from 1 (Not at all) to 5 (Severely).

3.3 Experimental Participants

We use a sample of traders and portfolio managers working in the city of London (UK). In addition, we also use a sample of UCL undergraduate students from all disciplines.

In 2019, we recruited 56 professional traders and 79 undergraduate students. Out of the original participants, 49 traders and 61 students participated again in 2020, for a participation rate of 88% for professional traders and 77% for students.[15] As mentioned above, our sample includes only those who participated in both experiments.

The sample of professional traders consists of 28 traders, 4 proprietary traders, 2 sales-traders, 9 portfolio managers, and 6 belonging to other categories (e.g., trading strategist or sales with management of virtual portfolios). Professional traders work in a variety of financial markets, such as equity, equity derivatives, FX, fixed income, and commodities.

[15] For one trader and one student the recording of risk preferences was incorrect. Hence, when analyzing risk preferences, the sample includes 48 traders and 60 students.

Twenty-seven participants are employed by an investment bank, 11 by an investment fund and the others by other types of institutions (or preferred not to report their employer). Traders' age ranges between 24 and 50, with a mean of 33 years and a standard deviation of 6.5 years. Their average job tenure is 9.43 years, with a range between 1.5 and 21 years and a standard deviation of 5.74 years. Thirty participants have a Master degree, 4 an MBA, and 14 a Bachelor degree.[16] Thirty participants studied economics or finance, 8 mathematics or physics, 8 engineering or computer science, and the remaining have a degree in other disciplines or did not declare it. Eighty-six percent of traders are men.

The sample of students comprises undergraduate students from all disciplines. The gender composition is similar to that of traders, with 80% of students being male.[17] Students are younger than traders, with a mean of 22 years and a standard deviation of 1.7.

Only the BRET was incentivized so that, in both sets of data, all participants were paid GBP 0.20 per box. In the Pre-COVID data, traders earned an average of GBP 3.70 while students earned an average of GBP 4.90. In the COVID data, traders earned an average of GBP 4.10 while students earned an average of GBP 4.90.[18]

3.4 Results

We first consider changes in risk preferences in subsection 3.4.1. Next, we focus on changes in noncognitive skills in subsection 3.4.2. We then look at differences in the impact of the COVID-19 pandemic on participants' lives (subsection 3.4.3) and at the extent to which it is reflected in changes in risk preferences and noncognitive skills in subsection 3.4.4.

[16] One participant declared both a Master degree and an MBA. Two participants did not declare their highest level of education.

[17] Because gender may play a role in many experiments, we recruited students in order to match the gender composition of our trader pool.

[18] As mentioned above, in the Pre-COVID data, participants took part in other market experiments. Traders earned an average of approximately GBP 250 (US$304) and students earned an average of approximately GBP 25 ($30.45). In the COVID data, all participants earned GBP 25 for participating in the online experiment in addition to their BRET earnings.

3.4.1 Risk Preferences

Table 3.1 reports the mean, median, and standard deviation of BRET choices in the Pre-COVID and COVID data for traders. As can be seen, there is no evidence that BRET choices change over time: the median BRET choice is 50 in both datasets, whereas the mean increases by 3.13 between Pre-COVID and COVID. Similarly, in Table 3.2, students show very little change across datasets: their median BRET choice increases by 2.5, whereas the mean increases by 0.37.[19] Using a two-tailed t-test, the difference in risk aversion across periods, $\Delta BRET = (BRET_{COVID} - BRET_{Pre-COVID})$, is not significantly different from zero for either traders (p-value=0.167) or students (p-value=0.846).[20]

Pre-COVID Data			COVID Data			$H_0 : \Delta BRET = 0$
Mean	SD	Med	Mean	SD	Med	p-value
50.25	12.40	50.00	53.38	14.97	50.00	0.167

Note: $N = 48$. $\Delta BRET$ is the individual-level difference in BRET between the COVID and the Pre-COVID data set. *: $p - value < 0.1$, **: $p - value < 0.05$, ***: $p - value < 0.01$.

Table 3.1: Traders' Risk Preferences in the Pre-COVID and COVID Data

[19] Our student participants record similar average measures of BRET to Crosetto and Filippin (2013)'s findings of 46.5 in the "Baseline" Treatment and 40 in the "High Stakes" Treatment. For a participant with CRRA preferences, a choice of 43 (our students' median choice) is equivalent to a coefficient of relative risk aversion equal to 0.25. This is in line with results presented by Holt and Laury (2002), who, using their elicitation mechanism, find that the coefficient for the median participant is between 0.15 and 0.41; similarly, Choi et al. (2007), using their elicitation method, estimate a median coefficient of 0.48. For a comparison of different risk elicitation methods, see Crosetto and Filippin (2016).

[20] We reach the same conclusions when using a Wilcoxon signed-rank test for the null that the central tendencies of the paired distributions are the same. Specifically, the p-values are 0.327 for traders, 0.715 for students. In Figure C.1 in the Appendix, we find that BRET increases significantly with age among students, but not among traders. One concern could be that students became less risk averse because they were older (approximately by 1 year) and this confounds the effect of COVID-19. Based on the estimated relationship between age and BRET in the Pre-COVID data, we run a counterfactual exercise estimating BRET choices in the absence of COVID-19. On average, these predicted BRET choices are 1.8 higher than those actually observed in the COVID period. However, this difference is not statistically significant (p-value=0.381).

	Pre-COVID Data			COVID Data			$H_0 : \Delta BRET = 0$
	Mean	SD	Med	Mean	SD	Med	p-value
	43.23	15.07	43.50	43.70	14.19	46.00	0.846

Note: $N = 60$s. $\Delta BRET$ is the individual-level difference in BRET between the COVID and the Pre-COVID data set. *: $p - value < 0.1$, **: $p - value < 0.05$, ***: $p - value < 0.01$.

Table 3.2: Students' Risk Preferences in the Pre-COVID and COVID Data

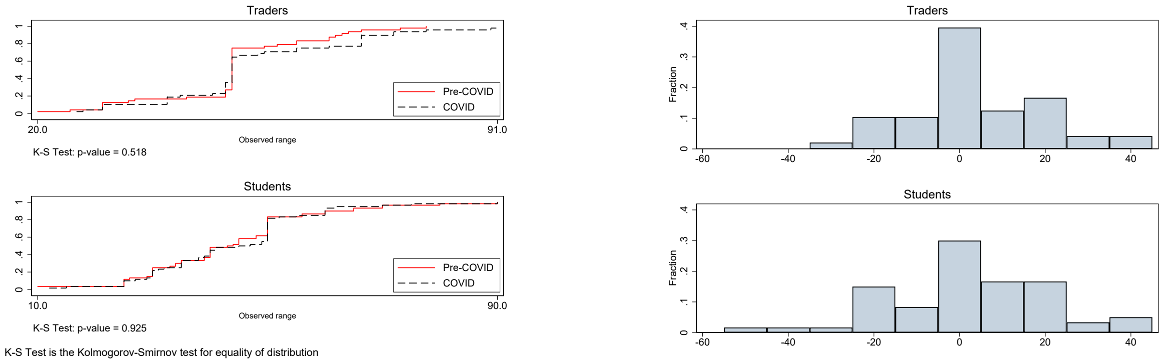
Tables 3.1 and 3.2 also show that the variability of the BRET choices does not change noticeably across datasets. For traders, the standard deviation increases from 12.40 to 14.97, whereas it decreases slightly for students from 15.07 to 14.19. We do not reject the equality of variances across periods either for traders (p-value=0.234) or for students (p-value=0.890).[21] Average BRET choices, however, differ across the two participant samples. In the Pre-COVID data, the mean BRET choice is 7.02 higher for traders than for students; in the COVID data this difference is 9.68. Using a t-test for the equality of means, and allowing for unequal variances between groups, both differences are significant at a 1% level (p-values = 0.009 in the Pre-COVID data, and 0.001 in the COVID data).[22]

Figure 3.1a compares the cumulative distributions of BRET choices across the two data sets and shows no differences for either traders or students. The p-values of the Kolmogorov-Smirnov test are 0.518 for traders and 0.925 for students. Among traders, the likelihood of observing very large values of BRET choices is relatively higher in the COVID data than in the Pre-COVID data. This explains the slight increase in mean BRET choice, while the median BRET choice remains the same.

Figure 3.1b presents histograms of $\Delta BRET$. The similarity of BRET choices between the Pre-COVID and the COVID datasets is apparent. About 27% of traders did not change their BRET choices at all; 8% changed them by a maximum of 2 (in either direction), 13% by a maximum of 5, and 31% by a maximum 10. Among students, 15%

[21]We rely on the statistic proposed by Brown and Forsythe (1974), using the median as an estimator of the central tendency of the distribution.

[22]We obtain the same results when using a Wilcoxon test, with p-values equal to 0.002 in both sets of data.



(a) **(b)**

Figure 3.1: Cumulative Distributions (a) and Histograms (b) of Changes in Risk Preferences

showed no change; 5% changed them by a maximum of 2 (in either direction), 22% by a maximum of 5, and 35% by a maximum 10. The correlation between BRET choices in the Pre-COVID data and the COVID data is 0.38 (significant at 1%) among traders, 0.20 (significant at 10%) among students.[23]

Given the previous results, one may ask whether we could have detected a shift in risk aversion given our sample size. With the t-test described above, assuming a 5% significance level, we would have detected a BRET change of 6 (i.e., 6 percent of the total) or larger with a power of at least 80% among traders. Similarly for students, we would have detected a BRET change of 7. Thus, we are confident that we would have been likely to detect a meaningful shift in risk aversion, had it occurred.

As discussed in the literature review, the few existing empirical studies on the topic have indicated that adverse events increase risk aversion; this is also how economic theory has proceeded in modeling investors behavior, when departing from the standard assumption of time unvarying risk preferences. Importantly, the participants in the COVID data choose an average of two additional boxes, thereby indicating a slight *decrease* in risk aversion. While this change is not statistically significant, it certainly does not support the hypothesis that risk aversion has *increased* amid the COVID-19 pandemic. To ad-

[23] We report the correlation between BRET and noncognitive skills in Table C.2 in the Appendix. BRET correlates negatively and significantly with Agreeableness for both traders and students. We do not detect a correlation between BRET and any of the other noncognitive skills.

dress this more thoroughly, we test the null $H_0 : \Delta E(BRET) = x \in \{-1, ..., -5\}$ against the alternative that $H_a : \Delta E(BRET) > x$. The p-values in the first column of Table 3.3 show that, among traders, we are able to reject these nulls at conventional significance levels. In other words, if the true population shift were indeed an average decrease in BRET (increase in risk aversion) even by only one box, then the probability of observing our sample data would be relatively low (3.5% for 1 box, 1.3% for two boxes, 0.4% for three boxes). Therefore, there is evidence against the hypothesis that there was a meaningful increase in risk aversion. Among students, who increased their BRET choices by just 0.5 boxes between the Pre-COVID and COVID datasets, the likelihood of observing our sample data is lower than 5% if there had been an average decrease in BRET of more than 3 boxes in the population (as a reference, with CRRA preferences, a decrease in BRET from the student population average of 44 to 41 is equivalent to an increase in the coefficient of risk aversion from 0.21 to 0.31).

	Traders	Students
$x = -1$	0.035	0.271
$x = -2$	0.013	0.153
$x = -3$	0.004	0.076
$x = -4$	0.001	0.033
$x = -5$	0.000	0.013

Table 3.3: Probability of Rejecting $H_0 : \Delta E(BRET) = x$ against $H_a : \Delta E(BRET) > x$ (p-values)

3.4.2 Noncognitive skills

Tables 3.4 and 3.5 report the mean, median, and standard deviation of noncognitive skills in the Pre-COVID and COVID data for traders and students.

In the Pre-COVID data, the two samples of participants exhibit similar levels of Agreeableness and Self-Monitoring. Using a two-tailed t-test for the equality of means and allowing for unequal variances between groups, we fail to reject the null that, on average, traders and students have the same Agreeableness and Self-Monitoring (p-values

= 0.695 and 0.372). On the other hand, the two samples of participants differ significantly with respect to the other three noncognitive skills, with traders showing higher levels of Conscientiousness, LoC and Grit (p-values = 0.002 for Conscientiousness and less than 0.001 for LoC and Grit).

Previous studies have shown that noncognitive skills may change over the life cycle.[24] Within each participant sample, we do not find evidence that age affects any of the 5 noncognitive skills (see Appendix C.7).

	Pre-COVID Data			COVID Data			$H_0 : \Delta Y = 0$
	Mean	SD	Med	Mean	SD	Med	p-value
Agreeableness	3.27	0.89	3.50	3.00	0.93	3.00	0.009
Conscientiousness	3.81	0.86	4.00	3.92	0.70	4.00	0.242
Locus of Control	4.32	0.52	4.43	4.11	0.52	4.28	0.005
Grit	3.74	0.66	3.75	3.62	0.56	3.62	0.102
Self-monitoring	0.53	0.21	0.50	0.50	0.24	0.55	0.192

Note: ΔY is the individual-level change in noncognitive skill Y between the COVID and the Pre-COVID data. *: $p-value < 0.1$, **: $p-value < 0.05$, ***: $p-value < 0.01$.

Table 3.4: Traders' Noncognitive Skills in the Pre-COVID and COVID data

To study whether these noncognitive skills have changed during the pandemic, we measure the difference of each skill between the Pre-COVID and COVID dataset: $\Delta Y = (Y_{COVID} - Y_{Pre-COVID})$

with

$$Y = \{Agreeableness, Conscientiousness, Locus\,of\,Control, Grit, Self-Monitoring\}$$

[24] In a meta-analysis of 92 studies, Roberts et al. (2006) observe positive and statistically significant changes for Conscientiousness in early adulthood (from 20 to 30, from 30 to 40 and from 40 to 50). Agreeableness, however, only significantly increased later in life (between ages 50 to 60). Gatz and Karel (1993) show that age significantly increase LoC in a longitudinal study. In cross-sectional studies, Duckworth et al (2007) show a monotonic increase in Grit with age, while Reifman et al. (1989) find that Self-monitoring significantly decreases with age.

	Pre-COVID Data			COVID Data			$H_0 : \Delta Y = 0$
	Mean	SD	Med	Mean	SD	Med	p-value
Agreeableness	3.20	0.98	3.50	3.14	0.94	3.00	0.512
Conscientiousness	3.40	0.71	3.50	3.63	0.68	3.50	0.005
Locus of Control	3.91	0.70	4.00	3.84	0.74	4.00	0.281
Grit	3.31	0.71	3.37	3.37	0.72	3.50	0.372
Self-monitoring	0.56	0.19	0.55	0.59	0.22	0.61	0.179

Note: ΔY is the individual-level change in noncognitive skill Y between the COVID and the Pre-COVID data. *: $p-value < 0.1$, **: $p-value < 0.05$, ***: $p-value < 0.01$.

Table 3.5: Students' Noncognitive Skills in the Pre-COVID and COVID data

and use a two-tailed test for the null hypothesis that the average change across the two data sets is zero. The results (p-values of the test) are reported in the last column of Tables 3.4 and 3.5.

Traders decrease their Agreeableness by 0.27 (8.4% of the Pre-COVID average — p-value = 0.009) and LoC by 0.20 (4.7% of the Pre-COVID average — p-value = 0.005). Traders also show a decrease in Grit, although this is of borderline significance (p-value = 0.103). The changes in Conscientiousness and Self Monitoring are not statistically different from zero (p-values = 0.242 and 0.192).

For students, we observe a significant increase in Conscientiousness by 0.23 (7% of the Pre-COVID average — p-value = 0.005), but no significant changes in Agreeableness, LoC, Grit, and Self-Monitoring.

It is interesting to note that for no skill do we observe one group increasing its mean value and the other decreasing it in a significant way. When we observe significant changes, they are never in opposite directions. At the time of the COVID-19 pandemic, the two samples of participants become more similar for most skills. In particular, the gaps between traders and students in terms of LoC and Grit, although still statistically significant, are reduced by about one-third. Importantly, noncognitive skills are highly and significantly correlated between their Pre-COVID and COVID level. For traders (students), the correlation between Pre-COVID and COVID measures are 0.70 (0.67) for

Agreeableness, 0.65 (0.61) for Conscientiousness, 0.56 (0.77) for LoC, 0.70 (0.76) for Grit, and 0.81 (0.75) for Self-Monitoring; correlations are significant at the 1% level.

One may wonder about the economic significance of the changes we observe in traders' Agreeableness and LoC and in students' Conscientiousness. Heineck and Anger (2010) have estimated the percent change in wages induced by a one standard deviation increase in these noncognitive skills. By multiplying the standard deviations of our observed changes by the corresponding estimated wage returns in Heineck and Anger (2010), we find that the decrease in LoC we estimate for traders is equivalent to a 3% decrease in wage. For Agreeableness, the change is more modest, equal to an increase in wage by 0.7%. For Conscientiousness, the observed increase for students implies a wage increase of 0.6%. As for the observed marginally significant change in Grit, we rely on Danner et al. (2019) who study, in a cross-country analysis, the association between Grit and relative personal income; based on their estimates, our observed decrease of Grit among traders implies a 0.9 percentage point decrease in relative income.[25]

As mentioned above, one of the questions in our Agreeableness measure captures Trust. Trust is an important aspect of Social Capital (Guiso et al., 2011). As we discussed in the Introduction, in the literature there is evidence that a decrease in income or an increase in unemployment negatively affects Trust. In our data, Trust decreases by 6% among traders and remains virtually constant among students. Even for traders, the observed change is not statistically significant (two-tailed test, p-value = 0.142). Thus, we see only weak evidence that Trust decreased during the COVID-19 pandemic.

Throughout this analysis, we interpret any change in risk preference and noncognitive skills between the Pre-COVID (February-May 2019) and the COVID data collection times as due to the COVID-19 pandemic. We believe that this interpretation is plausible since the COVID-19 pandemic is an event of such magnitude that its impact should dwarf any change due to other intervening factors. Nevertheless, we perform a robustness check to back this interpretation. As mentioned in Section 2.1, as part of a different experiment,

[25]These computations serve to illustrate how our observed changes may relate to meaningful real-world economic outcomes. Of course, the actual effects during a pandemic and in the aftermath of a pandemic remain a topic for future research.

we collected data on noncognitive skills for an additional pool of 34 students. These data were collected in November-December 2019 and again in April 2020, that is, for this additional sample of 34 students the Pre-COVID data refer to the end of 2019 instead of the first half of 2019. The shorter time gap between the Pre-COVID and COVID data collection times should reduce concerns about possible confounding effects. Thus, if our main results are mainly driven by the COVID-19 pandemic, we expect the results for these 34 students to be similar to those in our main sample. This is indeed the case. Similarly to the sample of students in our main analysis, these additional 34 students exhibit no sizable and statistically significant changes in Agreeableness, Locus of Control, Grit or Self-Monitoring. The only difference is observed for Conscientiousness, which increases significantly in our student sample; among the additional 34 students, the increase was not significant (see Table C.3 in Appendix C.8). This difference, however, is driven by the different gender composition of these two samples (see Table C.4 in Appendix C.8).[26]

3.4.3 Heterogeneous Impact of the COVID-19 Pandemic

As discussed in Section 3, in the COVID experiment, participants filled out a questionnaire about their experience with the COVID-19 pandemic.

Figure 3.2 reports the distribution of responses to two questions. The top panel shows the proportion of participants who reported that they or someone in their household have been infected with COVID-19. The bottom panel shows the proportion of participants who report having a relative or close friend infected with COVID-19.[27] Among all participants, 4.5% report that they or someone in their household have been infected with COVID-19, whereas about one-quarter report that they have relatives or close friends

[26]The main student sample is 80% male to match the gender composition of the traders' sample. Since the additional 34 students were recruited for a different experiment, we did not match the gender composition of traders. This sample is 40% male. As can be seen in Table C.4 in Appendix C.8, male students significantly increase Conscientiousness, while female students do not.

[27]The actual proportion of the population infected with COVID-19 is still unknown at the time we are writing this paper. For context, note that a home antibody testing study by Ward et al. (2020) showed that 6% of the population in England (13% in London) had been infected by COVID-19 by the end of June 2020. A majority of those infected by this date reported symptoms in March and April 2020.

infected with COVID-19.[28]

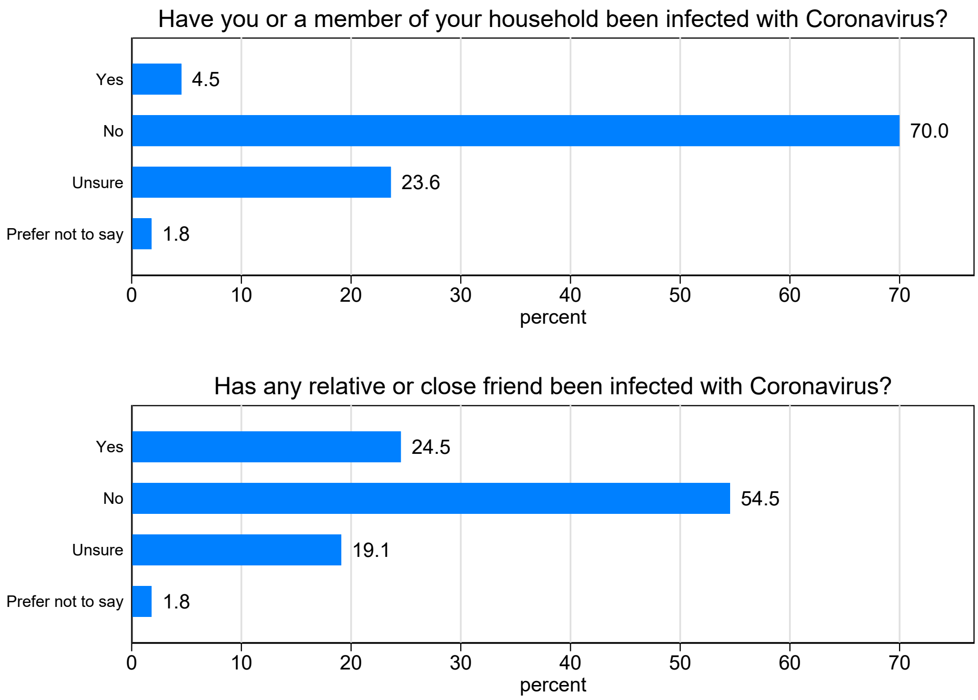


Figure 3.2: Impact of the COVID-19 Pandemic (I)

[28]Among traders, 6% report own or household members' infection, while students report 3%; the difference is not statistically significant (p-value=0.495). Among traders, 39% report infection of relatives or close friends, while students report 13%; the difference is statistically significant (p-value=0.003). Differences of proportions by participant pool are tested using a t-test with unequal variances across groups.

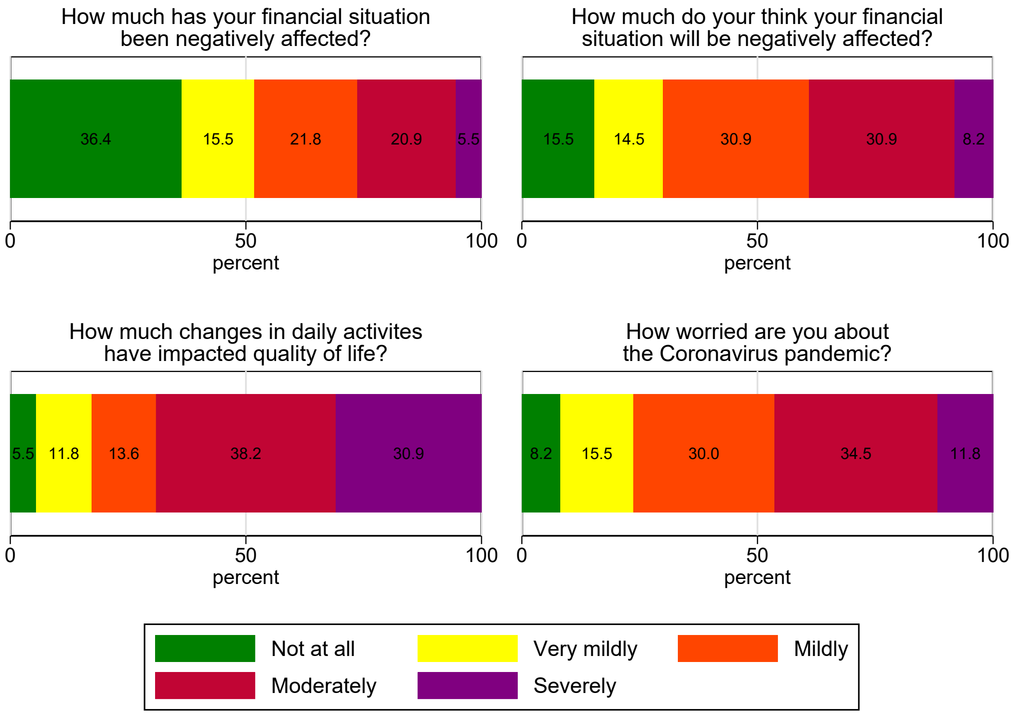


Figure 3.3: Impact of the COVID-19 Pandemic (II)

Figure 3.3 shows statistics on the impact of the pandemic on participants' lives. One-quarter of the participants state that their current financial situation has been either moderately or severely affected, whereas 36% state that it has not been impacted at all. About 40% think that their future financial situation will be negatively affected, whereas 15.5% believe that their finances will not be impacted at all in the future.[29] There is a large consensus among participants about how the pandemic impacted their quality of life. For approximately 70% of participants, disruption of regular activities has either moderately or severely affected their quality of life; only 5.5% of participants state that their quality of life has not been affected at all. About 46% of participants are very

[29]Among traders, 22% report a moderate or severe impact on current financial situation, while students report 29%; the difference is not statistically significant (p-value=0.404). Among traders, 43% report a moderate or severe impact on future financial situation, while students report 36%; the difference is not statistically significant (p-value=0.474).

worried about the pandemic and 8% are not worried at all.[30]

3.4.4 Experience of the COVID-19 Pandemic and Changes in Risk Preferences and Noncognitive Skills

In this section, we study whether the individual changes in risk preferences and noncognitive skills between the Pre-COVID and COVID data are related to a participants' experience of the pandemic. To this purpose, we create an Impact Index, by summing each participant's answers to the four questions shown in Figure 3.3. We then divide participants into two groups depending on whether their Impact Index is below the median ("Low Impact" of the pandemic) or above the median ("High Impact" of the pandemic). In addition, we create a binary indicator taking value one if the participant answers affirmatively to at least one of the two questions about infections ("Have either you or a member of your household been infected by the Coronavirus?"; "Has any relative or close friend been infected by the Coronavirus?") and zero otherwise; that is, we divide participants into two groups depending on whether they experienced an infection within their personal circle ("Infection") or not ("No Infection"). We then compare average changes in risk preferences and noncognitive skills with respect to these two measures, Low versus High Impact and Infection versus No Infection.

Figures 3.4a and 3.4b show average changes in traders' BRET and noncognitive skills by these two measures (along with the 95% confidence intervals). Traders' change in BRET is not affected by either measure. More specifically, Low-Impact and High-Impact traders as well as those with Infection and with No-Infection exhibit a similar, positive changes in BRET of about 3 boxes, none of which is statistically different from zero (p-value=0.350 and 0.310 for Low and High Impact; p-value=0.231 and 0.477 for Infection and No Infection). We conclude that there is no association between the experience of the pandemic and changes in risk preferences for traders.

[30] Among traders, 65% report a moderate or severe impact on quality of life, while students report 72%; the difference is not statistically significant (p-value=0.449). Among traders, 39% report being moderately or severely worried about the pandemic, while students report 52%; the difference is not statistically significant (p-value=0.154).

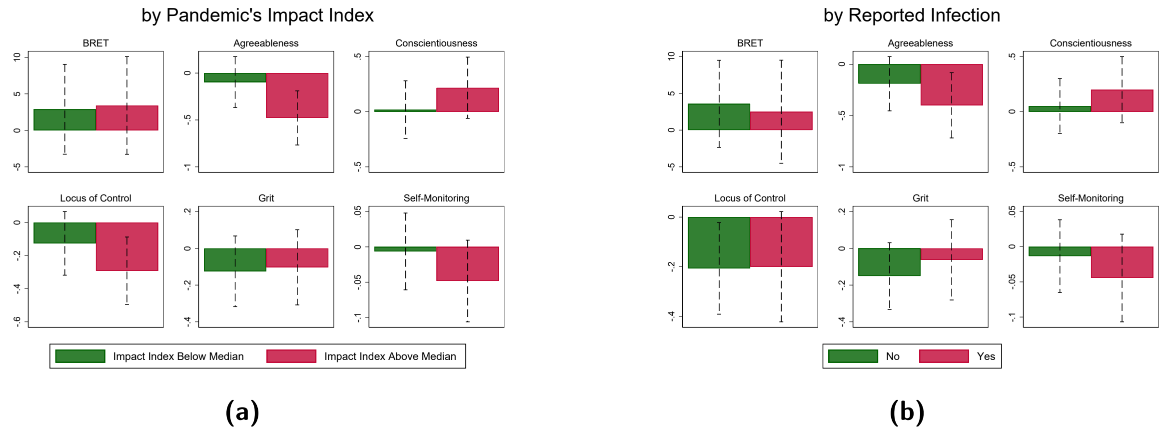
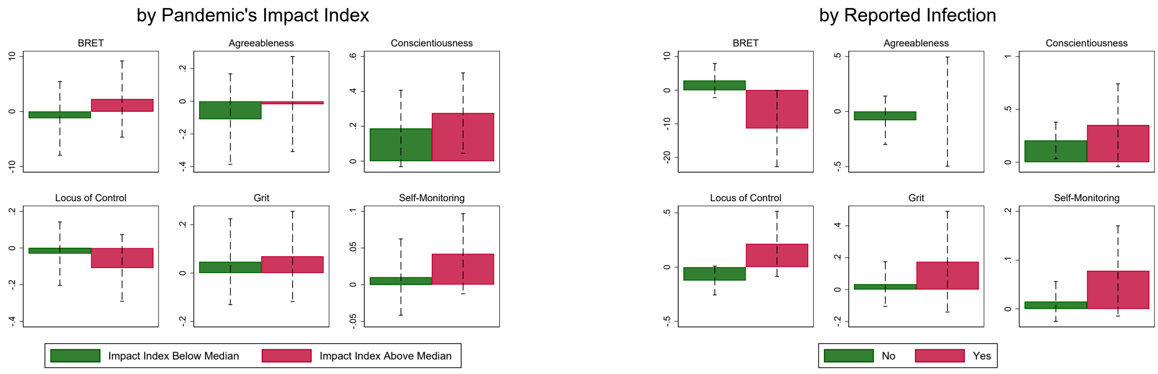


Figure 3.4: Changes in Outcomes by Pandemic's Experience: Traders

In contrast, a clear relationship is observed between perceived impact of the pandemic and changes in traders' Agreeableness and LoC. High-Impact traders show larger decreases in both skills. High-Impact traders significantly decrease Agreeableness by nearly 0.5 units (p-value=0.002), corresponding to a 16% drop relative to the Pre-COVID data; the decrease in Agreeableness for Low-Impact traders is not statistically different from zero (p-value=0.480). A similar pattern is observed when comparing changes in Agreeableness across Infection and No-Infection traders (Figure 3.4b). Infection traders significantly decrease their Agreeableness by 0.4 units (p-value=0.015), corresponding to a 12% drop relative to the Pre-COVID data; the decrease for No-Infection traders is much smaller (0.18 units) and not significantly different from zero (p-value=0.155).

High-Impact traders significantly decrease LoC by-0.29 (p-value=0.006), corresponding to a 7% drop relative to the Pre-COVID data. The average change for Low-Impact traders is only -0.13 and not statistically different from zero (p-value=0.192). However, unlike with Agreeableness, we do not observe a relationship between changes in LoC between Infection and No-Infection traders. Finally, we do not find statistically significant changes in the other noncognitive skills for High- or Low-Impact traders or for Infection or No-Infection traders.

Figures 3.5a and 3.5b show the results of the same analysis for student participants.



(a) **(b)**

Figure 3.5: Changes in Outcomes by Pandemic's Experience: Students

We do not observe any significant change in BRET choices for Low- or High-Impact students. However, Infection students decrease their BRET choice by 11 boxes, a change that is significantly different from zero(p-value=0.049). Students increase Conscientiousness regardless of their experience of the pandemic: the change is, however, larger among those with a more negative experience. More specifically, High- and Low-Impact students increase Conscientiousness by 0.28 (p-value=0.020) and 0.19 units (p-value=0.092), corresponding to a 8% and 5% increase relative to the Pre-COVID data. Analogously, Infection and No-Infection students increase Conscientiousness by 0.35 (p-value=0.079) and 0.21 units (p-value=0.021), corresponding to a 10% and 6% increase relative to the Pre-COVID data. For Agreeableness, LoC, Grit, and Self-Monitoring we do not observe statistically significant changes for High- or Low-Impact students or for Infection or No-Infection students.

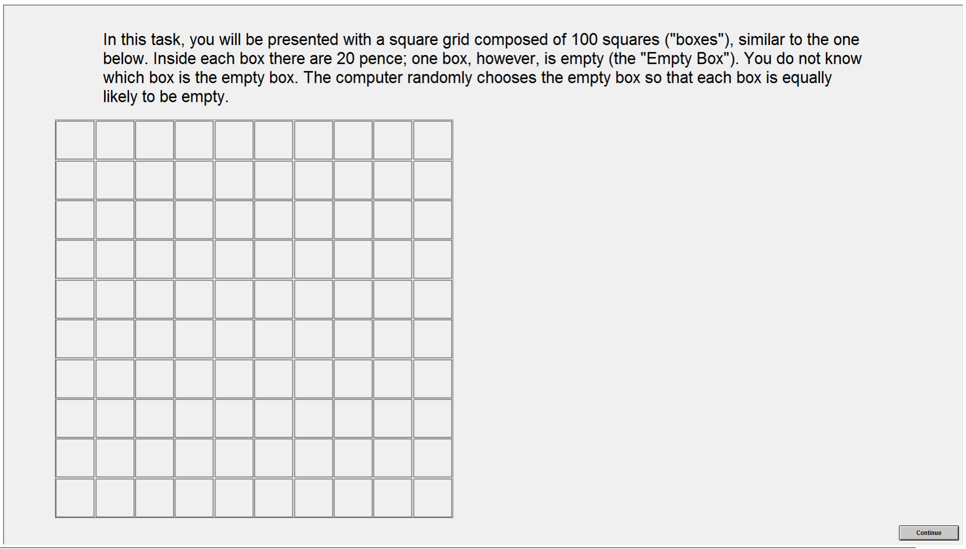
Overall, our analysis shows that for those traits that were impacted by the pandemic, the change was often driven by those participants that were more affected. Our clearest result is that the decrease in Agreeableness and LoC detected within the sample of traders (section 3.4.2) is mostly driven by those who have been highly affected by the pandemic.

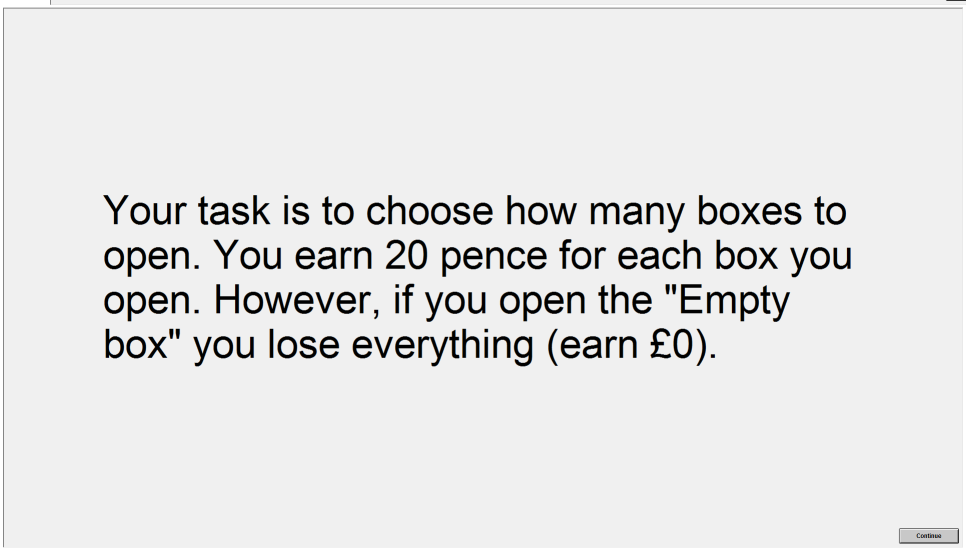
3.5 Conclusion

We have studied whether the COVID-19 pandemic has impacted risk preferences and noncognitive skills. We have done so for a sample of professional traders and students. We have shown that risk preferences are stable for both professional traders and students. This suggests that the swing in asset prices during the pandemic was not exacerbated by changes in investors' risk appetite. For noncognitive skills, we have found a significant effect of the pandemic on professional traders' Agreeableness, Grit, and Locus of Control and, on students' Conscientiousness.

Appendix to Chapter 3

C.1 Bomb Risk Elicitation Task (BRET) Instructions



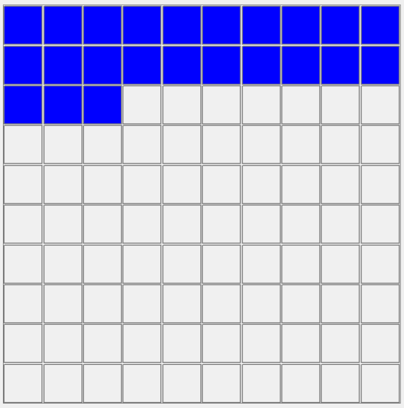


You make your choice by clicking on a box within the grid. This will highlight a set of boxes in blue (starting from the top-left corner).

On the right side of the screen, you will learn how your choice of boxes to open affects your potential earnings in GBP.

When you have made your mind, highlight the desired number of boxes and click "Submit".

The computer will not allow you to enter a choice of 0 boxes or 100 boxes (because you would always earn £0 with either choice).



Number of boxes to open =

Number of boxes remaining =

Potential earnings =

Submit

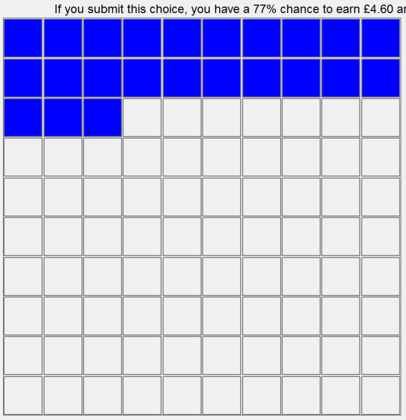
Continue

After you have submitted your choice, your earnings will be calculated.

For example, consider the choice below. (The grid and Submit button are deactivated for these instructions)

This choice is to open boxes 1-23. If the Empty Box is one of boxes 1-23, you will earn £0. However, if the Empty Box is one of boxes 24-100, you will earn £4.60.

If you submit this choice, you have a 77% chance to earn £4.60 and a 23% chance to earn £0.



Number of boxes to open = 23

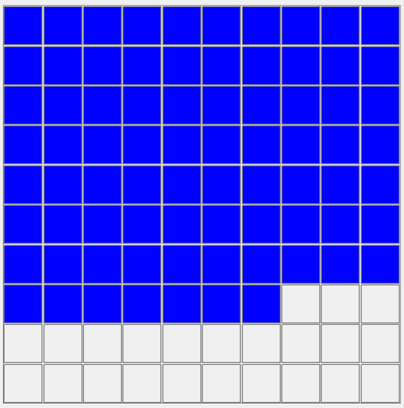
Number of boxes remaining = 77

Potential earnings = £4.60

Submit

Continue

Please select the number of boxes you want to open. Your choice will determine how much you are paid. After you are satisfied with your choice, please click Submit.

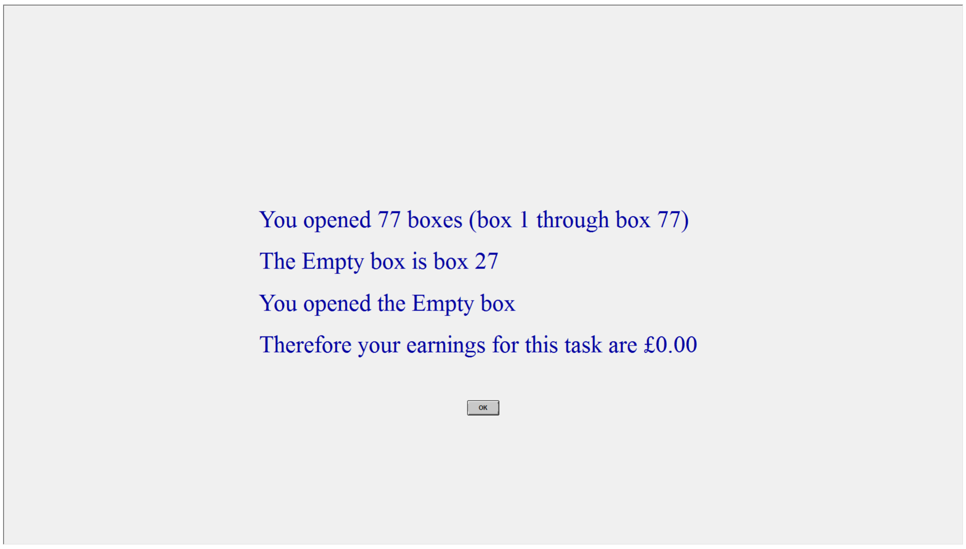


Number of boxes to open = 77

Number of boxes remaining = 23

Potential earnings = £15.40

Submit



C.2 Measures of Openness and Extroversion

We measure these two traits using the two-item measures from Rammstedt and John (2007).

Openness (to experience)

- *I have an active imagination.*
- *I have few artistic interests.*

The second measure is reverse coded and the unweighted average of both measures serves as our measure of Openness. Higher values of this measure reflect higher Openness.

Extroversion

- *I am outgoing, sociable.*
- *I am reserved.*

As for the measure of Openness, the second measure is reverse coded and the unweighted average of both measures serves as our measure of Extroversion. Higher values of this measure reflect higher Extroversion.

C.3 Measure of Locus of Control

We measure Locus of Control using the 7-item questionnaire developed by Cobb-Clark and Schurer (2013). Participants are asked to what extent they agree with the following 7 statements:

- *What happens to me in the future mostly depends on me.*
- *I can do just about anything I really set my mind to do.*
- *I have little control over the things that happen to me.*
- *There is really no way I can solve some of the problems I have.*
- *I often feel helpless in dealing with the problems of life.*
- *Sometimes I feel that I'm being pushed around in life.*
- *There is little I can do to change many of the important things in my life.*

The last 5 measures are reverse coded and the unweighted average of all 7 measures serves as our measure of LoC. Higher values of this measure reflect higher internal LoC.

C.4 Measure of Grit

We measure Grit using the 8-item questionnaire (GRIT-S) developed by Duckworth and Quinn (2009). Participants are asked to what extent they agree with the following 8 statements:

- *Setbacks don't discourage me.*
- *I finish whatever I begin.*
- *I am diligent.*
- *I am a hard worker.*
- *I often set a goal but later choose to pursue a different one.*

- *New ideas and projects sometimes distract me from previous ones.*
- *I have been obsessed with a certain idea or project for a short time but later lost interest.*
- *I have difficulty keeping my focus on projects that take more than a few months to complete.*

The last 4 measures are reverse coded and the unweighted average of all 8 measures serves as our measure of Grit. Higher values of this measure reflect higher Grit.

C.5 Self-Monitoring Questions

How I am in general (continued)

As on the previous page, this page lists a number of statements that may or may not apply to you. If a statement is true or mostly true as applied to you, make a mark in the "True" column as your answer. If a statement is false or not usually true as applied to you, make a mark in the "False" column as your answer. Please record your answers in the spaces provided below.

	True	False
I find it hard to imitate the behaviour of other people.		
At parties and social gatherings, I do not attempt to do or say things that others will like.		
I can only argue for ideas which I already believe.		
I can make impromptu speeches even on topics about which I have almost no information.		
I guess I put on a show to impress or entertain others.		
I would probably make a good actor.		
In a group of people I am rarely the centre of attention.		
In different situations and with different people, I often act like very different persons.		
I am not particularly good at making other people like me.		
I'm not always the person I appear to be.		
I would not change my opinions (or the way I do things) in order to please someone or win their favour.		
I have considered being an entertainer.		
I have never been good at games like charades or improvisations.		
I have trouble changing my behaviour to suit different people and different situations.		
At a party I let others keep the jokes and stories going.		
I feel a bit awkward in public and do not show up quite as well as I should.		
I can look anyone in the eyes and tell a lie with a straight face.		
I may deceive people by being friendly when I really dislike them.		

C.6 CRRA Values for BRET

# boxes	γ	# boxes	γ	# boxes	γ
1	> 0.985	34	[0.496; 0.473)	67	[-0.985; -1.077)
2	[0.985; 0.974)	35	[0.473; 0.450)	68	[-1.077; -1.175)
3	[0.974; 0.964)	36	[0.450; 0.425)	69	[-1.175; -1.279)
4	[0.964; 0.953)	37	[0.425; 0.400)	70	[-1.279; -1.390)
5	[0.953; 0.942)	38	[0.400; 0.374)	71	[-1.390; -1.509)
6	[0.942; 0.930)	39	[0.374; 0.347)	72	[-1.509; -1.636)
7	[0.930; 0.919)	40	[0.347; 0.319)	73	[-1.636; -1.774)
8	[0.919; 0.907)	41	[0.319; 0.291)	74	[-1.774; -1.922)
9	[0.907; 0.895)	42	[0.291; 0.261)	75	[-1.922; -2.082)
10	[0.895; 0.883)	43	[0.261; 0.230)	76	[-2.082; -2.255)
11	[0.883; 0.870)	44	[0.230; 0.198)	77	[-2.255; -2.444)
12	[0.870; 0.857)	45	[0.198; 0.165)	78	[-2.444; -2.651)
13	[0.857; 0.844)	46	[0.165; 0.131)	79	[-2.651; -2.878)
14	[0.844; 0.830)	47	[0.131; 0.095)	80	[-2.878; -3.128)
15	[0.830; 0.817)	48	[0.095; 0.058)	81	[-3.128; -3.405)
16	[0.817; 0.802)	49	[0.058; 0.020)	82	[-3.405; -3.714)
17	[0.802; 0.788)	50	[0.020; -0.020)	83	[-3.714; -4.061)
18	[0.788; 0.773)	51	[-0.020; -0.062)	84	[-4.061; -4.452)
19	[0.773; 0.758)	52	[-0.062; -0.105)	85	[-4.452; -4.897)
20	[0.758; 0.742)	53	[-0.105; -0.151)	86	[-4.897; -5.407)
21	[0.742; 0.726)	54	[-0.151; -0.198)	87	[-5.407; -6.000)
22	[0.726; 0.710)	55	[-0.198; -0.247)	88	[-6.000; -6.696)
23	[0.710; 0.693)	56	[-0.247; -0.299)	89	[-6.696; -7.524)
24	[0.693; 0.675)	57	[-0.299; -0.353)	90	[-7.524; -8.526)
25	[0.675; 0.658)	58	[-0.353; -0.410)	91	[-8.526; -9.765)
26	[0.658; 0.639)	59	[-0.410; -0.469)	92	[-9.765; -11.333)
27	[0.639; 0.621)	60	[-0.469; -0.532)	93	[-11.333; -13.385)
28	[0.621; 0.601)	61	[-0.532; -0.597)	94	[-13.385; -16.182)
29	[0.601; 0.582)	62	[-0.597; -0.667)	95	[-16.182; -20.222)
30	[0.582; 0.561)	63	[-0.667; -0.740)	96	[-20.222; -26.571)
31	[0.561; 0.540)	64	[-0.740; -0.817)	97	[-26.571; -38.000)
32	[0.540; 0.519)	65	[-0.817; -0.899)	98	[-38.000; -64.666)
33	[0.519; 0.496)	66	[-0.899; -0.985)	99	< -64.666

Table C.1: Estimates of γ for BRET, assuming CRRA u(c) $= \dfrac{c^{(1-\gamma)}}{1-\gamma}$

C.7 Risk Preferences and Noncognitive Skills by Age

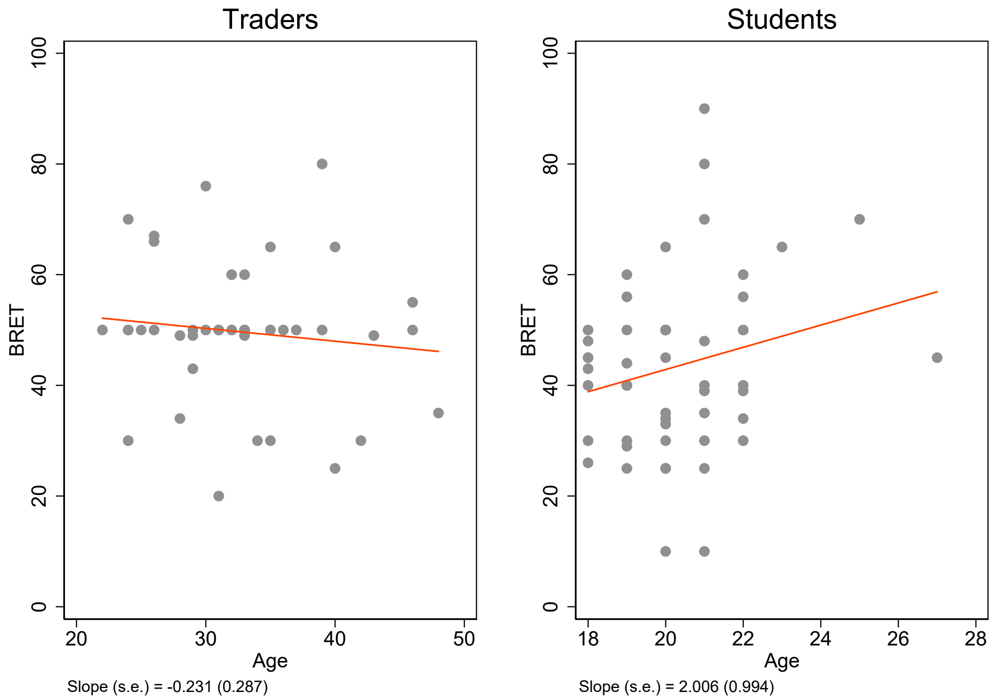


Figure C.1: Risk Preferences by Age in the Pre-COVID Data

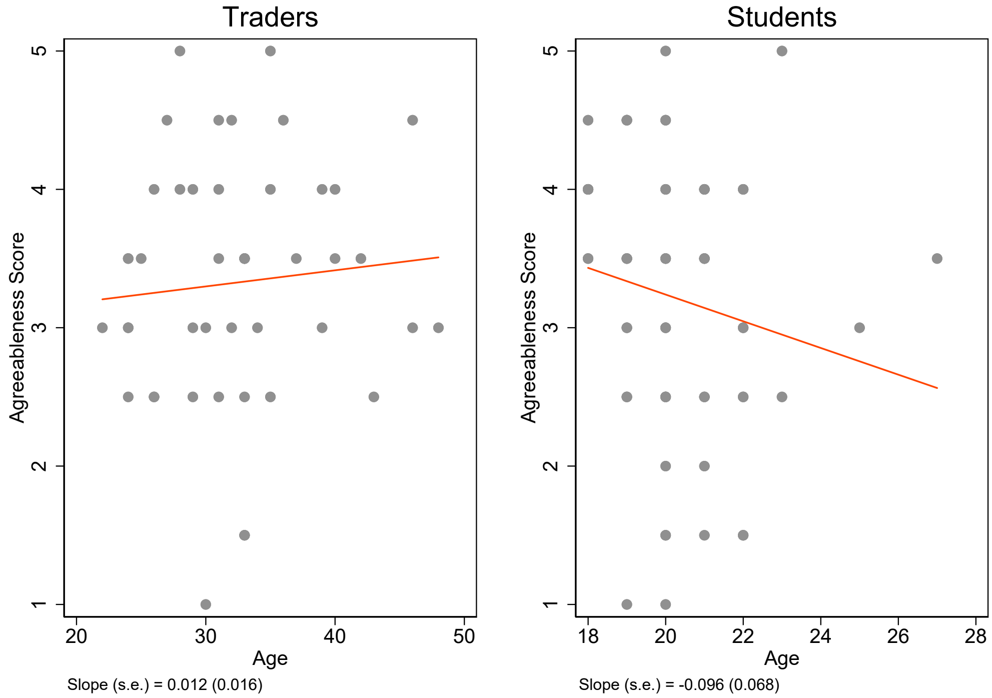


Figure C.2: Agreeableness by Age in the pre-COVID Data

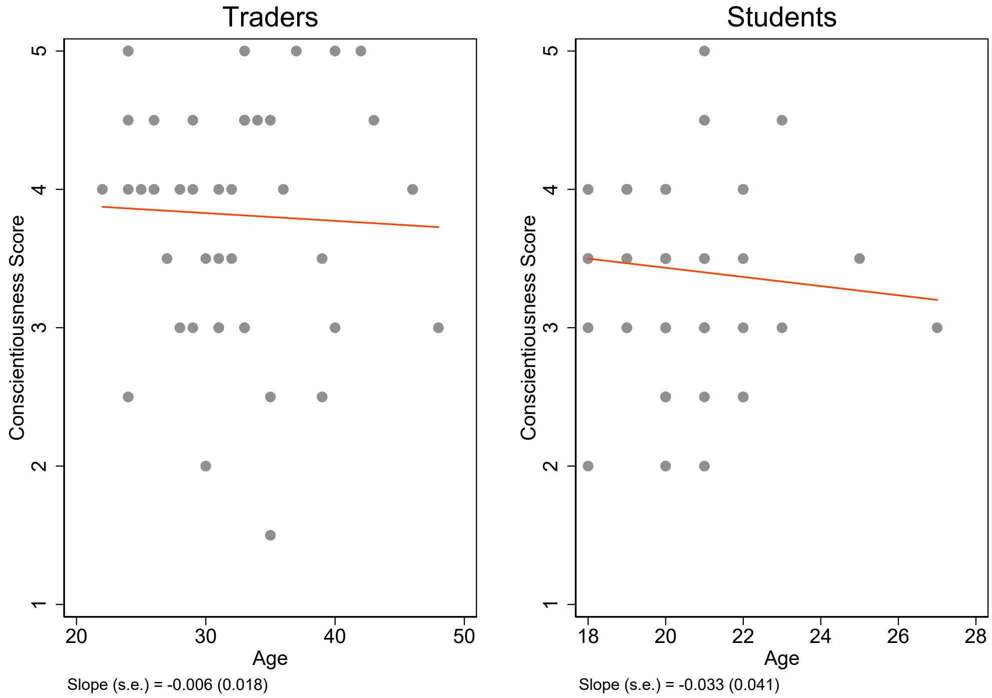


Figure C.3: Conscientiousness by Age in the pre-COVID Data

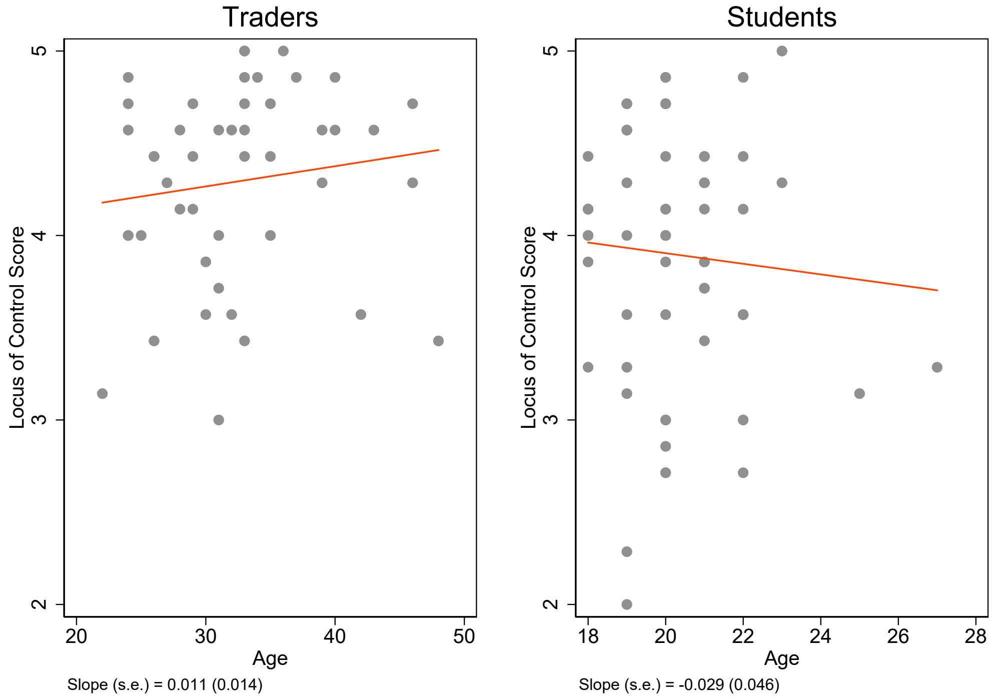


Figure C.4: Locus of Control by Age in the Pre-COVID Data

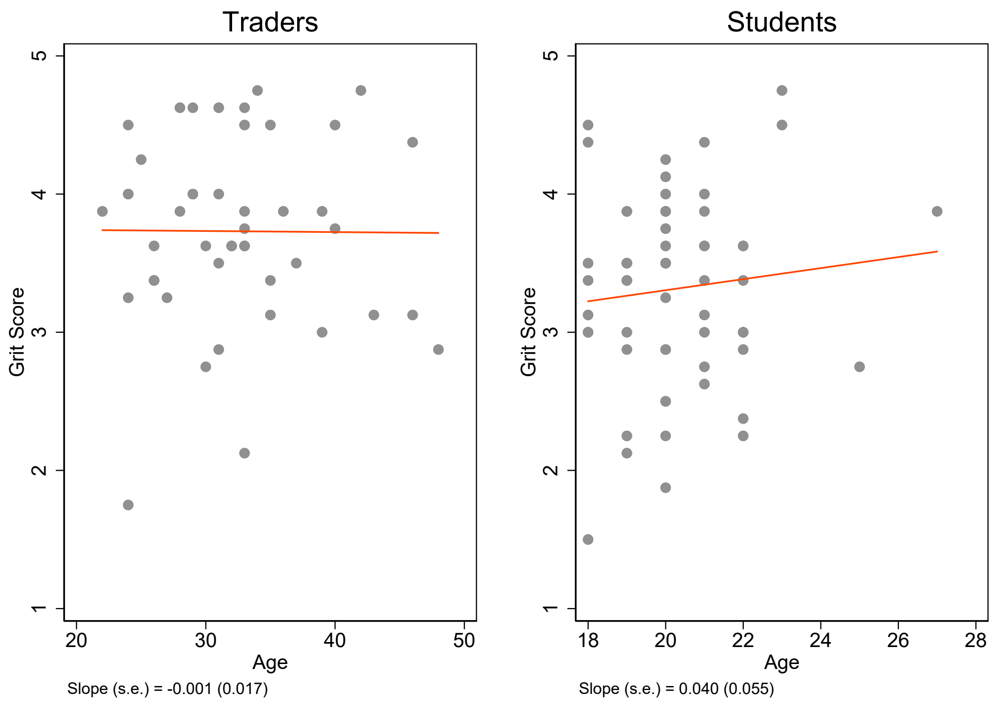


Figure C.5: Grit by Age in the Pre-COVID Data

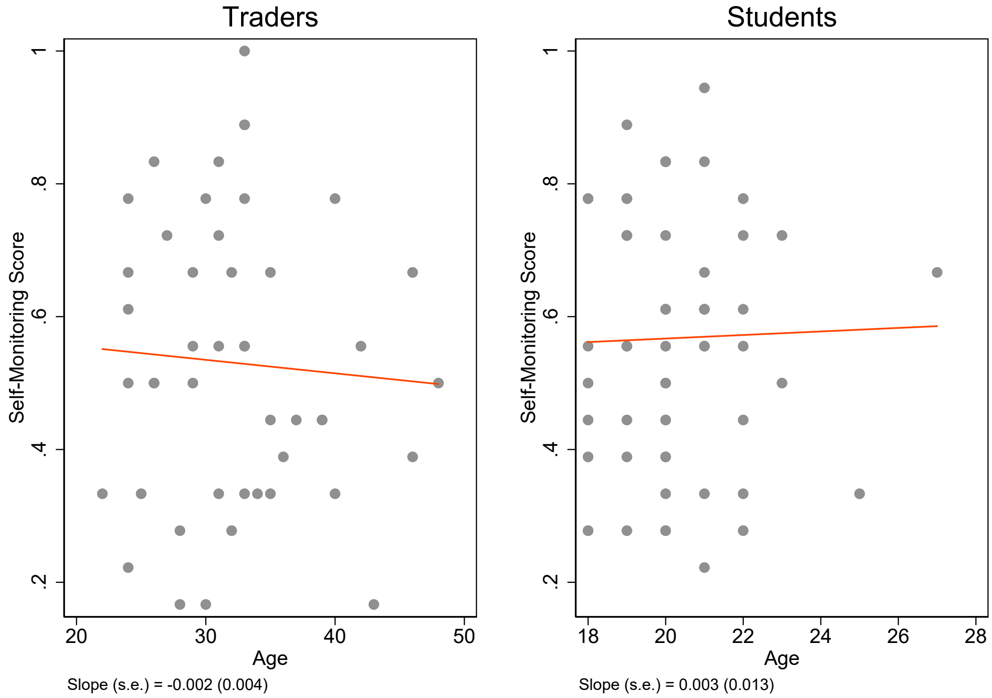


Figure C.6: Self-Monitoring by Age in the Pre-COVID Data

C.8 Correlation across Outcomes in the Pre-COVID Period

Traders

	BRET	Agreeab.	Conscient.	LoC	Grit	Self-Mon.
BRET	1.00					
Agreeableness	-0.31**	1.00				
Conscientiousness	-0.07	-0.04	1.00			
Locus of Control	0.22	-0.07	0.25*	1.00		
Grit	-0.12	0.15	0.59***	0.10	1.00	
Self-Monitoring	0.12	-0.25*	-0.12	0.18	-0.16	1.00

Students

	BRET	Agreeab.	Conscient.	LoC	Grit	Self-Mon.
BRET	1.00					
Agreeableness	-0.31**	1.00				
Conscientiousness	-0.00	0.01	1.00			
Locus of Control	0.04	-0.19	0.00	1.00		
Grit	-0.08	0.21	0.46***	0.32***	1.00	
Self-Monitoring	0.17	-0.19	0.05	0.30***	0.08	1.00

We test the null hypothesis that the correlation is equal to zero with a t-test. *: $p - value < 0.1$, **: $p - value < 0.05$, ***: $p - value < 0.01$

Table C.2: Correlation across Outcomes in the Pre-COVID Data

Changes in Noncognitive Skills among Students - Comparison with Additional Student Sample

	Pre-COVID Data			COVID Data			$H_0 : \Delta Y = 0$
	Mean	SD	Med	Mean	SD	Med	p-value
Agreeableness	3.29	0.83	3.50	3.11	0.82	3.00	0.211
Conscientiousness	3.25	0.62	3.25	3.28	0.66	3.25	0.794
Locus of Control	3.58	0.65	3.50	3.63	0.60	3.71	0.647
Grit	3.16	0.59	3.00	3.13	0.63	3.06	0.667
Self-monitoring	0.51	0.19	0.53	0.54	0.21	0.55	0.151

Note: $N = 34$. ΔY is the individual-level change in noncognitive skill Y between the COVID and the Pre-COVID data. *: $p - value < 0.1$, **: $p - value < 0.05$, ***: $p - value < 0.01$.

Table C.3: Changes in Noncognitive Skills in Additional Student Sample

	Males	Females		Males	Females
Δ Agreeableness			**Δ Conscientiousness**		
Students (main)	-0.031	-0.252	Students (main)	0.297***	-0.062
	(0.106)	(0.181)		(0.081)	(0.148)
Students (additional)	-0.040	-0.261	Students (additional)	0.251*	-0.108
	(0.151)	(0.169)		(0.133)	(0.131)
Δ Locus of Control			**Δ Grit**		
Students (main)	-0.074	-0.049	Students (main)	0.088	-0.061
	(0.070)	(0.108)		(0.109)	(0.118)
Students (additional)	0.031	0.055	Students (additional)	0.059	-0.090
	(0.071)	(0.085)		(0.082)	(0.118)
Δ Self-Monitoring					
Students (main)	0.026	0.016			
	(0.020)	(0.035)			
Students (additional)	0.038	0.028			
	(0.035)	(0.022)			

The data are obtained by pooling together the student sample described in the main text and the additional student sample, $N = 94$. The reported estimates are predicted changes for males and females in the two student samples from a regression of ΔY (Y is a noncognitive skill) on an indicator for main student sample and an indicator for male. Robust Delta Method standard errors are in parentheses. *: $p - value < 0.1$, **: $p - value < 0.05$, ***: $p - value < 0.01$.

Table C.4: Changes in Noncognitive Skills in Student Samples Conditional on Gender

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