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Abstract

This thesis examines how cognitive, psychological, and contextual factors shape financial and environmental decision-making, challenging traditional models of rational economic behavior. By integrating laboratory experiments, large-scale surveys, and facial emotion recognition, it provides a multidimensional perspective on decision-making processes. Specifically, it explores: (1) how cognitive processing influences decision speed under ambiguity, shedding light on the role of fluency and complexity in shaping response times; (2) the interaction between financial literacy, economic crises (e.g., the COVID-19 pandemic), and intertemporal preferences, revealing how uncertainty affects long-term financial planning; (3) the impact of emotions and cognitive appraisals on climate-related risk perceptions, quantifying how affective responses drive environmental choices; and (4) the combined effects of financial literacy, digital skills, and climate awareness on sustainable investment behavior, identifying key enablers and barriers. By bridging insights from economics, psychology, and behavioral science, this thesis contributes to a deeper understanding of how individuals navigate financial and environmental uncertainty. Its findings have implications for policy design, financial education, and sustainability initiatives, offering practical strategies to promote informed and responsible decision-making across disciplines.

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Introduction

Economic decision-making is a complex process shaped by cognitive abilities, psychological factors, and external conditions. Understanding how individuals make choices under uncertainty, across time, and in response to climate change is critical for designing policies that promote financial well-being and sustainability. While traditional economic theories often assume rational utility maximization, a substantial body of research in behavioral economics and psychology demonstrates that real-world decision-making frequently deviates from these models. These deviations arise from cognitive biases, varying risk preferences, and external influences, including emotions and environmental concerns.

This thesis advances the study of economic decision-making by integrating insights from behavioral economics, experimental methods, and survey data to examine how individuals navigate financial and environmental choices. This work incorporates experimental measures (decision time, facial emotion recognition) with large-scale survey data, providing a more comprehensive view of how individuals make real-world financial decisions. By combining laboratory experiments with survey methodologies, it offers a richer and more nuanced understanding of decision-making under diverse conditions, including ambiguity, time constraints, and climate-related concerns.

To achieve this, the thesis is structured around four key research questions. First, it investigates how individuals differ in their decision times under ambiguity and whether distinct decision-making models influence the time taken to reach a choice. By incorporating decision time as a behavioral measure, rather than focusing solely on decision outcomes, this study provides new insights into the cognitive processes underlying ambiguity. Second, it examines how financial literacy and economic conditions shape intertem-

poral preferences, particularly whether financial knowledge affects discount rates and how macroeconomic shocks, such as the COVID-19 pandemic, influence individuals' patience in financial decisions. Unlike previous studies that examine financial literacy in static settings, this research introduces a dynamic perspective by considering how financial literacy interacts with economic disruptions.

The third research question explores the psychological and cognitive determinants of risk attitudes in the context of climate change, focusing on how emotional responses to climate-related stimuli affect risk-taking behavior. While the role of emotions in economic decision-making has been widely discussed, this thesis provides empirical evidence using both self-reported emotions and objective facial recognition technology, allowing for more precise measurement of how emotions shape financial behavior. Finally, the fourth research question examines how financial literacy, digital literacy, and climate awareness influence sustainable investing. Although previous work has explored the relationship between financial literacy and green finance, this research expands the scope by incorporating digital financial literacy—an increasingly important factor in the digital economy—to explain why some environmentally conscious individuals fail to translate their awareness into concrete investment decisions.

To address these research questions, this thesis is structured into four chapters, each focusing on a distinct yet interconnected aspect of economic decision-making. Chapter 1, "The Determinants of Decision Time in an Ambiguous Context," examines how individuals process ambiguous choices and whether decision times vary based on different decision-making models. Using experimental data, it uncovers behavioral patterns that have been largely overlooked in prior studies of decision-making under uncertainty. Chapter 2, "Chronicles of Choice: Survey Insights into Intertemporal Preferences," leverages data from the Survey on Household Income and Wealth (SHIW) to analyze the effects of financial literacy on individuals' time preferences. It also considers how economic disruptions, such as the COVID-19 pandemic, may alter discount rates.

Building on this, Chapter 3, "Climate Change and Risk Attitude: An Empirical Study on the Role of Emotions and Knowledge," investigates the relationship between climate

change, emotions, and risk attitudes. This chapter contributes to the growing field of behavioral climate economics by examining the interaction between emotional reactions and financial decision-making in climate-related contexts. Finally, Chapter 4, "Green is the New Black: Bridging Climate Awareness and Sustainable Investing," integrates financial literacy, digital literacy, and climate awareness to explore their combined effect on sustainable investment behavior. It evaluates whether individuals with greater financial knowledge and digital proficiency are more inclined to engage in green finance and proposes policy interventions to promote sustainable financial behavior.

This thesis makes several key contributions to the literature on behavioral economics, financial literacy, and sustainability. First, it advances theoretical understanding by linking decision-making theories with empirical evidence from experiments and surveys. Second, it employs a novel methodological approach by integrating traditional survey data with experimental behavioral metrics, such as decision time and facial emotion recognition. Third, it contributes practical insights for policymakers, financial educators, and institutions by identifying barriers that prevent individuals from making financially sound and sustainable choices. By examining decision-making from multiple perspectives—uncertainty, intertemporal choices, climate-related risk, and sustainable investing—this research provides a comprehensive framework for understanding how individuals navigate complex financial environments. The findings are particularly relevant for policymakers designing financial education programs, financial institutions promoting sustainable finance, and educators seeking to enhance financial literacy and environmental consciousness among future generations.

Chapter 1

The determinants of decision time in an ambiguous context

1 Introduction

This paper uses data from Conte and Hey (2013) – henceforth C&H – that has hitherto been ignored. That paper, using an experiment in which subjects faced a decision problem under ambiguity, classified each subject into one of four *types*. These types depended upon the preference functional that was apparently used by the subject in reaching their decisions. The types were the Expected Utility Model, the Smooth Model, the Rank Dependent Expected Utility Model and the Alpha MaxMin Model. We will summarise these different models shortly.

The data from the experiment on the decisions that subjects took was used in this classification; data on the time that each subject took in coming to each decision *was not* used. This paper rectifies this omission, and shows that the analysis of the decision time data yields useful information about the cognitive processes of the subjects. In particular, we show here that decision time is closely related to the type of the subject. We present a *post hoc* analysis of the reasons why this might be so.

We start with a brief summary of the various identified types. As we say above, the identification depends upon the apparent preference functional used by each subject. One

type that we consider is the type that apparently uses the *Expected Utility* Model (*EU*) (von Neumann and Morgenstern, 1944), which states that agents compute the Expected Utility associated with each choice as the sum of the utility of the payoffs weighted by their associated probabilities (where these are necessarily subjective), and then chooses the option that gives the highest Expected Utility. A second type to explain choices under ambiguity is the Smooth Ambiguity Model (*SM*) proposed by Klibanoff et al. (2005). This can be interpreted as a *multiple prior* model which assumes that the decision-maker has a set of possible probabilities, and attaches a probability to each member of this set. The decision-maker then bases her¹ decision on the expected value of some function of expected utility for each member of this set. Another type is those that use the *Rank Dependent Expected Utility* Model (*RD*) of Quiggin (1982) which assumes that the decision-maker works with subjective probabilities and weights them in a way that depends on the rank of the possible outcomes. The final type is the *Alpha Expected Utility* model (*AM*) of Ghirardato et al. (2004) which also posits a set of possible probabilities and the decision-maker decides on the basis of a weighted average of the lowest and highest expected utilities over this set.

We focus our analysis on the four types described above. As shown by C&H, these four types are the best in describing and predicting behaviour of subjects in their experiment. We will assume from now on that this classification is correct.²

Our analysis in this current paper concerns decision times. Psychologists have been incorporating decision times in the study of decision processes for a long time, while it is only recently that this tool has started to be used in the context of economic choices. We will provide more details on this in Section 3.

The innovative approach of our work relies on the heterogeneity in terms of the decision-making types identified in the data from C&H. We study how different types differ in decision times. We then probe deeper: we analyse which features of the choice problem

¹For ‘her’ read ‘his or her’. And the same, *mutatis mutandis*, for ‘she’.

²Later, we will provide econometric evidence relating to this. Of course, it can always be said that there could be other types (including a catch-all of ‘any other behaviour’) but this does not detract from our analysis (though, of course, we cannot say anything about the decision times of these other types). It may be useful at this stage to point out that our classification exercise used 19,668 observations.

influence the decision times for each type of subject. In particular, for each type, we analyse which aspects of the decision problem are the most salient. To the best of our knowledge, no study has yet investigated the factors described below in the context of decision-making under ambiguity.³

- The characteristics of a choice that influences (lengthening, shortening), or not influences decision times. It is well established that decision times are positively correlated with cognitive effort, but usually we can only observe (and record) the amount of time taken by subjects to reach a decision. We do not observe how much time is allocated or spent among the different attributes of the problem, and different features of the same problem might lengthen or shorten decision times;
- The effect these characteristics have on subjects of different types. A particular feature of a choice might be relevant for an *EU* type, extending the time and cognitive effort necessary to make a decision, but the same feature of the same choice might be irrelevant for an *AM* type, allowing her to choose in a way that is less costly in terms of time and effort.
- Deepening the relationships between the characteristics of a choice problem and agents' choices is a key step in developing a theory that unites cognitive and decision-making processes and that is in line with empirical evidence. In addition, fully understanding the influence these characteristics have on decision times ensures that policymakers can develop increasingly effective welfare improvement tools.⁴

The rest of the paper is organised as follows. In Section 2, we describe the experiment. Section 3 contains an overview of the relevant literature about decision times and a description of the peculiarities of our data set. In Section 4, we present the econometric model. Section 5 describes the variables included in our model as controls and the estimation results. Section 6 shows a validation exercise that tests which of the estimated models

³Our analysis may also be useful for analysing behaviour in other contexts.

⁴Psychology, behavioural and experimental economics, through the study of behaviours and decisions, have repeatedly provided suggestions/insights that have resulted in improved collective welfare. Examples include the identification of so-called cognitive bias or nudge theory.

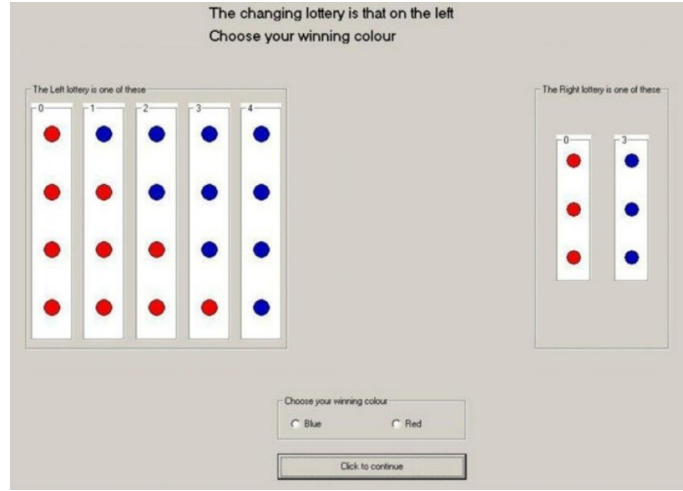
(one per type) predicts decision time for each of the types of decision-maker considered best. Section 7 concludes.

2 Experiment

The data analysed in this paper is based on the experiment reported in C&H. Here we recall only those features that are essential for understanding the analysis described in the rest of the present paper.

Subjects faced 49 tasks, each involving several rounds of decisions, and each decision involved a choice between two two-stage lotteries. Each two-stage lottery is made of several one-stage lotteries. A one-stage lottery is composed of a certain number of red balls and a certain number of blue balls. One of the two-stage lotteries displayed on the screen is labelled “unchanging lottery” and the other “changing lottery”. As the denominations suggest, the difference between the lotteries is that the changing one varies across rounds, the unchanging one staying the same until the end of the task. Before subjects are asked to make any choices, the computer randomly selects a one-stage lottery both for the changing and unchanging lottery, *but does not give this information to the subjects*. We refer to this as the “actual lottery” which is the one-stage lottery that will be played out for real at the end of the experiment if that task is selected.

A task proceeds as follows. First thing, subjects are asked to choose a “winning colour” (blue or red). This is the colour that they want to bet on, and once chosen, it cannot be changed for that specific task. A visual example of a task and colour choice is shown in Figure 1.1. A series of rounds starts at this point and subjects are required to make a choice between the two lotteries in each of them (an example is given in Figure 1.2). In the first round, (Figure 1.2, panel a) they face the same two options as for the colour choice but now they have to select which of the two-stage lotteries they prefer, the “changing” or the “unchanging” one. Then the second round starts (Figure 1.2, panel b) and one of the one-stage lotteries (crucially not the “actual lottery”) is selected at random by the computer and eliminated from the “changing lottery”, leaving a visual gap. Subjects are asked once again which is their preferred two-stage lottery, and then a new round starts.



Note: The “changing” and “unchanging” lotteries are displayed on the left- and right-hand side of the screen, respectively. Here, subjects have to choose their winning colour.

FIGURE 1.1

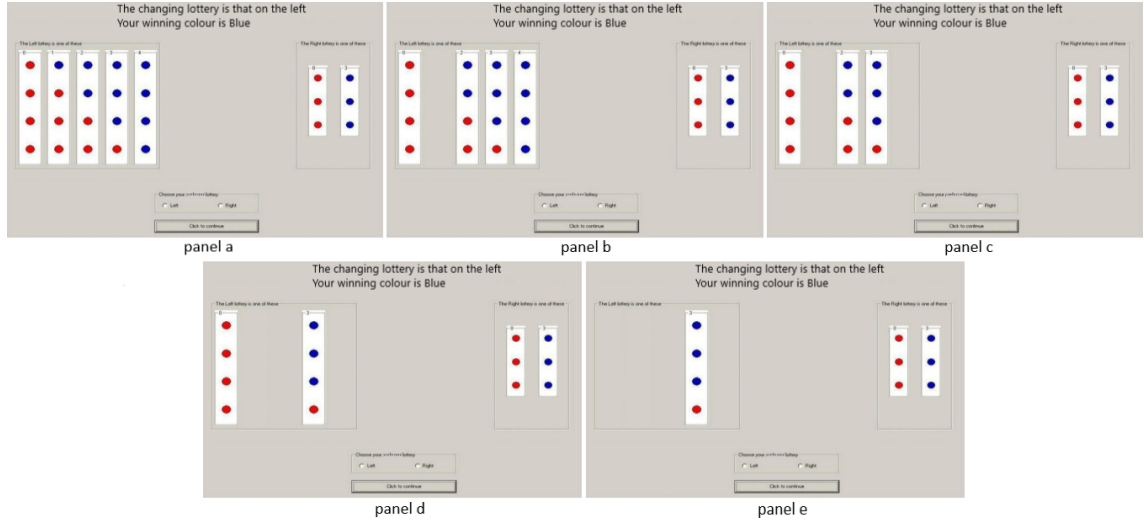
EXAMPLE OF A DECISION TASK USED IN THE EXPERIMENT

The process goes on until the “actual lottery” is the only one left in the “changing lottery” (Figure 1.2, panel e). This concludes the task and the subjects move on to the next one. Note that, in each task, the number of rounds in which the subject is required to make a choice between the two two-stage lotteries equals the number of one-stage lotteries in the changing lottery. In Figure 1.2, for example, having the changing lottery five one-stage lotteries, there are five rounds of choice between the changing and unchanging lotteries.

For each choice made, we collect decision times, which are the focus of the present work. We note that subjects are forced to wait for 5 seconds before they can make a decision between the two lotteries.

The experiment was conducted in the experimental lab of the Max Planck Institute of Economics, Jena, Germany, directed by Professor Werner Güth, with subjects recruited using the ORSEE system (Greiner, 2015). There was a total of 149 subjects.

The natural incentive mechanism was used. At the end of the experiment, for each subject, one of the 49 tasks was selected. The “actual lottery” chosen by the computer for that task was recalled. Then, the “actual lottery” for that task was revealed to the subject and the subject’s stated preference on that task was checked. According to the preference expressed, the corresponding “actual lottery” was played for real. If the extracted ball was



Note: In each round of the task, the computer randomly eliminates a one-stage lottery from the “changing lottery”. After every elimination, subjects are asked to choose the lottery they prefer. This process repeats for a number of rounds, i.e. until only one lottery (the “actual lottery”) in the “changing lottery” is left.

FIGURE 1.2

EXAMPLE OF A SEQUENCE OF ROUNDS (ELIMINATIONS AND CHOICES) FOR THE
DECISION TASK IN FIGURE 1.1

of the “winning colour”, then the subject was paid an extra €40 in addition to the €7.5 of the show-up fee. If it was not, then there was no extra payment. The entire procedure was repeated for each subject. The order in which the 49 tasks were presented was randomised by the computer for each subject, in each task. As we have already noted, the “actual lottery” for each of the two two-stage lotteries at stake was selected at random by the computer, individually for each subject, and the elimination sequence was randomised as well. The consequences of this procedure are that a particular task was faced by each subject at a different point in her sequence of tasks. The outcome of each of the two two-stage lotteries in that task could differ and the elimination sequence could also differ across subjects.

Here we provide some notational definitions whose summary is provided in Table 1.1. Let us denote a generic one-stage lottery by $O(r_k, r)$, where r is the number of balls and r_k ($0 \leq r_k \leq r$) is the number of winning balls (the winning colour is chosen at the outset of a task by the subject). Each of these r_k balls has an equal probability of being drawn so the probability of drawing a winning ball is r_k/r . Let us denote a two-stage lottery

by $\mathcal{R}(r_1, \dots, r_k, \dots, r_R; r)$, where r_k represents the number of winning balls in the k 'th one-stage lottery ($O(r_k, r)$) and R is the number of one-stage lotteries (priors) comprised in the two-stage lottery, so that $k = 1, \dots, R$. The probability of drawing each of the one-stage lotteries is $1/R$ and the probability of drawing a winning ball from the k 'th one-stage lottery is r_k/r . Finally, let $V_{PF}[O(r_k, r)]$ and $V_{PF}[\mathcal{R}(r_1, \dots, r_k, \dots, r_R; r)]$ denote the valuations for preference functional PF of the generic one- and two-stage lotteries, respectively.⁵

TABLE 1.1
DESCRIPTION OF NOTATION

Notation	Meaning
$O(r_k, r)$	one-stage lottery
r	number of balls in a one-stage lottery
r_k	number of winning balls in a one-stage lottery
r_k/r	winning probability in a one-stage lottery
$\mathcal{R}(r_1, \dots, r_k, \dots, r_R; r)$	two-stage lottery
R	number of one-stage lotteries in a two-stage lottery
$V_{PF}[O(r_k, r)]$	valuation for preference functional of generic one-stage lottery
$V_{PF}[\mathcal{R}(r_1, \dots, r_k, \dots, r_R; r)]$	valuation for preference functional of generic two-stage lottery

Note: The first column contains the name of the object. The second column gives a description of the object.

3 Related literature

Given the peculiarity of our dataset (and the model we use to analyse it), we will separate the literature review in two sections, one that is closely related to the current work and another one that explains the main paradigms used to analyse decision times but which are not directly related to this paper. The first is discussed here and it is followed by the description of the dataset, where we highlight the features which are most relevant in the explanation of decision time. The second branch of literature is discussed in Appendix B.

⁵Details of the 49 tasks are given in Table A.1. Up to this point, only the first three columns of which should be read – the remaining columns will be explained later.

3.1 Literature relevant to this paper

In psychology, decision times are commonly used as a tool for understanding cognitive processes. The idea of using decision times, or reaction times in general, to infer cognitive processes dates back to Donders (1868), who is known as the father of mental chronometry. Only recently has the literature on economic decision-making under risk begun to incorporate decision times to study the choices of agents. Observing individuals' choices is the most direct way to gain information about their preferences and allows us to build behavioural models to predict how they might act under different circumstances and with different preferences.

Using decision times in addition to decision data is an efficient way to gain information about preferences, without necessarily having to use strong and often unrealistic assumptions. Alós-Ferrer et al. (2021) show that it is possible to learn the preferences of subjects within the sample using data on choices and decision times, without the need for any assumptions while it is also possible to obtain information on pairs of options outside the dataset when using the symmetric noise assumption. The advantage of using decision times is that these are observable (as opposed to error terms) and can be collected easily in laboratory, field or natural experiments. Since the collection of decision times is costless, provides further information improving model selection, and can be done without disrupting or influencing the decision-makers, we do not see any reason why behavioural scientists should not collect such data during experiments. For a comprehensive analysis of the advantages and disadvantages of using decision times we refer the reader to the work of Spiliopoulos and Ortmann (2018). The current work contributes to the emerging literature studying decision timing in relation to economic choices under ambiguity. Although economic decisions incorporate a stochastic component, regularities in decision-making processes have been identified. Our work builds on some of this empirical evidence and specifically on what is known in psychology as the *chronometric function*, which describes the relationship between choice complexity and decision times. An individual will take longer to make a choice when the problem is more difficult, and the decision will be faster if the difficulty of the problem is low. This regularity was observed in psychophysics

(Cattell, 1902; Moyer and Landauer, 1967) but it is only recently that its implications for economic choices have begun to be studied. Chabris et al. (2009) studied this relationship for intertemporal choices showing that decision times decrease when the difference in utility between the two options widens. This implies that decision times can also be used as a proxy for the strength of preference for an option. Moffatt (2005) studied decision times for choices under risk and, by analysing data obtained from an experiment in which subjects had to choose between pairs of lotteries, found that decision times lengthen in the presence of more complex pairs of lotteries.

In our work, we study this relationship of choices to decision times under ambiguity but we probe deeper, distinguishing which features increase or decrease the difficulty of the problem and identify the ones that are most relevant for the choice, that is, the attributes that influence subjects' decision time the most. Moreover, the innovativeness of our work lies in the study of decision times for types of individuals that use different decision rules. Our aim is to identify which aspects of a decision problem are considered by each type, and how those aspects influence the actual choice.

Another observed regularity is what is commonly called the *psychometric function*, which links the difficulty of the problem and the probability of answering it correctly. In this case, easier problems are more likely to be answered correctly than more difficult problems. This relationship was also initially identified in the field of psychophysics, specifically in experiments in which there is a correct answer to the problem (Cattell, 1893; Laming, 1985; Klein, 2001; Wichmann and Hill, 2001), but the results have also been extended to subjective choices Dashiell (1937) and, in economics, to choices with risk. Mosteller and Nogee (1951) showed in their poker dice experiment that the percentage of subjects who chose the offer that guaranteed the highest expected utility increased as the difference in expected utilities between the two offers increased.

We show in the current work how these features of the psychometric function are also found in choices under ambiguity and how this is reflected in decision times. In our case, the objective similarity between options is the variable that influences the probability of choosing correctly, where the correct choice is understood as the choice that provides the

greatest utility. The idea is that as the similarity between the available options increases, the probability of choosing correctly decreases and vice versa. Obviously, objective similarity also influences decision times so that options that are very similar to each other require longer decision times than choosing between options that are at first sight different. This relationship was also found by Alós-Ferrer and Garagnani (2022): in their experiment, decision times are longer when subjects face choices in which the difference in utility is smaller. As for the previous hypothesis, we are going to look at the factors that influence decision times and cognitive effort of our different types of subjects.

An additional aspect that we examine in our paper concerns the relationship between decision times and cognitive effort. Although the idea that decisions entail a cost to economic agents is well established (Simon, 1955; Marshak, 1974; Selten, 1978), the literature on decision times has only recently explored the connection between the two. Wilcox (1993) uses decision time to measure the cost of making decisions under risk. In addition to using decision time as a proxy for effort, the author shows how an increase in incentives leads to an increase in subjects' willingness to incur higher decision costs. Similar results were found by Alós-Ferrer and Buckenmaier (2021) in their laboratory experiment whose design involved participants playing the beauty contest game (Nagel, 1995) and the 11-20 money request game (Arad and Rubinstein, 2012). The authors confirmed that a higher observed depth of reasoning leads to longer deliberation times and that cognitive depth reacts to monetary incentives.

3.2 Data description

As explained, we use decision times and classification into decision types from C&H. They collected observations from 149 subjects, each facing 49 tasks consisting of several rounds, resulting in a total of 256 observations per subject. Each subject's observations were divided into two roughly equal halves: one part was used for estimating the mixture models, the "estimation sample"; while the other part was employed for predicting types based on the mixture model estimation results, the "validation sample".⁶

⁶In C&H, the validation sample is referred to as the "prediction sample". Here, we have preferred a different label for the sake of clarity.

We relegate to Appendix C a detailed description of how C&H used the data to fit the different preference functionals. We summarise the classification that C&H reached in Table 1.2, which gives results based both on the basis of individual likelihoods and through the mixture estimation. They are reassuringly close. In what follows, we will use the classification by mixture estimation.

TABLE 1.2
ASSIGNMENT OF SUBJECTS TO TYPES FROM C&H

Type	Number of subjects classified by individual likelihoods	% of subjects classified by individual likelihoods	Number of subjects classified by mixture estimation	% of subjects classified by mixture estimation
<i>EU</i>	36	24.2	38	26.0
<i>SM</i>	83	55.7	74	49.2
<i>RD</i>	17	11.4	30	19.8
<i>AM</i>	13	8.7	7	4.9
Total	149	100.0	149	100.0

In this paper, we follow a conceptually similar approach to C&H. We use decision times from the estimation sample to estimate a model of decision times for each of the four types. Subsequently, we use these estimated models to predict data in the validation sample.

Here we describe the experimental data set that we use in this paper, and highlight differences and similarities between types.

The experimental design sets a 5-second waiting period before subjects could make a choice. This was meant to force subjects to think seriously about the decision problem and avoid them choosing at random. However, especially in later periods, the waiting time set could be binding. In effect, we have realised that, after approximately the 30th task, the variability in decision times dramatically reduces. Essentially, while the decision times associated with early tasks are informative of the decision process, in later tasks subjects are quicker and their decision process mostly resolves in the 5 seconds waiting time. Therefore, we acknowledge that a 5-second waiting time may be excessive for later rounds and limit the estimation and validation to the first 30 tasks. Moreover, we call for evidence that could demonstrate whether the sort of exercise described in this paper could yield different results if the 5-second waiting period were reduced or even eliminated.

Table 1.3 displays the summary statistics of decision time per type, distinguished be-

TABLE 1.3
SUMMARY STATISTICS OF DECISION TIME PER TYPE

type	subjects	Estimation sample				Validation sample			
		observations	mean	std. dev.	median	observations	mean	std. dev.	median
<i>EU</i>	38	3,180	12.62	14.65	7.57	2,783	12.10	12.42	7.25
<i>SM</i>	74	5,902	12.18	11.62	7.62	5,694	12.42	13.59	7.56
<i>RD</i>	30	2,466	12.76	11.40	8.00	2,254	12.84	11.64	8.09
<i>AM</i>	7	546	10.70	11.61	6.82	543	11.02	11.12	6.89

TABLE 1.4
DECISION TIME VARIANCE-COMPARISON (LEFT PANELS) AND MEAN-COMPARISON TEST
(RIGHT PANELS) PER PAIR OF TYPES

Estimation sample																																																	
	EU	SM	RD	AM		EU	SM	RD	AM																																								
EU	<table><tr><td>EU</td><td colspan="4"></td></tr><tr><td>SM</td><td>0.000</td><td colspan="3"></td></tr><tr><td>RD</td><td>0.001</td><td>0.000</td><td colspan="2"></td></tr><tr><td>AM</td><td>0.295</td><td>0.284</td><td>0.262</td><td></td></tr></table>				EU					SM	0.000				RD	0.001	0.000			AM	0.295	0.284	0.262		EU	<table><tr><td>EU</td><td colspan="4"></td></tr><tr><td>SM</td><td>0.489</td><td colspan="3"></td></tr><tr><td>RD</td><td>0.849</td><td>0.251</td><td colspan="2"></td></tr><tr><td>AM</td><td>0.076</td><td>0.126</td><td>0.060</td><td></td></tr></table>				EU					SM	0.489				RD	0.849	0.251			AM	0.076	0.126	0.060	
EU																																																	
SM					0.000																																												
RD					0.001	0.000																																											
AM	0.295	0.284	0.262																																														
EU																																																	
SM	0.489																																																
RD	0.849	0.251																																															
AM	0.076	0.126	0.060																																														
SM					SM																																												
RD					RD																																												
AM					AM																																												

Validation sample																																																	
	EU	SM	RD	AM		EU	SM	RD	AM																																								
EU	<table><tr><td>EU</td><td colspan="4"></td></tr><tr><td>SM</td><td>0.000</td><td colspan="3"></td></tr><tr><td>RD</td><td>0.000</td><td>0.000</td><td colspan="2"></td></tr><tr><td>AM</td><td>0.094</td><td>0.115</td><td>0.097</td><td></td></tr></table>				EU					SM	0.000				RD	0.000	0.000			AM	0.094	0.115	0.097		EU	<table><tr><td>EU</td><td colspan="4"></td></tr><tr><td>SM</td><td>0.605</td><td colspan="3"></td></tr><tr><td>RD</td><td>0.249</td><td>0.449</td><td colspan="2"></td></tr><tr><td>AM</td><td>0.198</td><td>0.067</td><td>0.031</td><td></td></tr></table>				EU					SM	0.605				RD	0.249	0.449			AM	0.198	0.067	0.031	
EU																																																	
SM					0.000																																												
RD					0.000	0.000																																											
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AM	0.198	0.067	0.031																																														
SM					SM																																												
RD					RD																																												
AM					AM																																												

Note: Left panels: in each cell, the p -value of the test on the equality of the standard deviations of decision times per pair of types, against the bilateral alternative, is reported. Under the null hypothesis, the test statistic distributes according to the F -distribution with degrees of freedom equal to the number of observations in each of the two samples (one per type) minus 1. Right panels: in each cell, the p -value of the two-sample t -test on the equality of the means of decision times for pair of types, against the bilateral alternative, is reported. In all the cases, except for when type *AM* is involved, unequal variance is assumed. The tests are bootstrapped by clustering at the individual level (1000 replications).

tween estimation and validation samples. On average, decision times range between about 10.5 and 13 seconds. Table 1.4 shows the p -value of pairwise variance-comparison (left panels) and mean-comparison tests of decision times (right panels). They suggest that there are significant pairwise differences in the variances but not in the means of the decision times for *EU*, *SM* and *RD* subjects. This holds for both the estimation and the validation samples. However, we cannot reject the hypothesis that the variance and the mean decision time of *AM* subjects do not differ from those of the other three types, except for the *AM-RD* pair whose mean decision time seems to differ in the validation sample.

These results do not seem to point out striking differences in decision time between types. The following econometric analysis will attempt to uncover which aspects of the decision problem influence the decision times of each type, if any. It may well be that decision times, while similar across types on average, are the result of different factors that each type of decision-maker weighs in their decision process.

4 Econometric model of decision time

Let y_{it} be subject i 's decision time in choice problem t and let x_{it} be a vector of characteristics of the two two-stage lotteries involved in the choice problem.⁷ Consider the log-linear regression model with individual-specific random effects under the hypothesis that subject i is of type $\tau \in \{EU, SM, RD, AM\}$

$$\ln(y_{it}) = \gamma^\tau + x_{it}'\beta^\tau + \alpha_i^\tau + \epsilon_{it}^\tau \quad (1.1)$$

for $i = 1, \dots, 149$ and $t = 1, \dots, 256$. Here, γ^τ is an intercept, β^τ is a vector of coefficients, α_i^τ is the individual-specific random effect $NID(0, \sigma_\alpha^2)$, and ϵ_{it}^τ is an idiosyncratic error

⁷It is worth recalling here that the vector of characteristics of the two lotteries is individual specific, because not only the order of the tasks, but also the “actual lotteries” and the elimination sequence of each task were randomised across subjects, and the “winning colour” chosen for that task by the subject. We also use some regressors that depend on the subject’s characteristics whose evaluation is based on the estimation results in C&H. We will expand on this in the next session.

term $NID(0, \sigma_\epsilon^{\tau 2})$, independent of α_i^τ and of anything else in the model.^{8,9}

This is a standard random-effects linear model, where subject i 's likelihood contribution is given by

$$l_i^\tau = \Pr(y_{i1}, \dots, y_{i256} | x_{i1}, \dots, x_{i256}, \gamma^\tau, \beta^\tau) = \int_{-\infty}^{\infty} \prod_t f(y_{it} | x_{it}, \alpha_i^\tau, \gamma^\tau, \beta^\tau) g(\alpha_i^\tau) d\alpha_i^\tau$$

where $g(\alpha_i^\tau)$ is the normal density function with mean 0 and variance $\sigma_\alpha^{\tau 2}$ evaluated at α_i^τ and $f(y_{it} | x_{it}, \alpha_i^\tau, \gamma^\tau, \beta^\tau)$ is given by

$$f(y_{it} | x_{it}, \alpha_i^\tau, \gamma^\tau, \beta^\tau) = \frac{1}{y_{it} \sqrt{2\pi\sigma_\epsilon^{\tau 2}}} \exp \left\{ -\frac{1}{2} \frac{[\ln(y_{it}) - \gamma^\tau - x'_{it}\beta^\tau - \alpha_i^\tau]^2}{\sigma_\epsilon^{\tau 2}} \right\}$$

The total log-likelihood that we maximise to estimate the parameters of interest is

$$\text{Log-likelihood}^\tau = \sum_{i=1}^{149} d_i^\tau \ln(l_i^\tau), \quad \tau \in \{EU, SM, RD, AM\} \quad (1.2)$$

The dummy d_i^τ taking the value 1 if subject i 's posterior probability of type τ is the highest, 0 otherwise, enables us to estimate each type's decision time only from those subjects who are assigned to that type according to the majority rule explained above.

In the next sections, we will present the estimation results.

⁸In previous versions of this paper, as participants were forced to wait for at least 5 seconds before reporting their preferred lottery, we assumed that those who took less than 5.5 seconds (inclusive of the 5 waiting seconds) to make a decision would have possibly been able to do it within the 5 waiting seconds. Essentially, we conceded 0.5 seconds of reaction time to those subjects who have already made up their mind during the waiting time. However, since the results change only marginally with respect to a model which assumes no censoring of decision time, we discuss the latter here.

⁹We note that the experimental software rounded to the nearest integer the decision time at which each decision problem is shown to participants. This results in an approximation in the range of $(-0.5, 0.5)$ seconds. Since subjects could not control the time in which the decision was made and they were not even aware that their decision times were recorded, we can consider this rounding completely random, which is a minor and unsystematic measurement error that cannot bias the results in any way.

5 Estimation

5.1 Description of variables

As previously noted, we obtain our estimates by separately maximising the total log-likelihood in Eq. (1.2) for each type of the decision-maker $\tau \in \{EU, SM, RD, AM\}$ as classified in C&H. The variables we use are described in what follows and listed in Table 1.5.

Definition 1: *“Experience” with the decision problem both across tasks and within each task can instigate “learning” phenomena. Boredom and fatigue can manifest themselves throughout the experiment as well, impinging on and even overcoming the effect of learning.*

Since the task position and the elimination process are randomly determined subject by subject, we include both the variable T , $T = 1, \dots, 49$, which indicates the position in the sequence of tasks in which a particular task is presented to the subject, and the variable *round*, which represents the position in the elimination sequence of the task in which a particular choice problem is encountered (we note that the number of rounds varies from task to task – Table A.1 gives the detail). The use of these variables is aimed at modelling two effects: learning and fatigue.

We should make clear that, in each task, subjects first choose the winning colour and then start with the first round of choices between the two two-stage lotteries. To control for the peculiarity of the decision in the first round of a task, where the decision time is inflated by the time spent to choose the winning colour and to familiarise ourselves with the lotteries, we use an indicator for the first round of each decision task, $\mathbf{1}(\text{round} = 1)$.¹⁰ Using this dummy, we purge the variable *round* of the extra time taken to carry out the first-round decision.

Following the literature on experience and decision time, we expect that all types of subjects will become faster in making choices as the experiment proceeds. This means

¹⁰Here, $\mathbf{1}(\cdot)$ has the standard meaning of an indicator function that takes the value 1 when the statement in the brackets is true; it is 0 otherwise.

TABLE 1.5
DETAILED DEFINITION OF THE VARIABLES USED IN THE ESTIMATION OF THE DECISION
TIME EQUATIONS

Variable	Formula	Category	Description
T		E	The position in the sequence of tasks in which a particular task is presented to the participant
$round$		E	The position in the elimination sequence of the task in which the choice problem is encountered
$\mathbf{1}(round = 1)$		E	The indicator for the first round in each decision task
$\#balls$	$m \times M + n \times N$	C	The total number of balls in the two lotteries
$dimension-1sl$	$m + n$	C	The number of balls in each of the one-stage lotteries in the unchanging two-stage lottery plus the number of balls in each of the one-stage lotteries in the changing two-stage lottery
$\#priors$	$M + N$	C	The number of one-stage lotteries in the unchanging two-stage lottery plus the number of one-stage lotteries in the changing two-stage lottery
$\mathbf{1}(\mathcal{M} \text{ is symmetric})$		C	1 if unchanging lottery is symmetric (if interchanging the winning and losing balls does not change the lottery)
$\mathbf{1}(\mathcal{N} \text{ is symmetric})$		C	1 if changing lottery is symmetric (if interchanging the winning and losing balls does not change the lottery)
$\mathbf{1}(\text{both } \mathcal{M} \text{ and } \mathcal{N} \text{ are symmetric})$		S	1 if both unchanging and changing lotteries are symmetric
$\mathbf{1}(\text{both } \mathcal{M} \text{ and } \mathcal{N} \text{ are symmetric}) \times \mathbf{1}(\text{round} = 1)$		S	1 if both unchanging and changing lotteries are symmetric and it is round 1
$\mathbf{1}(\mathcal{M} \text{ and } \mathcal{N} \text{ are identical})$		S	1 if the unchanging and changing lottery are identical
$ \Delta(\#priors) $	$ M - N $	S	The absolute difference between the number of one-stage lotteries in the unchanging two-stage lottery and the number of one-stage lotteries in the changing two-stage lottery
$ \Delta(\#win-balls) $	$ \sum_{k=1}^M m_k - \sum_{j=1}^N n_j $	S	The absolute difference between the number of winning balls in the unchanging two-stage lottery and the number of winning balls in the changing two-stage lottery
$ \hat{\Delta} $	$ V_{i\tau}(A) - V_{i\tau}(B) $	I	The difference in utility evaluation between the two lotteries that depends on the type at the individual-specific parameter for subject i for that type

Note: The first column contains the name of the variable. The second column shows the formula, if any, that computes it. The third column indicates what the variable is meant to control for: experience (E); complexity (C); objective similarity (S); closeness to indifference (I). The fourth column gives a description of the variable.

that, overall, experience should reduce decision time regardless of the process implemented by subjects. Moreover, we expect to find a significant reduction of response time both between (quicker decisions for tasks presented later) and within tasks (faster choices in the final part of the elimination sequence of one-stage lotteries).

Along similar lines to Moffatt (2005), we add variables to control for: (i) complexity; (ii) objective similarity; and (iii) closeness to indifference. In the following, we define and discuss in detail the variables in each category.

Definition 2: *The “complexity” level of a choice problem is related to the load of information the subject faces in a particular choice problem.*

The complexity of a decision problem is modelled by five variables: *#balls*, *dimension-1sl*, *#priors* and two indicators taking the value 1 if either the unchanging or the changing lottery is symmetric. The first represents the dimension of the decision problem. For example, if one of the two-stage lotteries consists of M one-stage lotteries, each containing m balls and the other consists of N one-stage lotteries, each containing n balls, then the variable *#balls* is equal to $m \times M + n \times N$. The second variable captures the dimension of the one-stage lotteries ($m + n$). The third measures the number of one-stage lotteries in a decision problem, that is the number of priors involved in the decision ($M + N$). Essentially, these indicators account for the dimensionality of the decision problem from three different points of view, each of these might play a particular role in the evaluation of the preferred two-stage lottery by the different types of the decision-maker. It is worth noting that, while *dimension-1sl* is constant within a specific task, *#priors* changes with the round number of the task sequence. In particular, N decreases by one at each elimination of a one-stage lottery. The two dummy variables $\mathbf{1}(\mathcal{M} \text{ is symmetric})$ and $\mathbf{1}(\mathcal{N} \text{ is symmetric})$ also gauge complexity, in that a symmetric lottery is visually easy to detect and does not require to count the number of balls it contains. A two-stage lottery is symmetric if it does not change when exchanging the winning colour with the losing colour.

Intuitively, we might expect that higher complexity embedded in a decision would increase the time required to make a choice, as prescribed by the chronometric function.

This might be true on average, but we expect to find different reactions to complexity from different types of subjects. Furthermore, subjects employing different decision processes might focus on different aspects of complexity of a choice. Subjects that employ simpler decision processes, like AM , might be less concerned by complexity variables. Finally, symmetry of one of the two lotteries should reduce the time it takes for a subject to make a decision, overall.

Definition 3: *The “objective similarity” refers to the similarity in the physical appearance of the two lotteries in a particular decision problem.*

The five variables included in category S in Table 1.5 are intended to measure objective similarity between two lotteries.

The dummy variable $\mathbf{1}(\text{both } \mathcal{M} \text{ and } \mathcal{N} \text{ are symmetric})$, with and without controlling for the peculiarity of the first round choice, captures similarity because, besides the number of balls being different, subjects can perceive two lotteries as being similar because they share the characteristic of being symmetric. The variable $|\Delta(\#priors)|$ indicates the absolute difference in the number of priors involved in the decision choice ($|M - N|$). The variable $|\Delta(\#win-balls)|$ gives the absolute difference between the number of winning balls of the two two-stage lotteries. The variables described so far decrease when the two-stage lotteries become similar in their physical appearance. However, when all these variables equal 0 simultaneously, it does not necessarily mean that the two-stage lotteries are the same.¹¹ For this reason, we add the dummy variable $\mathbf{1}(\mathcal{M} \text{ and } \mathcal{N} \text{ are identical})$, which takes the value 1 if the two lotteries are exactly the same and 0 otherwise.¹²

A possible way in which symmetry can influence decision time is given by the idea that the more similar the two lotteries in physical appearance, the longer the time required for a subject to make a decision. If this is the case, we should observe a strong, positive significant effect, especially from variables like $|\Delta(\#win-balls)|$ and $\mathbf{1}(\text{both } \mathcal{M} \text{ and } \mathcal{N} \text{ are symmetric})$

¹¹Consider, for example, the two lotteries $\mathcal{R}(1, 2; 3)$ and $\mathcal{R}(0, 3; 3)$. These share the number of one-stage lotteries, the number of balls in the one-stage lotteries, and the number of winning balls, but they are different, nevertheless.

¹²As a measure of objective similarity, Moffatt (2005) calculates the Euclidean distance between the probability vectors of the two lotteries. Here, we are unable to do the same because the structure of our two-stage lottery is such that it cannot be represented by a single probability vector.

since it should be easier to detect symmetry through them. Nevertheless, as for the case of complexity, we expect symmetry variables to have a different impact depending on the decision process of subjects.

Definition 4: *“Closeness to indifference” refers to the difference in terms of valuation between the two lotteries. It measures the extent to which the two lotteries are close to being indifferent (the difference in valuation can be interpreted as a measure of subjective similarity).*

To capture the difference in terms of utility between the two lotteries, we follow the approach described in Moffatt (2015, page 375, Equation 12) using the estimation results in C&H. Roughly speaking, this approach uses the estimated parameters of the preference functional to obtain individual-wise valuations of the lotteries and compute an estimate of their absolute difference, $|\hat{\Delta}|$. The intuition behind the use of such a measure is that being close to indifference may either have a positive or negative impact on the decision time. A subject that is close to being indifferent between the two lotteries, on the one hand, may need more time to accurately assess which is the preferred one and, on the other hand, may choose faster since the two lotteries provide about the same value.

In contrast to Moffatt (2005), C&H estimate a 4-type mixture model, where three out of four models are characterised by a single parameter, except for the *EU* type whose functional has no parameters at all. Hence, for each subject i conditional on being of a particular type, we calculate the posterior expectation of the parameter of interest which characterises the functional for that type. Finally, we use the parameters so obtained to calculate the absolute valuation differential for each subject’s decision problem, conditional on being of a certain type. We will refer to such absolute valuation differential as $|\hat{\Delta}_{EU}|$, $|\hat{\Delta}_{SM}|$, $|\hat{\Delta}_{RD}|$ and $|\hat{\Delta}_{AM}|$ in the Expected Utility, Smooth Model, Rank Dependent model and Alpha Model case, respectively.¹³

¹³The hats over the Δ ’s indicate that the valuations are obtained by using the Maximum Simulated Likelihood estimates of the parameter from Table 3 in C&H. The procedure is explained in Moffatt (2005).

5.2 Regression results

The regression results are reported in Table 1.6. Results are organised in four columns, one for each type. Note that not all variables enter into all four columns; the order of powers for T , *round* and $|\hat{\Delta}_\tau|$ were decided by using likelihood-ratio tests at a 5% significance level for each type separately. Powers are added to capture non-linearities.

Two important observations are in order. First, the significance and magnitude of the individual random effects, σ_α , testify that there is a large heterogeneity in the population whatever the type. Second, due to the log-linear specification of our model, the effects of the regressors on the decision time have to be interpreted in percentage terms.¹⁴ For example, a unit increase in the total number of balls produces an expected increase in the decision time in seconds of 1.2% for *RD*, of 0.2% for *AM*, and no significant effect for *EU* and *SM*.

In what follows, we examine the impact of the experience, complexity, similarity and closeness to indifference factors on decision time and itemise our findings.

Result 1: *Experience significantly reduces decision time both across and within tasks for all the types. This result is in line with our expectations and with the sequential effect described by Drift Diffusion Models.*

The position of a particular task, T , is clearly highly significant, not only in and of itself but also in its powers. Figure 1.3 displays the expected decision time against task position per type based on the estimation results in Table 1.6. The formula used is $E(\hat{y}_t^{*\tau}) = \exp(\hat{\gamma}^\tau + x_t' \hat{\beta}^\tau + \hat{\sigma}_\alpha^{\tau 2}/2)$, with all the regressors other than T and its relevant powers set to 0. Hence, what is seen in Figure 1.3 is the effect of *only* T on decision times. The slope and the level of the curves change with the characteristics of the lotteries under examination since they have different effects and importance for different types.

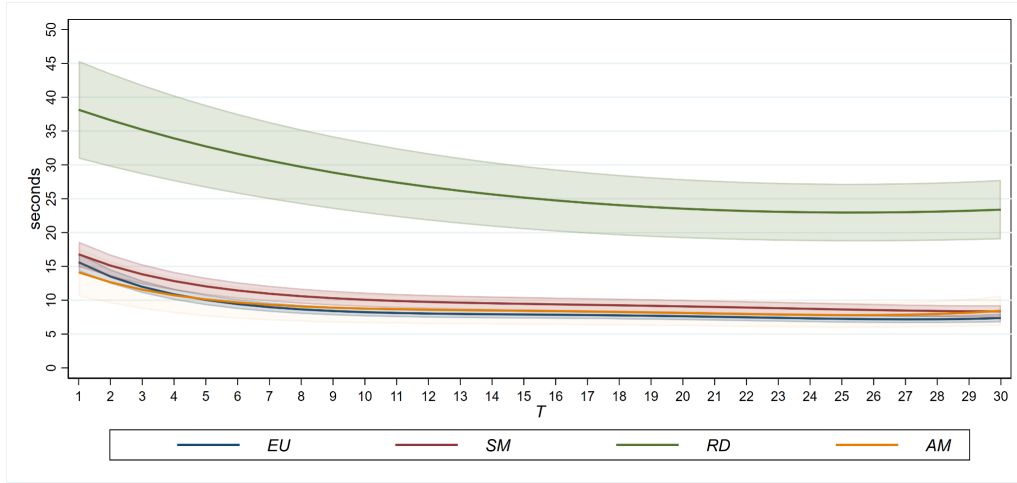
Figure 1.3 shows that decision time curves are all downward-sloping and generally

¹⁴This implies that each 1-unit increase in the explanatory variable, say x , multiplies the expected value of the decision time, y , by $\exp(\hat{c})$, where $\hat{c}$ is the estimated coefficient on x . Given that for small values of $\hat{c}$ (which is almost always our case), $\exp(\hat{c}) \approx 1 + \hat{c}$, we can loosely interpret $100 \times \hat{c}$ as the expected percentage change in y of a 1-unit increase in x .

TABLE 1.6
ESTIMATION RESULTS OF THE RANDOM EFFECTS LINEAR REGRESSION MODEL PER
TYPE

variable	category	τ			
		<i>EU</i>	<i>SM</i>	<i>RD</i>	<i>AM</i>
γ^τ	E	2.9052*** (0.0502)	2.9322*** (0.0603)	3.6738*** (0.0971)	2.8289*** (0.1377)
T	E	-0.1875*** (0.0147)	-0.1321*** (0.0107)	-0.0434*** (0.0033)	-0.1457*** (0.0331)
$T^2/10$	E	0.1565*** (0.0190)	0.0980*** (0.0138)	0.0085*** (0.0010)	0.1285** (0.0440)
$T^3/100$	E	-0.0579*** (0.0092)	-0.0335*** (0.0066)		-0.0511* (0.0217)
$T^4/1000$	E	0.0077*** (0.0015)	0.0041*** (0.0011)		0.0074* (0.0035)
$\mathbf{1}(\text{round} = 1)$	E	1.1859*** (0.0171)	1.0805*** (0.0385)	1.1645*** (0.0767)	0.9275*** (0.0617)
round	E		-0.0832*** (0.0176)	-0.1875*** (0.0318)	-0.1469** (0.0540)
round^2	E		0.0075*** (0.0021)	0.0160*** (0.0037)	0.0158* (0.0066)
$\#balls$	C			0.0120*** (0.0020)	0.0026* (0.0012)
dimension-1sl	C		0.0116** (0.0033)		
$\#priors$	C			-0.0565*** (0.0129)	
$\mathbf{1}(\mathcal{M} \text{ is symmetric})$	C	-0.0570** (0.0216)	-0.0392* (0.0165)	-0.1918*** (0.0291)	
$\mathbf{1}(\mathcal{N} \text{ is symmetric})$	C			-0.3234*** (0.0333)	
$\mathbf{1}(\text{both } \mathcal{M} \text{ and } \mathcal{N} \text{ are symmetric})$	S		0.0391** (0.0141)		
$\mathbf{1}(\text{both } \mathcal{M} \text{ and } \mathcal{N} \text{ are symmetric}) \times \mathbf{1}(\text{round} = 1)$	S		-0.1185** (0.0379)	-0.5022*** (0.0674)	
$\mathbf{1}(\mathcal{M} \text{ and } \mathcal{N} \text{ are identical})$	S		-0.1156* (0.0448)		
$ \Delta(\#priors) $	S		-0.0073* (0.0028)		
$ \Delta(\#win-balls) $	S			-0.0058*** (0.0017)	
$ \hat{\Delta}_\tau $	I	-0.3820** (0.1278)	-1.2525*** (0.1586)	-6.5295*** (0.4283)	
$ \hat{\Delta}_\tau ^2$	I	0.6118* (0.2459)	2.5019*** (0.6005)	19.4074*** (1.7403)	
$ \hat{\Delta}_\tau ^3$	I		-1.6703** (0.6251)	-17.5590*** (2.0239)	
σ_α		0.1755*** (0.0209)	0.1510*** (0.0130)	0.1402*** (0.0194)	0.1153*** (0.0331)
σ_ϵ		0.3133*** (0.0039)	0.3019*** (0.0028)	0.3358*** (0.0048)	0.2784*** (0.0084)
R^2		0.6764	0.6873	0.6497	0.7106
observations		3,180	5,902	2,466	546
subjects		38	74	30	7

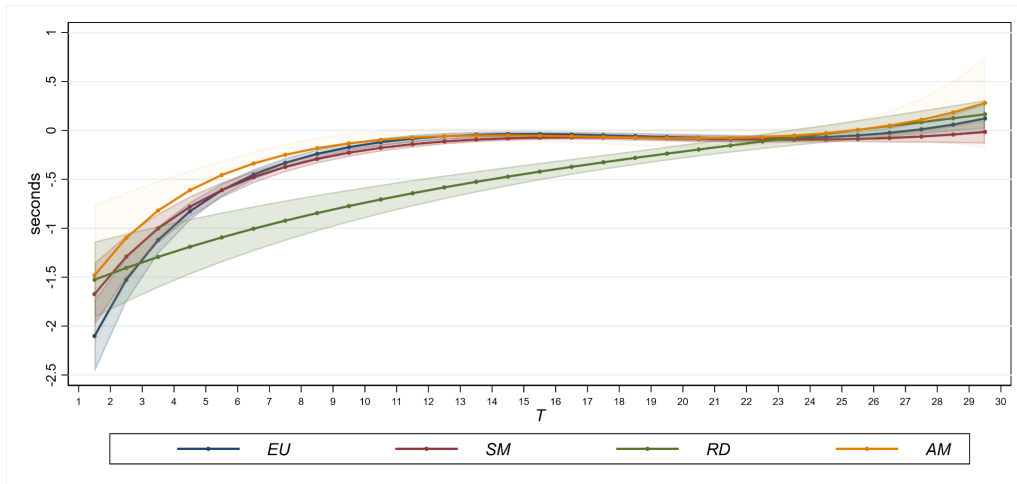
Note: Standard error in parentheses. ***, ** and * denote p -values < 0.001 , < 0.01 and < 0.05 , respectively.



Note: Shaded areas represent 95% confidence intervals.

FIGURE 1.3

EXPECTED DECISION TIME (IN SECONDS) AGAINST TASK POSITION PER TYPE



Note: Dots represent marginal effects between T and $(T - 1)$. Shaded areas represent 95% confidence intervals.

FIGURE 1.4

MARGINAL EFFECTS OF EXPECTED DECISION TIME (IN SECONDS) AGAINST TASK POSITION PER TYPE

convex. There is a similar pattern for all the types: decision time sharply declines in the first 10 tasks; furthermore, it shows that *RD* types are expected to spend the highest amount of time whatever the order of the task in the sequence. Instead, *EU*, *SM*, and *AM* types seem to behave similarly in terms of their expected decision times and spend less time than *RD* types.

Experience has a highly significant impact on decision time for all types in that it

reduces the time spent to make a decision but becomes marginally weaker with accumulated experience. We can appreciate the marginal effect of experience, task by task, throughout the experiment for all the types in Figure 1.4. Such a marginal effect is strong for the *EU*, *SM*, and *AM* subjects in the first 10 tasks, then the curve flattens and the effect is not anymore significantly different from 0, showing no further reduction of decision times due to experience. The *RD* subject behaves differently, demonstrating a monotonic and steady reduction with each task.

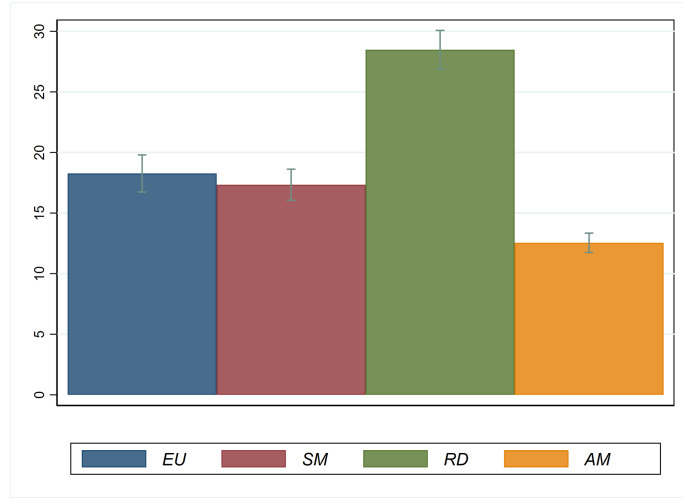
Figure 1.3 constitutes our baseline for the interpretation of the estimation results. Figuratively, in what follows, we will turn on and off the various regressors to analyse their effect on such curves.

Two other regressors used to examine the impact of experience on decision time are the dummy $\mathbf{1}(\text{round} = 1)$ and the variable *round*. Table 1.6 reveals that the former has a strong impact on decision times for every type of subject while the latter is relevant for all the types except for *EU*.

Figure 1.5 shows the effect of the first round of a task.¹⁵ For the *EU* and *SM* subjects the additional time due to the first round effect is very similar (approximately 18 additional seconds). The *RD* subject who seems to take the longest time throughout the experiment takes also the longest additional time in the very first round of each task (28 additional seconds). Not surprisingly, this effect is less pronounced for the *AM* subject with an additional time of about 12 seconds spent on the first round.

Now we consider how the decision time is affected across the rounds of a task. In order to purge the decision time from the time spent to decide on the winning colour in the very first round, we turn the dummy $\mathbf{1}(\text{round} = 1)$ off and the variable *round* on. That is, now all the variables except for γ , T and *round* are set to 0. Figure 1.6 shows how much, on average, the curves in Figure 1.3 shift when a certain round of a task is played.

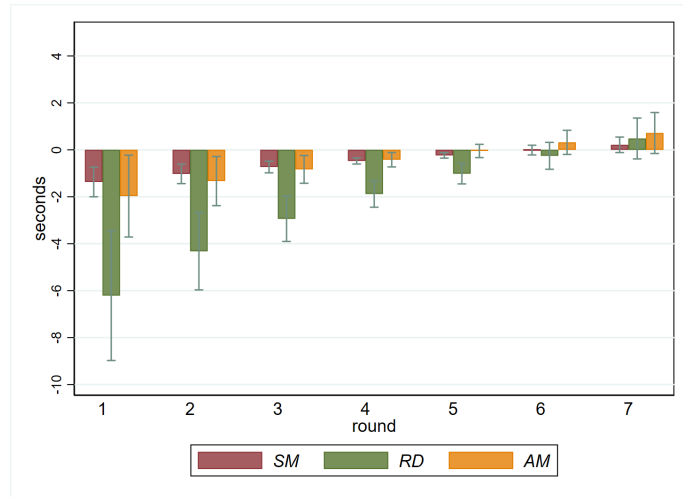
¹⁵Remember that the first round of each task is very special because it involves not only choosing between the two lotteries, but also deciding which colour the subjects want to bet on. An important remark that has to be done is that we cannot record the time spent choosing the colour separately from the time spent on the choice of the lottery. Subjects are probably developing a preference for one lottery over the other since the first part of the first round, when they are required to choose between blue and red balls. Separating the two response times would be pointless because we would have a bias in the time taken to choose between the lotteries, as the subjects would already be familiar with them. We decided to include the dummy $\mathbf{1}(\text{round} = 1)$ exactly to capture this feature of our experiment.



Note: Capped spikes represent 95% confidence intervals.

FIGURE 1.5

MARGINAL EFFECT OF $\mathbf{1}(\text{round} = 1)$ ON EXPECTED DECISION TIME (IN SECONDS)



Note: Capped spikes represent 95% confidence intervals.

FIGURE 1.6

MARGINAL EFFECT OF *round* ON EXPECTED DECISION TIME (IN SECONDS)

As we have seen in Figure 1.5, an *RD* subject spends more time with respect to other types in the very first round, but Figure 1.6 shows that this subject decreases the time spent by more than 5 seconds, on average, in the first 5 rounds. The decision time decreases also for the *AM* and *SM* subjects up to rounds 4, the effects for the following rounds are not statistically significant. However, the average reduction is much less than that of an

RD subject: 1.8 seconds for an *AM* and 1 second for an *SM* subject. The marginal effect of *round* for the *EU* subject is absent from the figure, because her decision time does not seem to change within a task.

Our next result concerns how complexity, defined as the load of information of a lottery, and represented by the variables *#balls*, *dimension-1sl*, *#priors*, $\mathbf{1}(\mathcal{M}$ is symmetric) and $\mathbf{1}(\mathcal{N}$ is symmetric) affects the decision time of each type.

Result 2: *A task appears more complex, so requiring a higher cognitive effort and increasing decision time, the higher the number of balls it contains. The same holds for the dimensionality of the first-stage lotteries. Rather surprisingly, the number of priors reduces the cognitive load for RD types, and consequently their decision times. The symmetry of the two-stage lotteries expedites decisions.*

According to the pattern described by the *chronometric function*, there exists a positive correlation between the complexity of a choice problem and decision time, meaning that an individual will take longer to make a decision when the difficulty of the problem is greater. When analysing the estimation results of the variables which control for complexity on decision time, we apparently get mixed results. In fact, we find that decision time increases with the total number of balls in a decision task (*#balls*), making the decision of the *RD* and *AM* subjects slower; the dimension of the first-stage lotteries, *dimension-1sl*, increases decision time for the *SM* subjects; while it decrease decreases when *#priors* increases for an *RD* subject. We estimate a significant and negative effect for subjects of type *EU*, *SM*, and *RD*, when the unchanging lottery is symmetric. Instead, the symmetry of the changing lottery is relevant only for the *RD* subject.

Some of these results may appear counterintuitive. A possible explanation could be the existence of a “complexity threshold” meaning that, when a choice becomes increasingly difficult, subjects cannot handle nor elaborate all the information provided and prefer to switch to simpler decision-making processes (heuristics) that are not vexing in terms of cognitive effort and make them save time. Another possible explanation, which, in some sense, relates to the previous one, is that the variables that control for complexity can be

strictly positively or negatively correlated. Therefore, the opposite effect of two variables may simply be capturing non-linearities in the effect of complexity on decision time.

Our next result concerns how objective similarity, defined as the similarity in the physical appearance of choice alternatives and represented by the variables $\mathbf{1}(\text{both } \mathcal{M} \text{ and } \mathcal{N} \text{ are symmetric})$, $\mathbf{1}(\text{both } \mathcal{M} \text{ and } \mathcal{N} \text{ are symmetric}) \times \mathbf{1}(\text{round} = 1)$, $|\Delta(\text{dimension-1sl})|$, $|\Delta(\#priors)|$, $|\Delta(\#win-balls)|$ and $\mathbf{1}(\mathcal{M} \text{ and } \mathcal{N} \text{ are identical})$, affect the decision time of each type.

Result 3: *Objective similarity is extremely relevant for SM subjects while RD subjects are affected only partially. It has no significant effects on decision time for EU and AM types.*

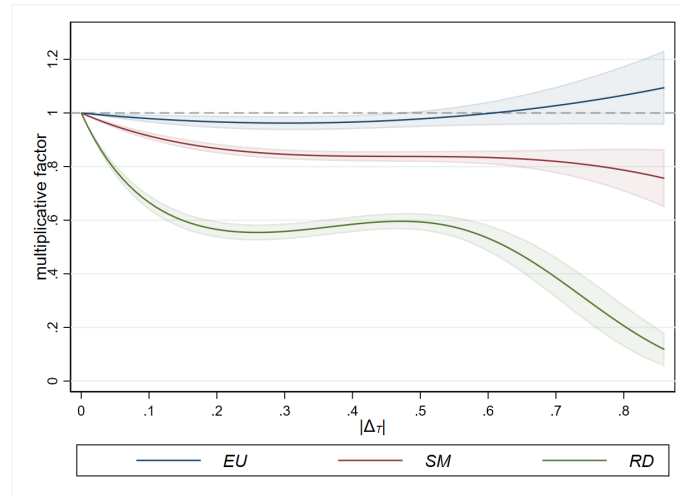
Among the variables that capture the *objective similarity* of the lotteries in a decision task, $\mathbf{1}(\text{both } \mathcal{M} \text{ and } \mathcal{N} \text{ are symmetric})$, which turns on when both lotteries in a decision problem are symmetric, seems to be relevant only for an *SM* decision-maker, increasing her decision time. $\mathbf{1}(\text{both } \mathcal{M} \text{ and } \mathcal{N} \text{ are symmetric}) \times \mathbf{1}(\text{round} = 1)$ considers the effect of the symmetry of the two-stage lotteries in the first round of the task only. It has a negative, significant effect for the *SM* and *RD* subjects.¹⁶ Two identical lotteries decrease the decision time of an *SM* decision-maker. The absolute difference in the number of priors, $|\Delta(\#priors)|$, has an effect for the *SM* subject only, which is estimated to be negative. The same goes for the absolute difference in the number of winning balls, which has a negative effect for *RD* subjects only.

Summarising, objective similarity seems to be very relevant in speeding up decisions for *SM* decision-makers. An *RD* type halves her decision time on average when the two two-stage lotteries are symmetric in the first round. Moreover, as the difference in the number of winning balls grows larger, the decision time of an *RD* subject decrease. Finally, similarity in physical appearance of the two lotteries is irrelevant for *EU* and *AM* decision-makers.

¹⁶Changing lotteries are always symmetric in the first round (because they contain all the possible priors) and may be symmetric or not in the following rounds, depending on the random elimination sequence explained in Section 2. Hence, the effect of the symmetry of the changing lottery can be partially captured by the first-round dummy. For this reason we have added the interaction effect $\mathbf{1}(\text{both } \mathcal{M} \text{ and } \mathcal{N} \text{ are symmetric}) \times \mathbf{1}(\text{round} = 1)$.

Now we turn our attention to the last factor: closeness to indifference. This variable is defined by the absolute difference between choice alternatives' utility evaluations according to each theory, hence it is type specific. We discuss the importance of closeness to indifference separately for each type because we cannot compare it across types, as they miss a common metric.¹⁷

Result 4: *The utility gap between the two two-stage lotteries in a decision problem and its powers, representing closeness to indifference, have a statistically significant effect on the decision times of EU, SM and RD subjects. As the utility gap grows, these subjects tend to reduce their decision times, although the effect is very strong for RD and mild for EU subjects. Closeness to indifference seems to be irrelevant for AM subjects.*



Note: Shaded areas represent 95% confidence intervals.

FIGURE 1.7

FRACTIONAL CHANGE IN EXPECTED DECISION TIME WITH RESPECT TO UTILITY GAP

Figure 1.7 shows how the expected decision time changes (in proportion) with the utility gap. On the vertical axis, the level of the multiplicative factor of decision time is reported: the distance between 1 (dashed horizontal line) and the curves indicate the fraction of time saved by subjects when the difference in utilities between the two lotteries widens. Looking at Figure 1.7, we can see that for a utility gap, $|\hat{\Delta}_{RD}|$, equal to 0.05 the *RD* subject is

¹⁷The $|\hat{\Delta}|$'s vary from 0 to 0.67, 0.86, 0.81 and 0.87 for *EU*, *SM*, *RD* and *AM*, respectively.

expected to save 20% of the time she would spend when making a decision between two lotteries whose utility gap is 0, i.e. when she is indifferent between the two. A utility gap of approximately 0.65, instead, halves the expected decision time (i.e., the multiplicative factor is 0.5). The multiplicative effect is weaker for an *SM* subject, marginal for an *EU* one, while somewhat in the middle between the two for an *AM* subject. Moving from the indifference point until $|\hat{\Delta}| = 0.25$, *SM* and *EU* subjects monotonically reduce their expected decision time by about 17% and 4%, respectively. The effect of closeness to indifference is, in general, non-linear. Overall we can nearly confirm the results obtained by Moffatt (2005) as far as the *RD* and to a lesser extent the *SM* subjects are concerned: when people are evaluating lotteries that have almost the same value they take more time. However, this is only marginally true for *EU* and not at all true for *AM* subjects.

We note that, when subjects classified as being non-*EU* types, as *RD* or *SM*, for example, are incorrectly treated *as if* they were *EU*, their pronounced reaction to the utility gap that we uncover for these types may average somewhat with the meagre reaction to utility gap of the true *EU* subjects. Therefore, the more marked reaction to utility gap of *EU* decision-makers reported in the literature may appear somewhat different from ours simply because it includes the presence of other types of decision-makers that C&H have successfully identified and separated.

6 Validation of decision times across types

Here we describe a validation exercise that enables us to test whether the decision times of a certain type of decision-maker under ambiguity are best predicted by the model of decision time estimated for that type with respect to that estimated for the other types.

We proceed as follows. We use the models estimated from the estimation sample in Section 5 (and displayed in Table 1.6) to predict data in the validation sample for each of the four types. We then regress the validation data of a certain type against the predictions from each of the estimated models, one at a time, and an intercept. For example, to test the performance of the various types in predicting *EU*'s response times in the validation sample, we regress data from the *EU* validation sample against "decision time predicted

by τ ” and an “intercept”, with τ being one of the four types at a time.

For a type $\tau \in \{EU, SM, RD, AM\}$ to be a good predictor, it must hold that the coefficient on the predicted decision time equals 1 and the intercept equals 0 jointly. This joint hypothesis is assessed for each model via an F -test, which under the null hypothesis is distributed according to an F distribution with degrees of freedom equal to the number of estimated parameters (which is always 2) and the number of subjects in the validation sample minus 1, $F(2, \text{subjects} - 1)$. When this joint null cannot be rejected for more than one model, we look at the R^2 , preferring the model with the higher measure. Another alternative way in which we assess the goodness-of-prediction of each model is the root-mean-square error (RMSE) between the validation sample and the prediction. According to this criterion, the “best” predictor is the model with the smallest RMSE.

Table 1.7 displays the results of this exercise. For the validation sample of each of the types, the aforementioned joint null hypothesis cannot be rejected always when the predicting model is that of the corresponding type, which is also the case with the highest R^2 when the joint null cannot be rejected for more than one predicting model (namely, predictors EU and SM for the EU validation data and RD and AM for the RD validation data). The RMSE criterion always indicates the best predictor of decision time for a particular type is the model specific to that type.

7 Conclusion

This work extends the findings of C&H on decision under ambiguity by examining the factors that influence decision time. They classified individuals into four types of decision-makers (Expected Utility Model, Smooth Ambiguity Model, Rank Dependent Expected Utility Model and Alpha Expected Utility Model) based on their decisions, analysed via a finite mixture model. However, they did not investigate the decision times corresponding to the choices. In this paper, we analyse the decision times of those experimental subjects with the purpose of exploring how decision-makers allocate their time when choosing between ambiguous lotteries discriminating between decision types. We consider various factors that can slow down or expedite decision time suggested by psychological theories of the

TABLE 1.7
VALIDATION OF DECISION TIMES

EU validation sample				
	τ			
	EU	SM	RD	AM
<i>decision time predicted by τ</i>	0.9833 (0.0179)	0.9912 (0.0163)	0.9224*** (0.0151)	1.0900*** (0.0182)
<i>intercept</i>	0.0387 (0.0384)	0.0103 (0.0354)	0.1467*** (0.0315)	-0.2024*** (0.0408)
observations	4,712			
subjects	38			
$F(2, 37)$	0.56	0.81	13.91	12.34
p -value	0.5774	0.4514	0.0000	0.0001
R^2	0.7509	0.7341	0.6293	0.7451
RMSE	0.3252	0.3342	0.3982	0.3288

SM validation sample				
	τ			
	EU	SM	RD	AM
<i>decision time predicted by τ</i>	0.9562** (0.0143)	0.9951 (0.0153)	0.9598** (0.0142)	1.0749*** (0.0162)
<i>intercept</i>	0.1069** (0.0301)	0.0128 (0.0326)	0.0840** (0.0295)	-0.1574*** (0.0348)
observations	5,694			
subjects	74			
$F(2, 73)$	9.88	0.18	4.07	10.73
p -value	0.0002	0.8391	0.0212	0.0001
R^2	0.7306	0.7496	0.7078	0.7358
RMSE	0.3354	0.3241	0.3527	0.3340

RD validation sample				
	τ			
	EU	SM	RD	AM
<i>decision time predicted by τ</i>	0.9058*** (0.0168)	0.9538* (0.0177)	0.9961 (0.0186)	1.0236 (0.0194)
<i>intercept</i>	0.2188*** (0.0363)	0.1017* (0.0385)	-0.0022 (0.0403)	-0.0522 (0.0420)
observations	2,254			
subjects	30			
$F(2, 29)$	18.69	3.50	0.79	0.77
p -value	0.0000	0.0435	0.4618	0.4703
R^2	0.6306	0.6796	0.7241	0.6459
RMSE	0.3769	0.3500	0.3288	0.3647

AM validation sample				
	τ			
	EU	SM	RD	AM
<i>decision time predicted by τ</i>	0.8908** (0.0257)	0.9085** (0.0247)	0.8739** (0.0255)	1.0007 (0.0268)
<i>intercept</i>	0.2465** (0.0408)	0.1960** (0.0422)	0.2541** (0.0393)	0.0096 (0.0432)
observations	543			
subjects	7			
$F(2, 29)$	45.10	13.87	65.98	0.46
p -value	0.0002	0.0056	0.0001	0.6496
R^2	0.7420	0.7434	0.6733	0.7468
RMSE	0.3194	0.3214	0.3603	0.3147

Note: Each panel corresponds to the validation of data for the specified type. Data from the validation sample of the specified type is regressed against predictions made using the estimated models of decision time in Table 1.6, along with a constant. The models are estimated via OLS with clustered standard errors at the individual level. ***, ** and * denote p -values < 0.001 , < 0.01 and < 0.05 , respectively. The stars refer to the test of the null hypothesis that the coefficient on *decision time predicted by τ* is equal to 1 and the *constant* equal to 0, against a bilateral alternative. The F tests (and the corresponding p -values reported below) pertain to the null hypothesis that the two aforementioned hypotheses hold jointly. The p -values in bold indicate that the joint null hypothesis cannot be rejected (which is what we want for a model to be a good predictor). When such a joint null hypothesis cannot be rejected for two or more predicting models, the one with the highest R^2 value is remarked in bold. Root-mean-squared errors (RMSE) are calculated between the validation data and their predictors. The smallest RMSE is highlighted in bold.

decision-making process, and which have been largely overlooked by economists.

To our knowledge, this study is the first to investigate decision times based on a classification of subjects into different types, specifically in the context of ambiguity rather than risk.

Building on the assignment to types established by C&H, we employ the same methodology to explain decision times. The data is divided into two parts: an “estimation sample” and a “validation sample”. The estimation sample is used to estimate the relationship between decision time and potential explanatory variables for each decision-maker type. Then, the validation sample is used to assess the accuracy of the predictions of decision time based on the model of decision time estimated for each type. We consistently find that the model that best predicts decision times for a particular type is that specific to that type. Consequently, we provide potential explanations for decision times for each decision-maker type.

At first sight, decision times seem not to differ between types greatly, as shown by the summary statistics in Section 3.2. However, when considering the various factors that could influence decision time, following the econometric analysis by Moffatt (2015), we discover significant differences between decision types. These differences are evident in how decision types allocate time to factors such as experience, complexity, similarity, and closeness to indifference.

Rather obviously, decision time decreases, at a decreasing rate, throughout the experiment for all types of subjects. What is interesting is that not only do different types have different preference functionals, but they also seem to be processing the problems differently. Indeed there seems to be a connection between the type of the subjects and the way they allocate their decision time.

Our analysis hints that theorists should investigate the *process* of pairwise choice, rather than seeing the decision as being arrived at by simply calculating the value of each lottery and comparing them discriminating by decision-making types. Crucially, our results strengthen the effectiveness of the mixture model in C&H in assigning subjects to types. Had the assignment been more casual, we would have not observed differences in decision

times and, more importantly, in decision processes as marked as those uncovered by our analysis. All in all, decision time emerges as a great predictor of decision types and should be analysed along with choice data in order to develop theories of decision-making under ambiguity that encompass both decision and cognitive processes.

In conclusion, the main contribution of this paper lies in its expansion of the literature on decision times, particularly in terms of understanding the decision-making processes of different types of decision-makers under ambiguity. By incorporating psychological theories regarding the cognitive processes underlying different decision rules, we delve deeper into the subject matter.

Chapter 2

Chronicles of Choice: Survey Insights into Intertemporal Preferences

1 Introduction

Intertemporal choices involve individuals balancing their preferences and opportunities over time, including how to allocate consumption and savings between the present and the future. Such choices are influenced by external factors (such as general economic conditions) and internal factors (like personal preferences).

Daily decisions often result in consequences that materialise later, reflecting the complexities of weighing costs and benefits across different periods. Individuals' time preferences play a significant role in shaping numerous economic decisions, particularly those that entail choosing between options with outcomes unfolding over time. Choices such as savings (Choi and Han, 2018), educational attainment (Golsteyn et al., 2014), and choices regarding investments in real estate (Donkers and Van Soest, 1999) are directly impacted by these preferences.

Intertemporal preferences are closely linked to the discount rate, which represents the rate at which future monetary rewards are discounted to their present value, reflecting individuals' preferences for immediate rewards over future ones. Intertemporal preferences influence how individuals discount future utility or benefits, directly affecting their discount

rate. A higher discount rate indicates a greater impatience towards the future, implying a greater preference for present consumption or benefits, while a lower discount rate suggests a higher valuation of future utility. Thus, understanding intertemporal preferences is essential for determining appropriate discount rates in economic decision-making contexts, such as investment appraisal, policy evaluation, and intergenerational welfare analysis, as they greatly impact an individual’s overall well-being.

Previous studies (Green et al., 1994, 1996; Laibson, 1997; Cohen et al., 2020) have shown that individuals exhibiting lower discount rates are more inclined towards positive behaviours such as long-term savings or achieving higher degrees of education.¹ Conversely, individuals with higher discount rates tend to exhibit greater impatience and are more inclined to engage in irrational behaviours (O’Donoghue and Rabin, 1998; O’Donoghue and Rabin, 1999). For example, impatience has been associated with increased credit card debt (Meier and Sprenger, 2010) or with addictive behaviours such as drug use, drinking, smoking and gambling (Kirby et al., 1999; García-Rodríguez et al., 2013; Ohmura et al., 2016).²

A key aspect of this work is that, when it comes to intertemporal decisions, we expect financial literacy to exert a mitigating effect by making individuals less impatient and impulsive. By enhancing individuals’ understanding of financial concepts, such as interest rates, compounding, and investment strategies, financial literacy empowers individuals to make more informed decisions regarding saving and investment. Consequently, individuals with higher levels of financial literacy could alleviate impatience, as they are better positioned to evaluate the long-term implications of their financial choices, reducing the inclination towards impulsive consumption behaviours and leading to more balanced decision-making that improves long-term financial well-being. Therefore, we expect individuals with higher financial literacy to exhibit lower discount rates.

Our research is based on the 2020 Survey on Household Income and Wealth (SHIW) conducted by the Bank of Italy. In addition to collecting comprehensive data on sociode-

¹For a comprehensive literature review about intertemporal choices, time preferences and time discounting we refer the reader to the work of Frederick et al. (2002).

²See Johnson et al. (2020) for a meta-analysis on delay discounting and risky choices.

mographic variables, the survey offers detailed insights into various financial aspects of Italian households, including income, wealth, savings, short-term borrowing, liquidity, and other economic and financial decisions.

This study aims to explore individuals' behaviour regarding time discounting, as we specifically focus on a survey question that directly asks respondents about their preferred discount rate. The question was introduced in the 2020 wave. Nevertheless, we acknowledge that 2020 may be a particular year due to COVID-19. The impact of the pandemic extends far beyond financial realms, influencing things such as daily routines, interpersonal relationships, work dynamics, and even the nature of work itself. Emotions triggered by this crisis mirror those experienced in the aftermath of significant tragedies such as terrorist attacks or natural disasters, evoking feelings of inevitability and helplessness in the face of an uncontrollable force. Therefore, our analysis includes a series of control variables to account for the potential effects of COVID-19 on individuals' time preferences.

The contribution of our paper is threefold. Firstly, we use a comprehensive survey representative of the Italian population to analyse individuals' intertemporal preferences. Secondly, we incorporate financial literacy as a relevant variable, acknowledging its significance in studying time preferences for monetary outcomes, as highlighted by recent literature on the topic (Conte et al., 2024a). Lastly, we incorporate controls for the COVID-19 pandemic, enabling us to identify the factors that undeniably impact individuals' time preferences.

The remainder of the paper is organised as follows. Section 2 describes the data set. Section 3 delineates the variable of interest and its manipulation, and presents the econometric model. Section 4 presents the estimation results. Section 5 concludes.

2 Data set description

We use data from the Italian Survey of Household Income and Wealth (SHIW), which the Bank of Italy has administered since the 1960s. Each survey wave is conducted in person by professional interviewers, typically aided by a laptop (Computer-Assisted Personal Interviewing-CAPI), and covers households representing the Italian population. The

survey is conducted every two years and occasionally every three years, and incorporates a rotating panel feature: approximately half of the participants are interviewed again in the subsequent wave. It gathers comprehensive data on the sociodemographic characteristics of households, as well as their income, savings, wealth, and other economic and financial decisions.

We focus our analysis on the 2020 wave of the survey, as the main variable of interest for our study, coded as “SCONTO”, has only recently become available for this year. While it was also collected in the 2004, 2008, 2010, and 2012 waves, the question was either framed differently or only collected from a random subset of respondents. Originally, the survey was intended to inquire about household (HH, henceforth) income and wealth in 2019, with interviews scheduled for early 2020. However, due to the COVID-19 pandemic, these interviews were postponed until 2021.

Compared to the previous 2016 edition, relevant methodological changes were made. Specifically, the selection of the sample HHs for the interview was based not only on traditional demographic variables but also on information regarding income and indebtedness conditions, which were previously unavailable. This allowed capturing segments of the population, such as the wealthier or more heavily indebted, who often go unnoticed due to their limited representation. These changes have strengthened the survey’s capacity to analyse population cohorts that possess significant portions of the key characteristics of interest.³

Our sample consists of 6,239 HHs, totalling 15,198 individuals. However, as the variable of interest in this analysis pertains to personal attributes and is only queried to the representative individual, we focus solely on the 6,239 HH respondents.

The variable of interest is described in the next section. Summary statistics and description of the other variables used in the analysis can be found in Table D.1 in the Appendix.

³For further details: <https://www.bancaditalia.it/pubblicazioni/indagine-famiglie/bil-fam20>
20/

3 Data analysis

The survey question analysed in this work reads:

Suppose you find yourself in this situation: you learn that you have won the lottery for an amount equal to your household's net annual income. The winnings will be transferred to you in one year. However, if you give up part of the winnings, you can receive the residual amount immediately.

- a.** *Would you give up **20 per cent** of the amount to claim the winnings immediately?*
 - Yes [$\Rightarrow$ End of Section]
 - No [$\Rightarrow$ Question **b.**]
- b.** ***10 per cent?***
 - Yes [$\Rightarrow$ End of Section]
 - No [$\Rightarrow$ Question **c.**]
- c.** ***5 per cent?***
 - Yes [$\Rightarrow$ End of Section]
 - No [$\Rightarrow$ Question **d.**]
- d.** ***2 per cent?***
 - Yes
 - No

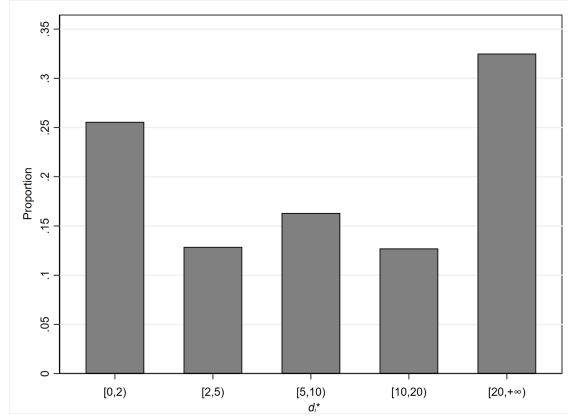
The answer to this question implies an interval of the intertemporal discount rate, where the suffix i , $i \in \{1, \dots, N\}$, indicates the HH respondent,

$$d_i^* = \begin{cases} [0, 2) & \text{if unwilling to give up **2 per cent** of the amount to claim the winnings immediately} \\ [2, 5) & \text{if unwilling to give up **5 per cent** but willing to give up **2 per cent** of the amount} \\ [5, 10) & \text{if unwilling to give up **10 per cent** but willing to give up **5 per cent** of the amount} \\ [10, 20) & \text{if unwilling to give up **20 per cent** but willing to give up **10 per cent** of the amount} \\ [20, +\infty) & \text{if willing to give up **20 per cent** of the amount} \end{cases} \quad (2.1)$$

Here, d_i^* is the latent intertemporal discount rate that we cannot directly observe but that we can allocate to one of the defined intervals via the answer to the question “SCONTO”.

The distribution of the recoded response is shown in Figure 2.1, where we can easily observe that the most popular choices fall within the two extreme intervals.

We model the logarithm of d_i^* as a function of a set of explanatory variables, x_i , which contains an



Note: The graph shows how the distribution of the proportion of responses of the recorded answers, as displayed in Eq. (2.1). Sampling weights were used to produce the graph.

FIGURE 2.1
DISTRIBUTION OF THE INTERTEMPORAL DISCOUNT RATE

intercept. These are linked to $\log(d_i^*)$ via the vector of parameters β :

$$\log(d_i^*) = x_i' \beta + \epsilon_i, \quad \epsilon_i \sim N(0, \sigma^2) \quad (2.2)$$

Here, ϵ_i is an error term following a normal distribution with mean 0 and variance σ^2 .

The probability of d_i^* falling in a particular interval is

$$\Pr(\log(\underline{b}) \leq d_i^* < \log(\bar{b})) = \begin{cases} \Phi\left(\frac{\bar{b} - x_i' \beta}{\sigma}\right) & \text{if } \underline{b} = 0 \\ \Phi\left(\frac{\bar{b} - x_i' \beta}{\sigma}\right) - \Phi\left(\frac{\underline{b} - x_i' \beta}{\sigma}\right) & \text{if } \underline{b} \neq 0 \text{ \& } \bar{b} \neq +\infty \\ \Phi\left(\frac{x_i' \beta - \underline{b}}{\sigma}\right) & \text{if } \bar{b} = +\infty \end{cases} \quad (2.3)$$

where $\underline{b}$ and $\bar{b}$ are the lower and upper bars of the intervals in Eq. (2.1), respectively, and $\Phi(\cdot)$ the cumulative distribution function of the standard normal distribution.

Estimating this model via the Maximum Likelihood technique entails maximising the sum over all the individuals in the sample of the individual likelihood contributions defined in Eq. (2.3). The model corresponds to an interval regression and is estimated in STATA using sampling weights.

4 Estimation results

Table 2.1 displays the estimation results of the interval regression model from the intertemporal discount rate data described above. The explanatory variables are described in Table D.1 in the Appendix. Sampling weights are used, and robust standard errors are reported.

TABLE 2.1
INTERVAL REGRESSION ESTIMATION RESULTS OF DISCOUNT RATE

	Coefficient	std. err.	p-value
Female	0.123	0.100	0.219
Age	0.020	0.010	0.043
<i>Education</i>			
Upper secondary school diploma	-0.126	0.112	0.262
University degree and higher	-0.149	0.136	0.274
Mother's education	-0.298	0.125	0.018
<i>Financial literacy</i>			
Compound interest	-0.309	0.093	0.001
Inflation	0.083	0.098	0.400
Risk diversification	-0.008	0.100	0.932
<i>Civil status</i> (base case = married/in civil partnership)			
Single	-0.083	0.136	0.540
Separated/divorced	-0.056	0.158	0.721
Widow/er	-0.122	0.060	0.042
<i>Employment status</i>			
Unemployed	-0.072	0.070	0.307
Employed	0.229	0.151	0.129
<i>HH income assessment</i>			
Insufficient HH income	0.310	0.105	0.003
Behind in paying utility bills	0.374	0.180	0.038
<i>Income support measures</i>			
Non-COVID-19-related financial assistance	-0.033	0.164	0.840
COVID-19 personal income support measures	0.257	0.151	0.089
COVID-19 HH income support measures	0.246	0.121	0.042
<i>Financial resilience and life satisfaction</i>			
Borrow in an emergency	-0.002	0.094	0.986
Happiness	-0.264	0.090	0.003
<i>Reasons for saving</i> (base case = major purchases (residences, vehicles, furniture, etc.), investments, paying off debts)			
Provision for unexpected events	-0.433	0.146	0.003
Old-age provision	-0.695	0.156	0.000
Education/economic support/legacy to children, grandchildren	-0.448	0.156	0.004
Travel, vacations	-0.229	0.305	0.453
Other	-0.283	0.307	0.356
<i>HH income quintile</i> (base case = I)			
II	0.091	0.155	0.559
III	-0.067	0.167	0.686
IV	-0.321	0.184	0.080
V	-0.444	0.200	0.026
<i>HH wealth quintile</i> (base case = I)			
II	-0.478	0.150	0.001
III	-0.376	0.146	0.010
IV	-0.506	0.149	0.001
V	-0.542	0.163	0.001
Intercept	1.839	0.839	0.028
σ	1.890	0.049	0.000
# Observations		6,239	
Left-censored obs.		1,785	
Right-censored obs.		1,711	
Log-likelihood		-9212.8673	

The literature indicates that cultural and societal differences may influence discount rates (Gong et al., 2014). As in Guiso and Zaccaria (2023), following the idea that social norms are transmitted across generations of individuals living nearby, we define five cohorts based on the year of birth of the household head as follows: 1st cohort < 1944 , 2nd cohort 1945–1953, 3rd cohort 1954–1961, 4th cohort 1962–1970, 5th cohort > 1970 . Each cohort includes approximately 20% of sample households. We then consider the three geographical areas (North, Centre and South of Italy) and create fifteen cohort- and area-specific dummies that identify relevant social group levels. The estimated coefficients on these dummies are omitted from Table 2.1.

We note that in interpreting the coefficient estimates, a decrease in the discount rate implies a move towards rationality, or in other words, being more patient, while an increase implies the opposite. Moreover, since the estimated behavioural equation (2.2) is expressed in log-linear form, a unit increase in the, say, k -th variable $x_{i,k}$ results in a change in the discount rate d_i^* by $\left(100 \times \hat{\beta}_k\right) \%$, where $\hat{\beta}_k$ represents the estimated coefficient on that variable.

The table reveals that being female does not have a significant effect, whereas age demonstrates statistical significance, with each additional year increasing the discount rate by 2%. This result contradicts some psychology literature that suggests a positive association between patience and age (Green and Myerson, 2004; Green et al., 1996; Scheres et al., 2006). Nevertheless, this result could be explained by considering that the answers were collected during the pandemic when older people were inundated with messages urging them to be cautious about their lives. In fact, using the same survey data, Conte et al. (2024a) find that the heightened sense of vulnerability among elderly people results in a higher aversion to financial risk.

The respondent’s level of education appears not to influence the discount rate, whereas those whose mothers were well-educated—taken as a proxy for being raised in a wealthy family—have a discount rate reduced by 30%.

The effect of financial literacy is evident in the knowledge of the answer to the question about compound interest only, reducing the discount rate by 30%. This is an interesting

result, as rational intertemporal decision-makers should compare their discount rate to the interest rate when deciding whether to anticipate or postpone consumption. We also observe that the financial literacy question concerning compound interest is the most challenging, typically yielding the lowest success rate. Surprisingly, knowledge about inflation does not appear to be statistically relevant, despite its potential significance for intertemporal consumption. However, considering that the question about the discount rate is limited to a one-year timeframe, individuals may be more inclined to focus on efficient methods of storing a large windfall rather than considering how it should be spent within such a restricted period. In relation to this, we must note that during the COVID-19 pandemic, Italy experienced a 0.2% increase of headline inflation on a monthly basis and a decrease by 0.2% on an annual basis, with an average annual rate of change of consumer prices of -0.2%.⁴ Having knowledge of risk diversification, which objectively has little to do with intertemporal preferences, does not appear to have any effect on discount rates.⁵

Marital status, whether single, separated, or divorced, does not show a statistically significant impact on our variable of interest compared to married individuals. However, widows and widowers appear to be more inclined to accelerate consumption, possibly due to an increased awareness of mortality resulting from their loss, which may be exacerbated by the mournful times of the pandemic.

Rather surprisingly, the employment status does not appear to accelerate or delay the need for consumption. However, if the household income was insufficient to cover expenses until the end of the month, or if the household had fallen considerably behind (90 days or more) in paying utility bills during the year under consideration, the discount rate increases by roughly 35%.

Receiving a form of income support unrelated to COVID-19 has no effect on the dependent variable. Instead, COVID-19 support measures, either for individuals and HHs,

⁴On average, in 2020, Harmonized Index of Consumer Prices (HICP) reversed the trend for households with less purchasing power (-0.4%, from +0.6% in 2019) and slowed down for those with greater purchasing power (+0.1%, from +0.7%) (Istat, 2021).

⁵In Appendix E, Table E.1, we also report the estimation results using an aggregate version of the financial literacy indicators. Following Conte et al. (2024b), the new indicator records a correct response if the participant answers all three questions correctly or at least two. It notes “don’t know” if the participant selects this option for all three or at least two questions. Otherwise, an incorrect response is logged if at least two answers are provided, with one or more being incorrect.

appear to increase discount rates and impatience. These support measures were introduced in the “Cura Italia” decree by the Italian government in March 2020.⁶ This result aligns with the notion that individuals and families receiving such support have likely experienced or are still experiencing distressing financial situations, which may make them more inclined toward immediate rewards.

Financial resilience does not seem to have any effect on discount rates, given that the coefficient on the variable “Borrow in an emergency” that captures the ability to borrow money from friends or relatives in an emergency is not statistically significant. The opposite holds for the coefficient on the variable “happiness”, which measures the overall life satisfaction of the respondents, being highly statistically significant. Moving one step upwards in the scale of happiness (running from 1 to 10), the discount rate decreases by 26%. This result is in line with Isen (2008), Ifcher and Zarghamee (2011), Lerner et al. (2013) and the literature that studies the connections between discount rates and emotions.

The respondents’ saving philosophies serve as proxies for their long-term perspectives in our analysis. These are represented by a set of mutually-exclusive dummies, with the base case being major purchases such as residences, vehicles, and furniture, as well as investments and paying off debts. We find that only the coefficients on saving for unexpected events, old age, and education and legacy for children and grandchildren are statistically significant, reducing the discount rate of the subjects compared to the base case, while those on saving for vacations and for other reasons are not. This result aligns with our expectations, as we have observed that lower discount rates are associated with forward-looking behaviours in both saving and investment choices. For instance, investments in education are prioritised over expenditures like purchasing a house or a vehicle.

Finally, we introduced the HH income and wealth quintiles among the regressors. The coefficient estimates indicate a consistent decrease in the discount rate with increasing income quintiles compared to the I quintile (the base case). However, only the coefficients on the IV and V quintiles are statistically significant, with p-values less than 10% and 5%, respectively. Particularly noteworthy is the substantial 44% reduction in the discount

⁶The decree introduced several economic support measures for individuals and families, including the “Reddito di Emergenza” (Emergency Income) and various allowances for different categories.

rate associated with the highest quintile. This trend aligns with the notion that higher income levels tend to foster greater patience among individuals, predisposing them to defer gratification in exchange for future rewards.

This pattern becomes even more pronounced when examining wealth quintiles. All coefficients are statistically significant compared to the I quintile (the base case), but they are not statistically different from each other (with the effect of reducing the discount rate by roughly 45%). This suggests that any level of wealth instils greater patience, resulting in lower discount rates than the least wealthy, regardless of its magnitude. While this conclusion mirrors the observations made regarding income quintiles, it holds greater significance due to the distinct nature of wealth (a stock variable) compared to income (a flow variable), as the former provides a more stable measure of economic well-being.

5 Conclusion

Using data from the 2020 Survey on Household Income and Wealth (SHIW), a comprehensive survey representative of the Italian population conducted by the Bank of Italy, our study has offered insights into the determinants of individuals' behaviour regarding time discounting. Intertemporal preferences play a crucial role in shaping numerous economic decisions, particularly those involving choices between options with outcomes evolving over time.

The idea explored is that financial literacy might serve as a mitigating factor for higher discount rates, generally regarded as problematic for leading to irrational behaviours. Our findings have supported our expectations since individuals with a greater understanding of compound interest reduce their discount rate by 30%. This result aligns with the expectation that rational intertemporal decision-makers should be able to compare their discount rate to the interest rate when determining whether to advance or delay consumption. Conversely, the other two questions on financial literacy, concerning inflation and risk diversification, do not affect discount rates. However, this result can be explained by the fact that the question about respondents' discount rate is restricted to a one-year timeframe, and knowledge about risk diversification is not directly related to intertemporal

preferences.

Financial resilience does not seem to have any impact on discount rates. Instead, age, widowhood, income difficulties, arrears in bill payments, and overall life satisfaction show a significant influence.

Since the question regarding the discount rate was first introduced in the 2020 wave, we have recognised that the emotions evoked by the pandemic might have influenced individual time preferences. To address this possibility, we have included control variables to account for the potential effects of COVID-19. Our findings indicate that COVID-19 support measures, whether for individuals or households alike, appear to increase discount rates and impatience. This outcome aligns with the notion that individuals and families receiving such support may have encountered, and likely continue to face, distressing financial circumstances, making them more inclined towards immediate rewards.

Chapter 3

Climate Change and Risk Attitude: An Empirical Study on the Role of Emotions and Knowledge in Shaping Preferences

1 Introduction

Climate change is reshaping the global economy, posing unprecedented challenges to sectors vital for human prosperity. Over the past decades, its economic repercussions have dominated public and academic debates (Stern, 2008; Tol, 2018). From agriculture (Nelson et al., 2014; Malhi et al., 2021) and fisheries (Allison et al., 2009) to tourism (Berritella et al., 2006), no industry remains untouched. Moreover, scientific evidence points to “mounting economic impacts [over time], mostly driven by changes in the right tail of the damage distribution—that is, by major disasters” (Coronese et al., 2019, p. 21450). Climate change is associated with the increase in the frequency and intensity of a multitude of natural disasters, such as floods, landslides, wildfires, extreme heat waves, droughts, storms, and hurricanes (AghaKouchak et al., 2020; Chiang et al., 2021).

Significant environmental changes are likely to affect mental states and decision-making,

including the economic one. There is a growing body of evidence on the effects of climate change on mental health (Doherty and Clayton, 2011; Hayes et al., 2018; Cianconi et al., 2020). In 2017 the American Psychological Association (APA) published the report “Mental Health and Our Changing Climate: Impacts, Implications, and Guidance”, in which it is stated that “Gradual, long-term changes in climate can also surface a number of different emotions, including fear, anger, feelings of powerlessness, or exhaustion”. In this regard, the definition of ecoanxiety was developed ad hoc, defined by the APA as the chronic fear of environmental cataclysm that derives from observing the apparently irrevocable impact of climate change and the associated concern for one’s own future and that of next generations.

There is also a growing scientific literature on how the mental state and emotions experienced by subjects influence their economic choices in various fields (Elster, 1998; Loewenstein, 2000), for example, in contexts in which the outcome is uncertain and depends on a known or unknown probability distribution (Lerner and Keltner, 2001).

This project aims to explore, through consolidated research methods in the fields of behavioral and experimental economics, the relationships that exist between climate change, exposure to environmental disasters and/or issues, emotions, and economic choices under risk. In more detail, based on an experimental design between subjects, we study the effect of exposure to video content on climate change and environmental issues on risk and loss aversion, measured according to the methodology developed by Tanaka et al. (2010), and on the emotional state of subjects. The latter is measured both with the most consolidated methodology in the literature, i.e. self-assessment through the use of PANAS (Watson et al., 1988), and through the measurement of emotions expressed at facial level carried out with Noldus’ FaceReader. In these analyses, a series of variables will be taken into account such as sustainability and sustainable finance literacy, and environmental locus of control (Fielding and Head, 2012) as moderating factors of the treatment effect.

In particular, regarding the locus of control, there is scientific evidence of its relationship with environmental behavior (Hines et al., 1987; Hwang et al., 2000; Alp et al., 2008; Fielding and Head, 2012). Furthermore, there is evidence in economic literature of a

relationship between locus of control and risk attitude. Kesavayuth et al. (2018) find that an internal locus of control is related to greater risk aversion. Salamanca et al. (2020) study the relationship between the locus of control and household investment, finding a positive relationship between internal locus of control and the probability to own equity and the share of equity in household portfolios.

2 Related literature

In this section we illustrate the different literatures related to this research work.

2.1 Risk Attitude

Risk and loss aversion are pivotal concepts in behavioral economics, explaining deviations from classical economic theories. Unlike traditional economic models, which assume rational agents making decisions to maximize utility, behavioral models incorporate psychological factors, revealing that individuals often exhibit preferences inconsistent with Expected Utility Theory (von Neumann and Morgenstern, 1944).

According to the definition given by Fox et al. (2015) a person is considered risk averse if she prefers a sure amount to a chance prospect of equal or higher expected value; she is risk seeking if she prefers a chance prospect to a sure amount that is equal to or less than its expected value, and she is risk neutral if she is indifferent between a chance prospect and a sure amount equal to its expected value.¹

Since Knight (1921), researchers have distinguished between decision-making under risk, where the decision maker knows the exact probability distribution of possible outcomes, and decision-making under uncertainty, where the probabilities are unknown and can only be assessed with some degree of vagueness or imprecision.

A significant departure from EUT was introduced by Kahneman and Tversky's Prospect Theory (Kahneman and Tversky, 1979). Prospect Theory illustrates that individuals value gains and losses differently, leading to loss aversion—the tendency to prefer avoiding losses

¹For a comprehensive literature review and quantitative analysis about risk aversion we refer the reader to the work of Meyer (2014)

over acquiring equivalent gains. An extension of prospect theory, named Cumulative Prospect Theory, was developed later on, again by Tversky and Kahneman (1992), to account not only for choice under risk but also uncertainty.

Risk attitude was studied across several contexts and different results were found. That is because of the many complications and inconsistencies in attempts to measure risk attitude. Such measurements are highly sensitive to design issues including framing effects, elicitation bias, preference reversal, and the gap between willingness-to-pay and willingness-to-accept.² There is much evidence that women are more risk-averse than men (Hartog et al., 2002; Agnew et al., 2008; Borghans et al., 2009). Also, scholars argue about the relationship between risk aversion and cognitive ability. Recent evidence (Lilleholt, 2019) shows that there exists a negative relationship between the two aforementioned variables, although it is domain specific and not as strong as suggested by previous studies (Benjamin et al., 2013).

Moreover, risk attitude is not constant over time. Sakha (2019) shows that the levels of risk aversion change as a consequence of macro- and micro-level shocks. This result supports the findings of Malmendier and Nagel (2011), suggesting that individuals who have experienced high stock market returns report higher tolerance of financial risk, are more likely to participate in the stock market, and allocate a higher proportion of their liquid assets to stock. Guiso et al. (2018) find an overall increase in risk aversion following the 2008 financial crisis that is mainly driven by negative emotions.

The literature presents mixed evidence on the impact of natural disasters and violent conflicts on risk preferences. Heaton and Lucas (2000), using survey data from the United States, find that higher levels of background risk are associated with a reduction in stock market participation. Similarly, Guiso and Paiella (2008) demonstrate that an individual's environment influences risk aversion; individuals who are more likely to encounter income uncertainty or liquidity constraints exhibit a higher degree of absolute risk aversion. In the context of natural disasters, Cameron and Shah (2015) observe that individuals who recently experienced a flood or earthquake display heightened levels of risk aversion. They

²Camerer and Thaler (1995) discuss about the context effects in the Ultimatum Game.

argue that such experiences lead individuals to perceive a higher likelihood of future disasters, thereby prompting a reduction in risk-taking behavior.

Conversely, other studies report opposing findings (Eckel et al., 2009; Voors et al., 2012). For instance, Eckel et al. (2009) investigate the risk preferences of Hurricane Katrina evacuees in the United States and find that these individuals exhibit more risk-loving behavior, attributing this tendency to the emotional state of participants shortly after the disaster. Chuang and Schechter (2015), in their review of the literature, further highlight the conflicting empirical evidence on how natural disasters and conflicts influence changes in risk preferences.

2.2 Emotions, Economics and Decision-Making Process

For a long time, the dominant thought in the scientific community has been anchored to the mind-body dualism theorized by Descartes. From this theory came the relegation of emotions outside of rational thought, identifying in them a role of disturbance of the rational decision-making process; this approach has long been followed also in the economic field. However, this dualistic approach is being overtaken by the work of neuroscientists, e.g. Antonio Damasio and Joseph LeDoux, who show that emotions are an integral and indispensable part of rational reasoning and decision-making. In many occasions, making a decision quickly can be more important than making the optimal one, which on the contrary would require complex evaluations and precious time; in contexts where procrastination may have catastrophic consequences, emotions that trigger immediate instinctive reactions, such as fear, have a beneficial impact (LeDoux, 1995). There is evidence that the lack of ability to experience emotions is associated with (if not the cause of) suboptimal decision making, both in terms of decision time and the appropriateness of the decision made (Damasio, 1994). These advances in neuroscience have prompted a reconsideration of the role of emotions in economic decisions. Two examples of seminal works on this topic are Elster (1998) and Loewenstein (2000), works that have opened and stimulated the debate on the integration of emotions in the modeling of economic decision-making processes. For a long time, economists have neglected emotions because they were considered transitory

and therefore not impactful, but as Loewenstein (2000) points out, many fundamental decisions in the course of life are taken under the strong influence of “visceral factors” such as anger, fear and embarrassment. Furthermore, he rightly points out that even a “visceral factor” that persists for a short period of time can be the driving force leading to actions that will have long-term and significant consequences.

In recent years, there has been extensive research on emotions that has yielded useful insights in various economic contexts, such as trust (e.g. Capra, 2004; Aimone et al., 2014; Engelmann et al., 2019; Kugler et al., 2020; Schniter et al., 2020; see Farolfi et al., 2021 for a survey on the topic), market behavior (e.g. Breaban and Noussair, 2018), tax evasion (e.g. Coricelli et al., 2010; Coricelli et al., 2014; Enachescu et al., 2019), bargaining (e.g. Barry et al., 2004; Ben-Shakhar et al., 2007; Fabiansson and Denson, 2012; Leary et al., 2013; Olekalns and Druckman, 2014), prosocial behavior (e.g. Haselhuhn and Mellers, 2005; Gummerum et al., 2010; Drouvelis and Grosskopf, 2016; Ibanez et al., 2017; Aknin et al., 2018; Pérez-Dueñas et al., 2018), and decision time (e.g. Duque et al., 2013; Treffers et al., 2020).

Another field in which extensive research has been and is conducted in relation to emotions is that of risk perception (e.g. Böhm and Pfister, 2008; Lerner et al., 2003; Yang and Chu, 2018) and attitudes (e.g. Fessler et al., 2004; Callen et al., 2014; Campos-Vazquez and Cuijty, 2014; Dijk, 2017; Conte et al., 2018). The latter, that of the relationship between emotions and risk attitudes, is the domain in which the present study finds its place. A seminal paper on these topics is that of Lerner and Keltner (2001), where the authors find that fearful (angry) people expressed pessimistic (optimistic) risk estimates and risk-averse (risk-seeking) choices, consistent with an appraisal-tendency framework (Lerner and Keltner, 2000). However, evidence on the relationships between emotions and risk attitudes is mixed. A recent meta-analysis on the effect of incidental emotions (happiness, sadness, fear, and anger) on financial risk-taking, based on the results of 26 previous studies, found a causal impact of fear on risk aversion, while it found average null effects of happiness, sadness, and anger (Marini, 2023).

Most of the studies that make up this branch of scientific literature are based on the

induction of emotions to study their effect on the decision-making process. Over the years, different emotions induction procedures have been implemented that can be categorized into active and passive procedures. The former are based on the elaboration of an emotion, for example by asking subjects to retrieve from their memory events that have stimulated a certain emotion and to write a text about it (e.g. Callen et al., 2014). The latter consists of the consumption by a subject of a content that should arouse a certain emotion, for example, a film clip (e.g. Conte et al., 2018). Our study is based on the use of this second methodology of emotions induction.

One part of the story is the induction of emotions; another part is the measurement of the emotions experienced by the subjects. The most widely used method to date consists of self-declaration by subjects of the intensity of emotions felt, through the use of specific questionnaires such as PANAS (Watson et al., 1988). In recent years, algorithms have been developed that can measure the emotions expressed by an individual through her face. In our research, we use both methodologies; in particular, we use a version translated into Italian of the PANAS-C (Ciucci et al., 2017) and the FaceReader software by Noldus. Although not yet particularly widespread, a line of research is emerging in the fields of behavioral and experimental economics that uses Noldus' FaceReader to measure emotions (e.g. Van Leeuwen et al., 2018; Breaban and Noussair, 2018; Cooper et al., 2019; Doyle and Schindler, 2019), a line that will also be enriched by this research project.

3 Experiment

The data analyzed in this paper was collected in the lab. The experiment is about individual decision making, which means that there is no interaction between subjects during the experiment. We adopted a between-subjects approach and each participant took part in only one experimental session. The experiment consists of three parts which are illustrated in detail below.

3.1 Part 1

Part 1 consists of four tasks. First, subjects complete a self-report form to assess their current emotions and moods. To this end, we implement a version of PANAS-C translated into Italian and already scientifically validated by Ciucci et al. (2017). This form is composed of 30 objects representing emotions or moods, randomly ordered on the screen, for which subjects have to declare how intensely they felt that emotion/mood (Likert scale from 1 to 5).

After completing the first task, we ask the subjects with an on-screen message to wear the headphones provided and to perform a soundcheck to verify the correct functioning of the equipment. The soundcheck was programmed in z-Tree and consists of playing an audio file in which a number is pronounced. The subjects are then asked to enter the number they heard in a special field. The experiment proceeds when the sound check has been performed correctly by all participants.

Second, subjects are shown a video clip. The control group is shown a video that should induce a neutral mood. To this end, we selected a video extracted from a documentary about a small Italian town, Calamonaci, already validated in literature for the induction of this type of mood (Maffei and Angrilli, 2019). The treatment group is shown a video containing images of natural disasters associated with climate change and human activity.

The third task involves eliciting risk and loss aversion through Multiple Price Lists (Holt and Laury, 2002). We employ the variant developed by Tanaka et al. (2010) and implement a single-switching protocol known as the switching MPL (sMPL from now on). Each sMPL consists of a series of paired lotteries (see Table 3.1). Each single lottery specifies the possible payoffs along with their associated probabilities (e.g. 30% chance of winning ECU 40 and 70% chance of winning ECU 10).³ The switching points from Lists 1 and 2 are used to estimate the parameters of a risk preference functional form, while those from List 3 are used to estimate individuals' degree of loss aversion. The order in which the three lists are presented is randomised at individual level. The two lotteries

³During the experiment, both positive and negative payoffs were expressed in Experimental Currency Units (ECUs). The exchange rate was ECU 10 : euro 0.75 and it was made known to the subjects at the beginning of the experiment.

that form a pair are arranged side by side to facilitate comparison by the subjects, and are identified as “Lottery A” and “Lottery B”. All the pairs of lotteries that form a single sMPL are lined up and shown to the participants at the same time. For each sMPL, subjects must indicate the switching point, that is, the point at which they want to switch from betting on Lottery A to betting on Lottery B. The experiment is programmed such that a subject is allowed to never switch (always betting on lottery A), or even switch in the first line (always betting on lottery B), or any combination in between. In our experiment we imposed (with appropriate precautions in the programming of the z-Tree code) that subjects cannot make multiple switches in an sMPL. Furthermore, a subject’s choice becomes definitive only when she presses a button to confirm it, in order to avoid selections made by mistake.

As for the two sMPLs for estimating risk aversion, Lottery A remains unchanged throughout the lists, i.e., it is the same in each pair of lotteries. As for Lottery B, it keeps the winning probabilities of the two sums of money fixed but the payoffs increase each time, increasing the expected value of the subsequent lotteries (i.e. $\mathbb{E}[B_1] < \mathbb{E}[B_2] < \dots < \mathbb{E}[B_N]$). Using the switching points of the first two MPLs we jointly estimate the parameter α , measuring the concavity of the value function, and the one-parameter of the Prelec weighting function γ . The mechanism behind the two sMPLs for risk aversion is the same, but the winning probabilities and payoffs differ between the two. As for the sMPL that measures loss aversion, this is slightly different in some aspects from the previous ones. The peculiarity of this sMPL is the presence of negative payoffs in one of the two outcomes of each lottery. This means that both lotteries contained in a pair have a non-negative probability of making the subject lose a sum of money. Furthermore, the payoffs of Lottery A and Lottery B are decreasing unlike the previous cases (in which those were constant or increasing). Using the switching point obtained from this sMPL we estimate the loss aversion parameter λ .

Finally, the subjects perform the fourth task, which consists of a reiteration of the first task. Also in this case, the 30 objects that make up the PANAS-C are presented on the screen in a randomized order. The randomization of this order is carried out both between

TABLE 3.1
THE PAIRED LOTTERY CHOICES USED

<i>LIST 1</i>									
Row	Lottery A				Lottery B				expected payoff difference (A-B)
	probability	payoff	probability	payoff	probability	payoff	probability	payoff	
1	0.3	40	0.7	10	0.1	68	0.9	5	7.7
2	0.3	40	0.7	10	0.1	75	0.9	5	7.0
3	0.3	40	0.7	10	0.1	83	0.9	5	6.2
4	0.3	40	0.7	10	0.1	93	0.9	5	5.2
5	0.3	40	0.7	10	0.1	106	0.9	5	3.9
6	0.3	40	0.7	10	0.1	125	0.9	5	2.0
7	0.3	40	0.7	10	0.1	150	0.9	5	-5
8	0.3	40	0.7	10	0.1	185	0.9	5	-4.0
9	0.3	40	0.7	10	0.1	220	0.9	5	-7.5
10	0.3	40	0.7	10	0.1	300	0.9	5	-15.5
11	0.3	40	0.7	10	0.1	400	0.9	5	-25.5
12	0.3	40	0.7	10	0.1	600	0.9	5	-45.5
13	0.3	40	0.7	10	0.1	1,000	0.9	5	-85.5
14	0.3	40	0.7	10	0.1	1,700	0.9	5	-155.5

<i>LIST 2</i>									
Row	Lottery A				Lottery B				expected payoff difference (A-B)
	probability	payoff	probability	payoff	probability	payoff	probability	payoff	
1	0.9	40	0.1	30	0.7	54	0.3	5	-0.3
2	0.9	40	0.1	30	0.7	56	0.3	5	-1.7
3	0.9	40	0.1	30	0.7	58	0.3	5	-3.1
4	0.9	40	0.1	30	0.7	60	0.3	5	-4.5
5	0.9	40	0.1	30	0.7	62	0.3	5	-5.9
6	0.9	40	0.1	30	0.7	65	0.3	5	-8.0
7	0.9	40	0.1	30	0.7	68	0.3	5	-10.1
8	0.9	40	0.1	30	0.7	72	0.3	5	-12.9
9	0.9	40	0.1	30	0.7	77	0.3	5	-16.4
10	0.9	40	0.1	30	0.7	83	0.3	5	-20.6
11	0.9	40	0.1	30	0.7	90	0.3	5	-25.5
12	0.9	40	0.1	30	0.7	100	0.3	5	-32.5
13	0.9	40	0.1	30	0.7	110	0.3	5	-39.5
14	0.9	40	0.1	30	0.7	130	0.3	5	-53.5

<i>LIST 3</i>									
Row	Lottery A				Lottery B				expected payoff difference (A-B)
	probability	payoff	probability	payoff	probability	payoff	probability	payoff	
1	0.5	25	0.5	-4	0.5	30	0.5	-21	6
2	0.5	4	0.5	-4	0.5	30	0.5	-21	-4.5
3	0.5	1	0.5	-4	0.5	30	0.5	-21	-6
4	0.5	1	0.5	-4	0.5	30	0.5	-16	-8.5
5	0.5	1	0.5	-8	0.5	30	0.5	-16	-10.5
6	0.5	1	0.5	-8	0.5	30	0.5	-14	-11.5
7	0.5	1	0.5	-8	0.5	30	0.5	-11	-13

Note: In each list, subjects are asked to start choosing between lottery A (safer) and B (riskier) from the first row, and to proceed through the rows in order until lottery B is chosen. Prizes are expressed in ECUs.

subjects and between the first and fourth tasks.⁴ Collecting data on emotions again through

⁴In this way we try to minimize the recall effect for each subject, avoiding that in the fourth task the subjects fill out the questionnaire in a mechanical way by replicating the answers given in the first task (therefore not reporting the emotions/moods actually felt at that moment).

the questionnaire allows us to make a pre- and post-treatment comparison in order to verify whether the video clip had the desired effect in arousing emotions in the subjects. This comparison is made both with the results obtained in the questionnaire prior to the video clip and with the results obtained from the FaceReader relating to the emotions expressed at facial level during the viewing of the video clip. Comparing the declared emotions with those observed by the software allows us to verify any discrepancies between the two methods applied. It should be noted that the presence of differences between the emotions analyzed and those reported is not necessarily to be understood as a negative aspect. Depending on the type of difference, we can obtain more or less important information from this analysis.

Upon completion of the second PANAS-C questionnaire, the video recording stops and Part 1 of the experiment ends.

3.2 Part 2

Part 2 consists of a task designed to study subjects' beliefs updating about a probability distribution under ambiguity. Specifically, subjects are asked to estimate the quantity of black balls present in a virtual opaque urn, knowing that it contains six balls that can be either black or white based on an unknown probability distribution. This task consists of ten rounds in which a ball is drawn and the subject is informed of the color of this ball, then the subject must declare the presumed composition of the urn. In each round, the results of the previous extractions are also reported and the drawn ball is put back into the urn, therefore the urn's composition is kept constant across the ten rounds.

This procedure is repeated three times by varying the composition of the urn. The subjects are notified of the variation in the composition of the urn. Therefore, the subjects estimate the composition of the opaque urn for a total of thirty times. In the first 10 rounds, the actual composition of the urn is 3 black balls and 3 white balls, in the next 10 rounds it is 1 black ball and 5 white balls, while in the last 10 rounds it is 5 black balls and 1 white ball.

When reading the instructions in Part 2, the subjects are given useless information

about the balls, namely that the black ones are “winning” ones while the white ones are “losing”. This information is communicated to verify whether a meaningless characterization of the object to be estimated induces a bias in the belief updating process.

3.3 Part 3

In Part 3, the subjects are asked to fill out questionnaires. In particular, they have to fill out an incentivized questionnaire regarding sustainability and sustainable finance literacy.

To assess sustainability literacy, we implement the questionnaire developed by Zwickle et al. (2014). Since this questionnaire was developed for Swiss subjects, we adapted it to the Italian context. It consists of six questions on topics like Sustainable Development Goals, causes of pollution, poverty threshold and GDP growth.

Finally, we submit to the subjects a questionnaire on sustainable finance literacy (Filippini et al., 2024) consisting of eight questions. Like the questionnaire on sustainable finance, this one was also designed for Swiss subjects, so we adapted it for Italian subjects.

In addition to the above questionnaires, we collected a series of socio-demographic variables. More details about these are provided in Section 4.5.

3.4 Payments

Subjects received a participation fee of €5 and were economically incentivized to complete all three parts. The details of the incentive method for each part, shown below, were made known to subjects as they read the instructions. As mentioned above, the earnings achieved for each part are communicated only at the end of the experiment.

For Part 1, subjects were paid for a randomly selected pair of lotteries for each of the three sMPLs. At the end of the experiment, the software randomly selected a row from 1 to 14 for the risk sMPLs, and from 1 to 7 for the loss sMPL with equal probability. Then, the software recalls the choice that the subject made in that row and plays the associated lottery. The outcome of each lottery will be added (or subtracted in the case of negative payoff).

For Part 2, subjects are paid for one round out of thirty randomly selected with equal

probability. In detail, if the estimate made in that round matches the actual composition of the virtual opaque urn, the subject earns €20, otherwise she earns €0.

Finally, for Part 3, the incentive mechanism is slightly more complex than those implemented for the previous parts. In short, subjects earn chances of winning a unique jackpot of €40 through the answers given in the questionnaires on financial, sustainability and sustainable finance literacy.⁵ In detail, each subject is endowed with one point. Then, participants earn one extra point for each correct answer given in incentivized questionnaires. At the end of the experiment, each participant has a probability of winning the unique jackpot of €40 equal to the ratio between the points earned by her and the total points earned by all the participants. According to this probability distribution, one of the participants in the session is drawn to be awarded the jackpot. Previous experimental evidence on incentive methods shows that the implementation of a grand contest maximizes the effort expended by subjects compared to the presence of numerous smaller prizes (Sheremeta, 2011).

The total payoff is therefore the sum of the payoffs achieved for Parts 1, 2 and 3. The average payoff of the experiment was €16.96 (standard deviation €12.06). In more detail, the average gain achieved in the treatment and control group was €18.53 (standard deviation €14.13) and €15.34 (standard deviation €9.30), respectively.

3.5 Procedures

The experiment was conducted in the CESARE Laboratory for Experimental Economics (Luiss University), Rome, Italy, directed by Professor Daniela Di Cagno, with subjects recruited using the ORSEE system (Greiner, 2015). There was a total of 136 subjects. The experiment was programmed and conducted with z-Tree (Fischbacher, 2007). The average duration of an experimental session, including reading the instructions for each phase, was approximately 90 minutes.

At the beginning of the experiment, the experimenters read the general instructions and those for the first part only. Subjects are told that the experiment consists of three

⁵The jackpot size was calibrated in each session to be equal to $€2 \times \text{Number of participants}$. The above stated amount of €40 refers to sessions with 20 participants.

parts from the beginning of the experiment, but the instructions for each part are read sequentially after all participants have completed the previous part. Furthermore, the pay-offs for each part, and thus the total gain for the experiment, are communicated privately only at the end of the experiment.

The subjects are filmed through the PC station’s webcam from shortly before the beginning of Part 1 until the end of it. Synchronization between the video timing and the experiment phases is achieved through the *μCap* software (Doyle and Schindler, 2019). The videos recorded during the experiment are then analyzed post-experiment by Noldus’ FaceReader software, available at the CIMEO laboratory of Sapienza University of Rome. This software quantifies a measure defined in $[0, 1]$ of the intensity with which the subjects experienced 6 emotions (an independent measure for each emotion) every tenth of a second. The emotions measured by the software are happiness, sadness, anger, surprise, fear, and disgust.

4 Description of the dataset and variables

In this section, the variables measured in the experimental sessions and the descriptive statistics are presented in detail. As for the latter, we stress that these are partial results, since the project is still ongoing and the current sample size of 136 subjects (67 assigned to the control group and 69 to the treatment group) is approximately half of the target size.

4.1 Emotions

To measure the emotions experienced by the subjects, we use two methodologies.

First, we use the PANAS-C translated into Italian by Ciucci et al. (2017). It consists of 30 items divided into 15 positive affects (interested, alert, excited, happy, strong, energetic, calm, cheerful, active, proud, joyful, fearless, delighted, daring, lively) and 15 negative affects (sad, frightened, ashamed, upset, nervous, guilty, scared, miserable, jittery, afraid, lonely, mad, disgusted, downhearted, gloomy).⁶ This questionnaire is administered before

⁶The reader is referred to the paper Ciucci et al. (2017) to see the Italian translation of the individual

watching the video clip and after completing the task relating to the three sMPLs. From now on we will refer to the emotions measured in the first PANAS-C as “emotion1” and those measured in the second as “emotion2”. Tables 3.2 and 3.3 show summary statistics of these variables by treatment for the first and the second PANAS-C respectively.

TABLE 3.2
Summary statistics of the first PANAS-C

Variable	Treatment group			Control group		
	Mean	Stand. dev.	Median	Mean	Stand. dev.	Median
Interested1	3.61	0.99	4.00	3.69	1.02	4.00
Alert1	3.61	0.94	4.00	3.78	0.90	4.00
Excited1	2.43	1.06	2.00	2.24	1.14	2.00
Happy1	3.38	0.93	3.00	3.16	0.91	3.00
Strong1	3.30	1.10	3.00	3.03	0.92	3.00
Energetic1	2.91	1.07	3.00	3.01	1.05	3.00
Calm1	3.64	1.24	4.00	3.72	1.08	4.00
Cheerful1	3.14	1.00	3.00	3.25	1.09	3.00
Active1	3.45	1.21	4.00	3.58	0.96	4.00
Proud1	3.06	1.20	3.00	2.85	1.16	3.00
Joyful1	2.88	0.95	3.00	3.01	1.02	3.00
Fearless1	3.13	1.25	3.00	3.15	1.16	3.00
Delighted1	2.51	0.95	2.00	2.45	1.05	2.00
Daring1	3.28	1.04	3.00	3.25	1.09	3.00
Lively1	2.97	1.08	3.00	3.10	1.21	3.00
Sad1	1.81	0.97	2.00	1.87	0.95	2.00
Frightened1	1.41	0.77	1.00	1.61	1.00	1.00
Ashamed1	1.39	0.81	1.00	1.40	0.87	1.00
Upset1	2.03	1.03	2.00	1.94	1.06	2.00
Nervous1	1.86	0.96	2.00	1.97	1.24	2.00
Guilty1	1.26	0.68	1.00	1.43	0.97	1.00
Scared1	1.43	0.72	1.00	1.49	1.01	1.00
Miserable1	1.55	0.74	1.00	1.57	0.76	1.00
Jittery1	2.16	1.13	2.00	2.25	1.35	2.00
Afraid1	1.74	0.85	2.00	1.87	1.07	2.00
Lonely1	1.93	0.96	2.00	2.10	1.16	2.00
Mad1	1.52	0.83	1.00	1.57	0.96	1.00
Disgusted1	1.39	0.81	1.00	1.34	0.81	1.00
Downhearted1	1.88	0.95	2.00	1.97	1.19	2.00
Gloomy1	2.41	1.24	2.00	2.37	1.34	2.00

Note: Summary statistics (Mean, Standard Deviation, and Median) of PA and NA for treatment and control groups in the first PANAS-C.

Second, we measure facially expressed emotions (happiness, sadness, anger, surprise, items.

TABLE 3.3
Summary statistics of the second PANAS-C

Variable	Treatment group			Control group		
	Mean	Stand. dev.	Median	Mean	Stand. dev.	Median
Interested2	3.49	0.93	4.00	3.66	1.02	4.00
Alert2	3.52	0.85	4.00	3.91	0.90	4.00
Excited2	2.35	1.03	2.00	2.34	1.15	2.00
Happy2	2.91	1.01	3.00	3.13	0.97	3.00
Strong2	3.16	1.13	3.00	2.96	0.96	3.00
Energetic2	2.74	1.01	3.00	2.97	1.11	3.00
Calm2	3.41	1.02	3.00	3.67	1.15	4.00
Cheerful2	2.68	1.02	3.00	2.99	1.05	3.00
Active2	3.04	1.12	3.00	3.34	0.99	3.00
Proud2	2.80	1.18	3.00	2.81	1.12	3.00
Joyful2	2.57	0.93	3.00	2.82	1.07	3.00
Fearless2	2.87	1.20	3.00	2.88	1.37	3.00
Delighted2	2.28	1.07	2.00	2.58	1.09	3.00
Daring2	3.00	1.04	3.00	3.21	0.96	3.00
Lively2	2.68	1.04	3.00	2.90	1.03	3.00
Sad2	1.86	1.00	2.00	1.66	0.84	1.00
Frightened2	1.80	0.88	2.00	1.58	0.94	1.00
Ashamed2	1.45	0.87	1.00	1.31	0.72	1.00
Upset2	2.19	1.09	2.00	1.72	0.95	1.00
Nervous2	2.13	1.08	2.00	1.73	1.01	1.00
Guilty2	1.48	0.76	1.00	1.31	0.87	1.00
Scared2	1.75	0.99	1.00	1.46	0.86	1.00
Miserable2	1.83	0.95	2.00	1.60	0.78	1.00
Jittery2	2.19	1.07	2.00	2.03	1.21	2.00
Afraid2	1.86	0.97	2.00	1.66	0.96	1.00
Lonely2	1.67	0.87	1.00	1.96	1.04	2.00
Mad2	1.80	1.01	2.00	1.57	0.92	1.00
Disgusted2	1.75	1.13	1.00	1.21	0.54	1.00
Downhearted2	2.01	1.08	2.00	1.81	0.89	2.00
Gloomy2	2.35	1.21	2.00	2.09	1.20	2.00

Note: Summary statistics (Mean, Standard Deviation, and Median) of PA and NA for treatment and control groups in the second PANAS-C.

fear, disgust, contempt) throughout Part 1. This is done using Noldus' FaceReader, which quantifies such emotions by analyzing videos recorded during the experiment that frame the subjects' faces. In particular, we isolate the emotions expressed by the subjects in the following phases: (I) in the first ten seconds of the video recording (immediately before the administration of the first PANAS-C, to measure the baseline emotional state); (II) during the administration of the first PANAS-C; (III) while watching the video clip; (IV) during the administration of the three sMPLs (separately for each sMPL); (V) during the administration of the second PANAS-C. These results will not be presented here, since the dataset is still under construction (the analysis of video clips and the extrapolation of these data requires a long time); they will be part of the paper at the end of the data collection. For each phase illustrated above, each emotion will be constructed as the average of the value expressed by the subject during the phase (the raw data consist of an observation every tenth of a second). These data will allow, first of all, to measure the effect of the treatment on the emotions collected with a second methodology and to verify any discrepancies with respect to what was self-declared by the subjects; secondly, they will provide a dynamic measure of the emotions expressed by the subjects, while the PANAS-C only allows to take a snapshot of the emotional state at a given moment.

4.2 Risk attitude

To measure the subjects' risk attitudes, we implemented the three sMPLs developed by Tanaka et al. (2010). Table 3.4 shows the descriptive statistics regarding the switching points for the control and treatment groups.

TABLE 3.4
Summary statistics of switching points

	Treatment group	Control group
Switching point List 1	8.00	7.00
Switching point List 2	10.00	8.00
Switching point List 3	4.00	4.00

Note: Median of switching points for treatment and control groups in the three administered sMPLs. No-switching cases are coded as 15 in Lists 1 and 2 and as 8 in List 3 (see Table 3.1.)

4.3 Sustainability and sustainable finance literacy

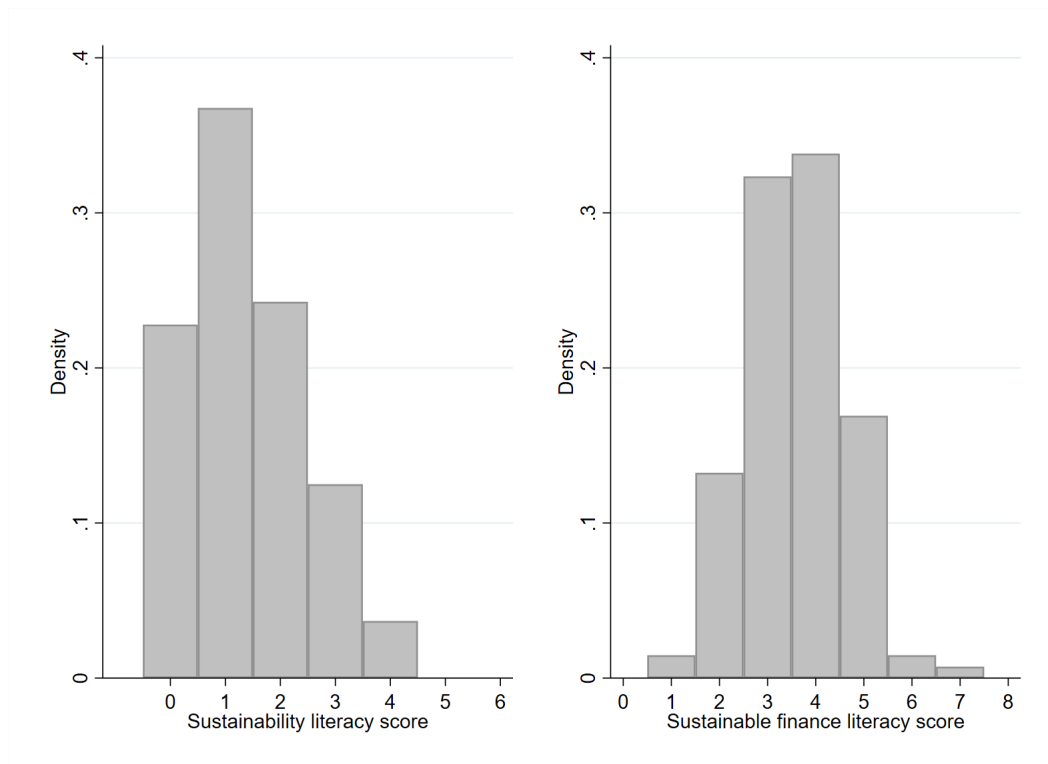
We include in our analysis two measures of knowledge in the form of Sustainability literacy and Sustainable Finance literacy. Sustainability literacy (SL from now on) is used to assess knowledge about three key domains that are central to sustainable development: environmental, economic and social. Sustainable finance literacy (SFL from now on) is a measure assessing the understanding of financial products designed to support sustainable development which involves also awareness of the products. SL is quantified using a set of 6 questions that was developed and validated by Zwickle et al. (2014), that includes all the three separate domains of sustainability. Instead, to measure SFL, we use 8 questions proposed by Filippini et al. (2024) that include knowledge of concepts related to ESG.⁷ In contrast with Zwickle et al. (2014) and Filippini et al. (2024), we incentivize the questionnaire as explained in Section 3.4. This incentive mechanism allow us to reduce the carelessness, improving quality of answers (Bruttel and Wolff, 2018).

Then, we constructed two indicators to measure SL and SFL by adding the number of correct answers for each subject. This means that SL indicator takes values from 0 to 6 and SFL indicator from 0 to 8, since our questionnaire had 6 and 8 questions to assess SL and SFL, respectively. Figure 3.1 shows the distribution of correct answers about SL (left side) and SFL (right side) in our sample.

The distribution of correct answers is different for SL and SFL. More than 20% of the sample incorrectly answered to all 6 SL questions. Moreover, no one got more than 4 correct answers (the median is 1 correct answer). The distribution of correct answer of SFL resembles a normal distribution, with the majority of subjects that answered 4 questions correctly.

We can conclude that our sample has a decent level of education about sustainable finance while struggling a lot on topics related to sustainability, environment, and social responsibility.

⁷We refer the reader to Appendix F for the comprehensive list of questions.



Note: The figure shows the distribution of correct answers for sustainability literacy (left panel) and sustainable financial literacy (right panel) in our sample. N= 136.

FIGURE 3.1
Comparison between sustainability literacy and sustainable finance literacy scores

4.4 Environmental locus of control

Following Fielding and Head (2012), we measure the locus of control regarding environmental issues. Specifically, we ask the subjects to indicate their level of agreement, on a scale from 1 to 5, with the following three statements: “My individual actions can make a difference to the environment” (Statement1); “I can influence decisions now, that will help protect the environment in the future” (Statement2); “I am only one person, I can’t make a difference to the environment” (Statement3, reversed). By summing the first two indices and subtracting the last one, we obtain a measure of how much the locus of control is internalised—i.e., the extent to which the subject believes they have power in determining outcomes, particularly regarding environmental protection. Table 3.5 shows descriptive statistics regarding the three above statements for the control and treatment groups.

TABLE 3.5
Summary statistics of environmental locus of control

Variable	Treatment group			Control group		
	Mean	Stand. dev.	Median	Mean	Stand. dev.	Median
Statement1	3.78	1.16	4.00	3.66	1.09	4.00
Statement2	3.81	1.10	4.00	3.79	1.08	4.00
Statement3	2.13	1.08	2.00	2.15	1.18	2.00

Note: Summary statistics (Mean, Standard Deviation, and Median) of the degree of agreement expressed in relation to the three statements regarding the environmental locus of control.

4.5 Socio-demographic variables

In this section we present the socio-demographic variables that are pertinent to the aim of this research and that we included in the analyses. “Treatment” is a dummy variable equal to 1 if the subject was assigned to the treatment group and 0 otherwise. “Female” is a dummy variable equal to 1 if the subject is female and 0 otherwise. “Urgent goal env.” is a dummy equal to 1 if the subject has declared that “Protect the environment and combat climate change” is an urgent goal, 0 otherwise. This variable is interpreted as an indicator of pro-environmental intention. “Donate env.” is a dummy equal to 1 if the subject answered “yes” to the question “Have you made at least one donation to an environmental organization in the last 12 months (e.g. Greenpeace, WWF, Legambiente,

etc.)?”. This variable is interpreted as a proxy of pro-environmental behavior. Political orientation is a variable that enters the analyses in the form of 2 dummies; “Left” equal to 1 if the subject declared to be left-wing, 0 otherwise (Center or Right); “Right” equals 1 if the subject declared to be right-wing, 0 otherwise (Center or Left). This variable is controlled because a different political affiliation could be associated with different beliefs and positions on many issues, including environmental protection.

Following the standard procedures in survey data, we also collected other variables such as age, education, civil status, or geographic area of origin. Anyway, we did not include such variables in the analyses given that our sample is made of university students with a background in economics and law, and that there is no heterogeneity in the answers.

Table 3.6 shows summary statistics for the above variables.

TABLE 3.6
Summary statistics of socio-demographic variables

Variable	Treatment group		Control group	
	Mean	Stand. dev.	Mean	Stand. dev.
Female	0.62	0.49	0.55	0.50
Urgent goal env.	0.75	0.43	0.60	0.49
Donate env.	0.17	0.38	0.10	0.31
Left	0.43	0.50	0.34	0.48
Right	0.25	0.43	0.28	0.45

Note: Summary statistics (Mean and Standard Deviation) of the socio-demographic dummy variables by treatment.

5 Results

5.1 Treatment effect on emotions

First, we test the effect of video clip viewing on self-reported emotions. Table 3.7 shows these effects on each component of the PANAS-C.

From this analysis, it appears that the treatment had a significant positive effect (subjects reported experiencing negative emotions more intensely after watching the treatment video clip) on all components of negative affect, except lonely. As for positive affect, we find a significant negative effect only on some components (alert, excited, happy, cheerful,

TABLE 3.7
Test of Treatment Effect on Emotions

	Emotion	Coefficient	Std. err.	P-value
Positive Affect	interested	-0.121	0.146	0.407
	alert	-0.438	0.110	0.000***
	excited	-0.248	0.131	0.058*
	happy	-0.578	0.186	0.002***
	strong	-0.010	0.129	0.937
	energetic	-0.152	0.206	0.459
	calm	-0.277	0.291	0.342
	cheerful	-0.394	0.208	0.058*
	active	-0.223	0.124	0.074*
	proud	-0.152	0.163	0.349
	joyful	-0.333	0.131	0.011
	fearless	0.009	0.141	0.947
	delighted	-0.681	0.170	0.000***
	daring	-0.176	0.199	0.375
	lively	-0.095	0.096	0.325
Negative Affect	sad	0.622	0.310	0.045**
	frightened	0.629	0.191	0.001***
	ashamed	0.456	0.274	0.097*
	upset	0.422	0.153	0.006***
	nervous	0.850	0.218	0.000***
	guilty	0.961	0.230	0.000***
	scared	0.540	0.218	0.013**
	miserable	0.494	0.177	0.005***
	jittery	0.424	0.184	0.021**
	afraid	0.385	0.166	0.020**
	lonely	-0.195	0.135	0.151
	mad	0.486	0.182	0.008**
	disgusted	1.046	0.319	0.001***
	downhearted	0.402	0.189	0.033**
	gloomy	0.329	0.198	0.096*

Note: The table presents the test results for the treatment effect on each emotion elicited from the subjects. The effect of the treatment on each emotion is estimated using the ICOprobit model described in Appendix G. The number of observations is 136. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

active, delighted). However, it is likely that the treatment effect may depend on other personal characteristics. For example, a subject who cares about environmental issues could react to the treatment in a significantly different way from a subject who is not interested in such issues. For this reason, we perform an analysis of the treatment effect on positive and negative affect also including other variables that could have influenced the treatment effect. Given the current sample size, among the various socio-demographic information collected, we select those that presumably play a decisive role in moderating the treatment effect.⁸

TABLE 3.8
Test of Treatment Effect on Positive Affect with Controls

	Interested	Alert	Excited	Happy	Strong	Energetic	Calm	Lively
Treatment	0.952	-0.628	-2.698**	0.28	0.169	1.483	-0.892	1.352
Urgent goal env.	0.073	0.072	0.746**	-0.307	-0.035	0.36	0.344	0.171
Treatment×Urgent goal env.	0.489	0.003	-1.139**	0.233	0.024	0.07	-0.941*	-0.048
Donate env.	-0.568	-0.537	0.243	-0.019	-0.477	-0.107	-1.204**	1.298**
Treatment×Donate env.	0.533	1.233**	-0.094	-0.944	0.492	0.065	0.878	-1.753**
SL score	-0.029	0.034	0.033	0.024	0.045	-0.028	0.171	0.057
Treatment×SL score	-0.14	0.106	0.199	0.076	0.048	0.036	-0.098	0.097
SFL score	0.26	0.111	-0.335	0.03	0.007	-0.203	-0.086	0.169
Treatment×SFL score	-0.228	-0.027	0.378*	0.16	-0.014	0.06	0.364*	-0.201
LoC	0.048	0.051	-0.189	0.029	-0.01	-0.383**	0.221	-0.019
Treatment×LoC	-0.057	0.014	0.33	-0.08	0.009	0.264	0.137	-0.222
Left	-0.095	0.098	-0.483	0.78***	0.282	-0.13	0.282	-0.094
Treatment×Left	-0.244	-0.312	0.472	-1.488***	-0.516	-0.392	-0.995*	-0.692
Right	0.156	0.009	-0.182	0.002	0.133	-0.326	-0.071	0.229
Treatment×Right	-0.346	0.07	0.611	-0.181	-0.351	0.458	-0.27	0.646

	Active	Proud	Joyful	Fearless	Delighted	Daring	Lively	PA
Treatment	-0.546	0.701	-0.149	1.259	-1.919	-0.713	0.855	1.594
Urgent goal env.	0.477	-0.235	-0.361	0.756**	0.638*	0.275	-0.072	0.785**
Treatment×Urgent goal env.	-1.349***	-0.176	-0.145	-0.798	-1.11**	0.527	-0.261	-1.938***
Donate env.	0.712	0.062	-0.553	-0.453	-0.584	-0.539	0.174	-0.564
Treatment×Donate env.	-0.767	-0.584	-0.487	-0.17	0.575	0.148	0.225	-0.68
SL score	0.156	-0.023	-0.108	-0.103	0.054	0.045	-0.054	0.087
Treatment×SL score	-0.223	0.119	0.096	0.214	0.081	0.038	0.208	-0.064
SFL score	-0.007	-0.247	-0.089	-0.032	-0.316*	0.065	0.164	-0.22
Treatment×SFL score	0.075	0.39*	0.111	0.038	0.098	-0.169	-0.207	0.319
LoC	-0.311*	0.142	0.058	0.072	0.17	-0.234	0.08	0.073
Treatment×LoC	0.384	-0.306	-0.126	-0.178	0.19	0.259	-0.162	-0.349
Left	-0.652*	-0.054	-0.021	0.64*	-0.358	0.351	-0.086	0.149
Treatment×Left	0.096	-0.426	-0.387	-0.405	0.651	-0.821*	0.444	-0.619
Right	-0.35	0.282	-0.434	0.767**	-0.36	0.379	0.047	0.037
Treatment×Right	-0.267	-0.741	0.438	-1.289**	1.518**	0.062	0.423	-0.733

Note: The table presents the test results for the treatment effect on each positive affect elicited from the subjects controlling for other regressors. The effect of the treatment on each emotion is estimated using the ICOprobit model described in Appendix G. The number of observations is 136. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Tables 3.8 and 3.9 show the results regarding the treatment effect, controlling for the aforementioned moderators, on the components of positive and negative affect respectively.

⁸Once a higher sample size is reached, we will also control for other potential moderators.

TABLE 3.9
Test of Treatment Effect on Negative Affect with Controls

	Sad	Frightened	Ashamed	Upset	Nervous	Guilty	Scared	Miserable
Treatment	0.333	-0.735	-0.670	3.000**	0.336	-1.608	2.351	0.941
Urgent goal env.	-0.329	-0.381	0.252	-0.373	-0.161	-0.773	-0.290	0.195
Treatment×Urgent goal env.	0.879	0.538	-0.293	0.557	0.184	1.047	1.187*	-0.562
Donate env.	-0.060	0.917*	0.302	0.406	0.167	0.827	0.650	-0.126
Treatment×Donate env.	1.244*	-0.661	-0.803	0.413	0.596	-0.646	-0.337	0.157
SL score	0.044	-0.313*	-0.189	-0.052	-0.131	-0.054	-0.077	0.218
Treatment×SL score	-0.150	0.170	-0.174	0.203	0.378	-0.127	-0.170	-0.590***
SFL score	-0.160	0.118	0.006	0.356*	0.110	0.160	0.323	0.082
Treatment×SFL score	-0.390	-0.273	0.095	-0.634**	0.033	0.201	-0.159	0.050
LoC	-0.199	-0.173	-0.228	0.213	0.014	0.103	0.582**	-0.221
Treatment×LoC	0.182	0.538**	0.347	-0.242	0.025	0.193	-0.568*	0.100
Left	0.213	-0.100	-0.192	0.151	-0.260	0.307	-0.477	-0.139
Treatment×Left	0.311	-0.394	0.167	-0.328	-0.470	0.723	0.374	0.301
Right	-0.115	0.150	0.061	-0.153	0.481	-0.043	-0.891	-0.595
Treatment×Right	0.771	-0.225	-0.464	0.244	-0.629	1.146	1.016	0.398

	Jittery	Afraid	Lonely	Mad	Disgusted	Downhearted	Gloomy	NA
Treatment	0.426	0.016	1.100	2.604*	1.669	0.783	-1.543	2.867**
Urgent goal env.	-0.175	-0.159	0.170	-0.167	-0.009	-0.471	-0.036	-0.282
Treatment×Urgent goal env.	0.336	0.991*	0.232	0.978	1.750*	0.137	0.724	0.650
Donate env.	0.101	0.620	0.147	1.074*	-0.429	-0.010	-0.426	0.797
Treatment×Donate env.	0.284	-0.336	-0.286	-0.613	0.779	-0.004	0.095	-0.339
SL score	0.015	-0.197	0.244	-0.073	0.273	-0.073	0.325**	-0.160
Treatment×SL score	-0.406*	0.231	-0.311	-0.152	-1.038*	0.014	-0.147	0.012
SFL score	0.184	0.168	0.185	0.402*	-0.042	0.190	-0.150	0.406**
Treatment×SFL score	0.237	-0.302	0.059	-0.251	0.219	-0.125	0.043	-0.289
LoC	-0.070	0.054	0.370*	0.414**	0.195	-0.028	-0.186	0.278
Treatment×LoC	-0.122	0.175	-0.273	-0.426	-0.247	-0.027	0.302	-0.263
Left	0.076	0.285	-0.516	0.198	1.055	0.221	0.118	0.369
Treatment×Left	-0.109	-0.456	-0.090	0.053	-0.921	0.229	0.353	-0.572
Right	0.440	0.180	0.271	0.355	0.370	-0.504	-0.289	0.363
Treatment×Right	-0.231	-0.340	-0.306	-0.544	-0.844	0.153	0.706	-0.719

Note: The table presents the test results for the treatment effect on each negative affect elicited from the subjects controlling for other regressors. The effect of the treatment on each emotion is estimated using the ICOPROBIT model described in Appendix G. The number of observations is 136. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

As for the positive affect, we find that the treatment has a negative and significant effect on Excited. The interaction between the treatment and Urgent goal env. has a negative and significant effect on Excited, Calm, Active, Delighted and PA (the latter constituted as the difference between the sum of the positive affects declared in the first PANAS-C and the sum of those declared in the second). The interaction between the treatment and Donate env. has a positive and significant effect on Alert and a negative effect on Cheerful. The interaction between the treatment and SFL score has a positive and significant effect on Excited, Calm and Proud. The interaction between the treatment and Left has a significant negative effect on Happy, Calm and Daring. Finally, the interaction between the treatment and Right has a significant negative effect on Fearless, and a positive effect on Delighted.

Regarding negative affects, we find that the treatment has a positive and significant effect on Upset, Mad and NA (the latter constituted as the difference between the sum of the negative affects declared in the first PANAS-C and the sum of those declared in the second). The interaction between treatment and Urgent goal env. has a significant positive effect on Scared, Afraid and Disgusted. The interaction between treatment and Donate env. has a significant positive effect on Sad. The interaction between treatment and SL score has a significant negative effect on Miserable, Jittery and Disgusted, while that between treatment and SFL score has a significant negative effect on Upset. The interaction between treatment and Locus of Control has a significant positive effect on Frightened, and a negative effect on Scared.

Given the above analyses, we conclude that the treatment had a significant effect on the subjects' self-reported emotional state. In particular, a worsening of negative affect in aggregate and of various of its components. However, it is also evident that the effect of the treatment depends on the personal characteristics of the individuals.

5.2 Treatment effect on risk attitude

As explained in Section 3.1, we use sMPLs to elicit preferences for risk, and assume Rank-Dependent Expected Utility (Quiggin, 1982). Then, we use a CRRA power utility function,

and 1-parameter Prelec Probability Weighting function (Prelec, 1998).

Using the switching points from Lists 1 and 2, we jointly estimate the risk preference and probability distortion parameters of each subject in our sample, respectively, α_i and γ_i . We assume that the two parameters are normally distributed, meaning that we have to estimate the moments of the underlying bivariate normal distribution (the mean μ , the standard deviation σ , and the correlation ρ).

The estimation is done using the Bivariate Heterogeneous Preference (BHP) model developed by Conte et al. (2025a). We refer the reader to Appendix H for all the details about the BHP estimator.

We tested four different specifications of our model. Specification (1) is a constant-only model with no regressors. Specification (2) includes the regressor “Treatment”. In Specification (3), “Treatment” is replaced with the dummy “Female”. Finally, Specification (4) includes both “Treatment” and “Female” as regressors.

Table 3.10 shows the results. We report in the upper part of the table the coefficients of the mean μ_α and standard deviation σ_α associated to the risk aversion coefficient α . The mean and standard deviation for the probability distortion parameter γ (μ_γ and σ_γ) are reported in the lower part.

Model (2) shows a negative and significant coefficient of the treatment on μ_α but not on μ_γ . This means that the treatment made the subjects more risk averse while having no effect in influencing their probability-weighting behavior. On the other hand, model (3) shows that the coefficient of the dummy Female is not significant for μ_α while it is positive and significant for μ_γ . The interpretation of this result is that female subjects have a probability-weighting function that is closer to linearity (the case in which $\gamma = 1$) with respect to male subjects. In the domain of risk, there are no significant differences between females and males. Model (4) confirms the results of model (2) and (3) showing that, when including both regressors, the direction and statistical significance of the effects still hold. As usual, Model (1) is included as a benchmark to compare the performance of the other three models that we included.

TABLE 3.10
Estimates of risk preference and probability distortion parameters

		(1)	(2)	(3)	(4)
μ_α	Treatment		-0.2099*		-0.2000*
			(0.1169)		(0.1168)
	Female			-0.1445	-0.1284
				(0.1197)	(0.1186)
σ_α	Constant	-0.6424***	-0.5356***	-0.5573***	-0.4650***
		(0.0593)	(0.0833)	(0.0917)	(0.1054)
		0.6814***	0.6723***	0.6778***	0.6695***
		(0.0455)	(0.0449)	(0.0452)	(0.0447)
μ_γ	Treatment		-0.0200		-0.0700
			(0.0882)		(0.0871)
	Female			0.1902**	0.1894**
				(0.0886)	(0.0888)
σ_γ	Constant	-0.4862	-0.4962***	-0.5991***	-0.6021***
		(0.0442)	(0.0629)	(0.0686)	(0.0796)
		0.5065***	0.5062***	0.4982***	0.4980***
		(0.0341)	(0.0341)	(0.0336)	(0.0335)
ρ		-0.0760	-0.0729	-0.0617	-0.0605
		(0.0930)	(0.0932)	(0.0932)	(0.0934)
loglikelihood		-759.599	-758.002	-756.745	-755.297
obs		136	136	136	136

Note: The table reports the coefficients of the mean and standard deviation for α and γ , and the coefficient of ρ , with standard errors in parenthesis. The columns represent the four different specifications adopted. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

6 Conclusion

This study has analyzed the impact of emotions induced by exposure to multimedia content on climate change on risk preferences, using a between-subject experimental design. The integration of self-reported measures (PANAS-C) and facial expression analysis (Facereader) has allowed for a detailed assessment of the emotional response and its effect on economic decisions.

The results have shown that exposure to a video containing images of natural disasters associated with climate change has led to a significant increase in the intensity of negative emotions among treated subjects. Specifically, compared to the control group, the treatment has resulted in a significant increase in fear, sadness, nervousness, and disgust. At the same time, a decrease in certain positive emotions, such as happiness and enthusiasm, has been observed, suggesting a general negative effect on emotional well-being.

The analysis of interactions between the treatment and individual characteristics has revealed that subjects with greater sensitivity to environmental issues (measured by declaring

environmental protection as a priority goal) have exhibited an amplified emotional reaction, with a significant increase in fear and disgust post-treatment. Additionally, the level of sustainability and sustainable finance literacy has moderated the treatment effect, with more informed subjects showing a lower variation in negative emotions.

The analysis of risk choices, based on multiple price lists (sMPLs), has shown that treated subjects have exhibited greater risk aversion compared to the control group. Specifically, the median switching point in binary choice tasks has increased from 7 to 8 in the first sMPL and from 8 to 10 in the second, suggesting a stronger preference for less risky options after video exposure. The analysis using the Rank-Dependent Expected Utility (RDU) model has confirmed a significant variation in the risk aversion parameter (α), with an average reduction of -0.21 in treated subjects, indicating a more cautious attitude.

No significant effects have been found on probability distortion (γ), suggesting that the treatment has primarily influenced utility evaluation rather than probability weighting. However, we have found that females exhibit a lower degree of probability distortion compared to males.

These results suggest that emotions triggered by climate change-related content can significantly influence risk attitudes, with important implications for understanding economic behavior in uncertain environmental scenarios. The increase in risk aversion among exposed subjects indicates that communication about climate-related disasters may impact financial decisions, sustainable investments, and insurance choices against extreme events.

Future research could explore the persistence of these effects over time and the role of additional individual factors, such as environmental locus of control and institutional trust, in moderating the relationship between emotions and risk-taking. Additionally, comparative studies could examine whether content emphasizing positive solutions to climate change induces different emotional and behavioral responses.

Chapter 4

Green is the New Black: Bridging Climate Awareness and Sustainable Investing

1 Introduction

“Like the meteor that wiped out the dinosaurs, we are having an outsized impact. In the case of climate, we are not the dinosaurs. We are the meteor. We are not only in danger. We are the danger. But we are also the solution.”

UN Secretary-General António Guterres, 2024

Climate change is one of the most pressing challenges of our time, impacting people’s well-being and posing significant risks to the economy and financial system (Cavallo et al., 2013; Felbermayr and Gröschl, 2014; Litterman et al., 2020; Liu et al., 2024). In 2015, two landmark international agreements were established: the United Nations’ Sustainable Development Goals (SDGs) and the Paris Agreement on climate change to drive global sustainability and climate action. Initiatives like RE100 and the Portfolio Decarbonization Coalition support these efforts. The European Union, a strong advocate for a low-carbon

economy, launched the European Green Deal on 11 December 2019 to make Europe climate-neutral by 2050.

Increasing social awareness of climate change, pollution, and inequality has driven significant shifts in investor behaviour. In recent years, concepts such as corporate social responsibility (CSR), environmental, social, and governance (ESG) factors, and financial sustainability have gained substantial prominence and investors' interest. According to Eurosif (2021) institutional investors play a much more significant role in terms of volume invested compared to retail investors. Nevertheless, there is evidence that individual investors are very important for public acceptance (Revelli, 2017; Gutsche et al., 2021).

People's perception and beliefs about the future effects of climate change have significant consequences, influencing both their present decisions and asset prices in financial markets (Bernstein et al., 2019; Baldauf et al., 2020; Giglio et al., 2021). Awareness of climate change is key in shaping the acceptance and effective implementation of both mitigation and adaptation policies (Dechezleprêtre et al., 2022), as well as in promoting collective action toward sustainable practices. Understanding the diverse factors that influence beliefs and attention to climate change is essential for shaping effective communication strategies, informing policy decisions, and fostering a collective commitment to mitigating the global climate crisis.

According to the European Commission "Sustainable finance refers to the process of taking environmental, social and governance (ESG) considerations into account when making investment decisions in the financial sector, leading to more long-term investments in sustainable economic activities and projects".¹ Sustainable finance is crucial for achieving the policy goals outlined in the European Green Deal and fulfilling the EU's international commitments to climate and sustainability objectives, by directing private investments toward the shift to a climate-neutral, resilient, resource-efficient, and equitable economy, complementing public funding in the process. Transitioning to a climate-neutral economy will demand substantial financing. Anderson and Robinson (2022), using a large sample of Swedish households, find that subjects who exhibit stronger pro-environmental values

¹https://finance.ec.europa.eu/sustainable-finance/overview-sustainable-finance_en

do not hold greener investment portfolios. This is largely because such households often demonstrate a lack of engagement in financial decision-making. On the contrary, there is extensive literature documenting how some investors prefer socially responsible (Hartzmark and Sussman, 2019; Bauer et al., 2021) and climate-conscious investment products (Ceccarelli et al., 2024). Global ESG integration had surged by 143% between 2016 and 2020, with total assets under ESG management now reaching USD 25.2 trillion (Global Sustainable Investment Alliance, 2021). The shift toward responsible investing has accelerated significantly, particularly over the past five years. A key driver of this trend has been the EU’s adoption of a taxonomy for sustainable activities, which took effect on July 12, 2020. Over half of the investment inflows into European financial products are directed towards sustainable options (Morningstar, 2021). Nevertheless, according to IEA (2023), achieving a low-carbon economy will require scaling up clean energy investments to around USD 4 trillion annually by 2030, a fourfold increase compared to the 2022 investment levels.

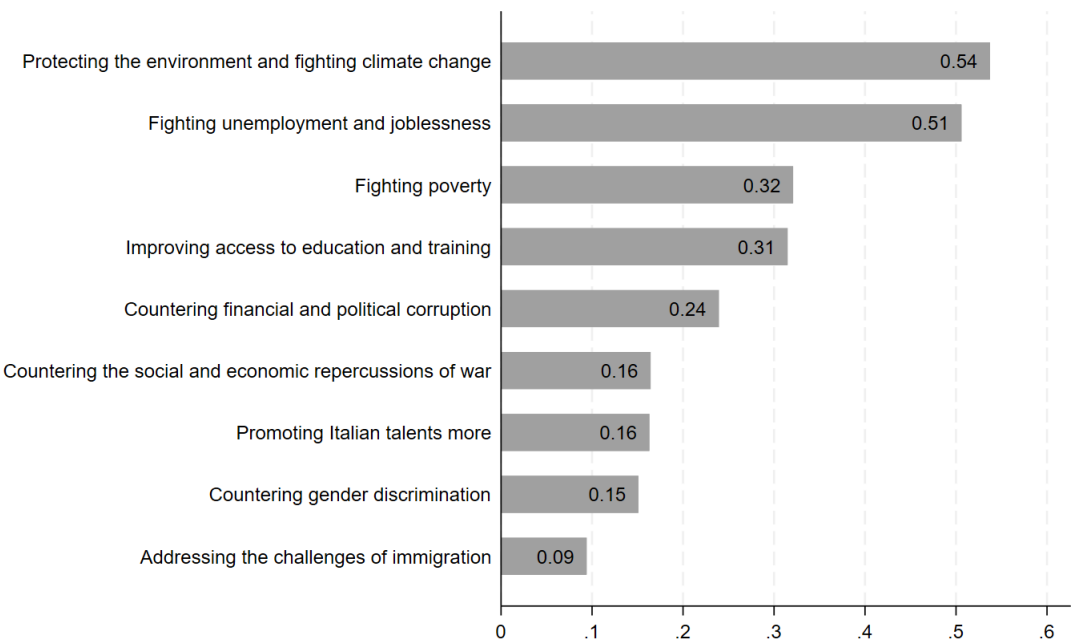
This paper examines the factors driving demand for ESG products, focusing on the impact of climate awareness and different forms of literacy, and investigates whether this awareness influences investors’ preferences for sustainable products. A substantial body of literature, particularly environmental psychology research highlights a gap between environmental awareness and actual pro-environmental behaviour—actions aimed at reducing negative impacts, such as reducing resource and energy consumption, using non-toxic substances, and minimizing waste production.

To address our research question, we use the recent *Survey on Financial Literacy and Digital Financial Skills in Italy: Young Adults*, carried out by the Bank of Italy on over 5,000 young adults in 2023. Surveys are widely used to measure climate change awareness and gather opinions on its severity, environmental preservation efforts, individual actions, and governmental and corporate responsibilities in tackling climate issues (see Baiardi, 2023, for a review).

Young people, who will bear the greatest burden of climate change, are also the most concerned about its impact. According to a recent study surveying 10,000 young people aged 16 to 25 in ten countries, nearly 70% said they were either extremely or very worried

about climate change (Hickman et al., 2021). This result aligns with findings observed at the European level. According to the 2021-2022 European Investment Bank Climate Survey (EIB, 2021), which explores citizens' perception of climate change, 88% of Italians believe that tackling climate change and its consequences is the biggest challenge of the 21st century – 7% points above the EU average of 81%.

The survey we use prompts participants to identify up to three goals they consider most urgent at present with the question: “Which of the following goals do you consider most urgent at this time?” As shown in Figure 4.1, the responses highlight "Protecting the environment and fighting climate change" as the most pressing concern, receiving over 54% of the votes. This is followed closely by “Fighting unemployment and joblessness” which received 51%. In contrast, “Fighting poverty” ranks third, with a significantly lower 32% of the responses.



Note: The figure shows the percentage of responses for each goal listed in the survey. Respondents can choose up to three answers. N= 5,364. Sampling weights are used to generate the figure.

FIGURE 4.1
Responses to the question: “Which of the following goals do you consider most urgent at this time?”

However, concern for the climate does not always translate into knowledge of effective

action or the willingness to take it. Thus, we explore the factors that lead young people to prioritise protecting the environment and fighting climate change, so they are motivated to adopt behaviours that align with this goal. Moreover, investments in green finance are essential for supporting environmental initiatives. Growing climate concerns, particularly among younger generations, may influence investment preferences. However, if the desire to improve the environment is not linked to sustainable finance, this could pose a challenge. Our focus is exploring whether individuals who are more climate-conscious are also more likely to invest in sustainable products. Policy interventions could focus on aligning “environmental consciousness” with the ability to identify sustainable investments.

Examining Italy provides a compelling case study of climate-related physical risks, as the country faces significant hydrogeological threats driven by both natural and human factors (Trigila et al., 2013).² The impact of natural disasters extends beyond physical destruction, influencing expectations, reshaping perceptions of disaster risk, and increasing uncertainty about the future, all elements that influence profitability and investment returns in the aftermath of a disaster (Zhou et al., 2023). In a recent study, Crispino and Loberto (2024) construct a Twitter-based indicator to track public awareness of climate change in Italy between 2016 and 2022. The study reveals a growing public interest in climate change, with notable surges following significant events, such as the global spread of the *Fridays For Future* social movement and unprecedented heatwaves that impacted much of Europe during the summer of 2022. Environmental hazards create uncertainty, which intensifies when such events occur, resulting in lasting impacts (Sheng et al., 2022). This uncertainty significantly shapes economic decisions related to consumption, investment, and income inequality ultimately harming the real economy (Bloom, 2009; Jurado et al., 2015; Errico et al., 2025).

In addition to the question mentioned above, the survey also assesses financial literacy (FL) and digital financial literacy (DFL), allowing us to explore their relevance.

²These physical risks are also a concern for key Italian economic sectors. Climate change is expected to have major repercussions, particularly on agriculture, affecting vital crops such as corn, durum wheat, and grape for winemaking (Accetturo and Alpino, 2023). The tourist compartment will also face significant challenges due to rising temperatures and declining snowfall in the mountains (Mariani and Scalise, 2022), along with the negative effect of high temperature on house prices (Cascarano et al., 2023).

While there is broad consensus on the importance of FL for various aspects of life, such as impacts stock market participation (Van Rooij et al., 2011; Hermansson et al., 2022; Yeh and Ling, 2022), portfolio choices (Chu et al., 2017) retirement planning (Yeh, 2022; Lusardi and Mitchell, 2017), wealth accumulation (Stango and Zinman, 2009; Behrman et al., 2012; Van Rooij et al., 2012; Jappelli and Padula, 2013), and debt management (Lusardi and Tufano, 2015; Brown et al., 2016), its influence on socially responsible preferences is still debated in the literature.

The connection between financial literacy and preferences for sustainable financing and investing has been studied in the context of individual retail investors and small and medium firms. Nevertheless, the empirical evidence remains inconclusive on whether FL directly translates into sustainable investment behaviour. While some research indicates that individuals with greater financial literacy are more likely to invest in socially responsible investment (SRI) products, as they better understand the trade-off between financial returns and sustainability objectives (Gutsche et al., 2021; Aristei and Gallo, 2021; Riedl and Smeets, 2017; Borgers and Pownall, 2014), or choose socially responsible financial intermediaries (Cucinelli and Soana, 2023); other studies document a limited or even negative impact (Gutsche et al., 2023; Filippini et al., 2024).

Given the recent proliferation of financial products with sustainable characteristics—and the lack of clear evidence on how financial literacy influences sustainable investment decisions—a new measure of literacy has been developed to account for sustainability preferences. The concept of sustainable financial literacy (SFL) aims to capture individuals' knowledge of financial products designed to support sustainable development (Filippini et al., 2024).

The rapid growth of digital financial services and products, accelerated by the significant advancements in financial technology (FinTech), and exacerbated by the COVID-19 pandemic, has led to increased availability and adoption of digital financial services (Fu and Mishra, 2022; Ferilli et al., 2024). With the introduction of new technology in financial products, consumers increasingly need to acquire both financial knowledge and digital competences. While traditional FL remains crucial, it may not be the sole determinant

of financial well-being in a digital economy. As such, it should be complemented with digital skills so that individuals can apply their knowledge efficiently and safely on digital platforms. (Choung et al., 2023)

This trend has led to the development of the concept of digital financial literacy (DFL), reflecting the growing importance of digital skills for engaging with financial markets, as digital platforms have become the primary access point for investment opportunities (Lyons and Kass-Hanna, 2021). However, there is no consensus in the literature regarding the impact of these changes on financial well-being. FinTech and technology can, in fact, negatively impact financial well-being by encouraging impulsive spending behaviour. Instantaneous access to financial services through online platforms, apps, and e-wallets may lead to impulsive consumption, harming consumers' welfare (Lee et al., 2023).

Research suggests that individuals with higher DFL are more likely to engage in sustainable finance, as they are better equipped to assess ESG products and manage digital financial risks (Van Rooij et al., 2011; Kass-Hanna et al., 2022). The findings from both Kass-Hanna et al. (2022) and Lyons and Fontes (2021) consistently show that FL and digital competences are key factors in building positive financial behaviour and long-run financial security. Lyons and Kass-Hanna (2022) posit that while digital solutions like robo-advisors, virtual and hybrid advisors, and personal finance communities offer efficient and appealing alternatives to traditional services, there are accessibility and usability barriers that underscore the importance of digital financial literacy. Challenges such as online security concerns and limited accessibility continue to hinder widespread involvement in green finance initiatives (Marconi et al., 2024).

In parallel, climate awareness is a growing determinant of financial behaviour. Studies demonstrate that environmental concerns are increasingly shaping investors' portfolio choices, with a notable shift toward ESG-aligned investments (Ceccarelli et al., 2024; Gutsche and Zwergel, 2020). Bolton et al. (2020) further highlight the financial system's role in addressing climate change, arguing that sustainable finance is crucial for aligning capital flows with low-carbon economic growth. However, ESG ratings divergence and greenwashing concerns remain significant challenges (Berg et al., 2022).

The contribution of this paper is threefold. Firstly, we explore a relatively underutilised survey which, to the best of our knowledge, has only been previously used to investigate the role of financial literacy in shaping young people’s entrepreneurial aspirations (Lamboglia et al., 2024). Secondly, while prior research has examined the intersection of financial literacy and sustainable investing (Lanciano et al., 2024; Aristei et al., 2024), this study extends the literature by exploring how DFL, FL, and climate awareness jointly influence young adults’ engagement with sustainable finance. Thirdly, we use a large representative sample, a novel aspect compared to previous studies that focus on SFL within a selected group of experts. Moreover, our sample consists of young adults, who are the future financial decision-makers.

The reminder of the paper is organised as follows. Section ?? describes the data. Section ?? presents the econometric model to estimate the data. Section ?? discusses the estimation results. Section ?? concludes.

2 Data and variables

We use data from the *Survey on Financial Literacy and Digital Financial Skills in Italy: Young Adults* conducted by the Bank of Italy. This survey, carried out for the first time in 2023, was administrated to a sample of 5,372 young adults between 18 and 34 years old, interviewed online through Computer Assisted Web Interviews (CAWIs). The sample accurately represents the young adult population in Italy, as respondents were selected using quota sampling to ensure proportional representation by age and geographical area of residence (Marinucci et al., 2023). The survey collects detailed information on the understanding of fundamental economic and financial concepts, as well as financial behaviour and attitude, alongside individual preferences, such as risk aversion, a range of socio-demographic characteristics, and their preference for sustainable investments. Our estimation sample consists of 5,364 observations with complete data for all variables used in the empirical analysis.

2.1 Key variables

In this section, we outline the variables included in our analysis. Table I.1 in Appendix I presents the definitions and summary statistics for all variables used in the empirical analysis, while Appendix J provides the exact survey questions.

2.1.1 Dependent variable

The main focus of this work is to investigate the determinants of the demand for ESG products. The literature on this topic is extensive, examining both actual investments (Døskeland and Pedersen, 2016; Gutsche et al., 2021; Riedl and Smeets, 2017; Bauer et al., 2021; Anderson and Robinson, 2018) and hypothetical choices (Barreda-Tarrazona et al., 2011; Gutsche and Zwergel, 2020; Heeb et al., 2023; Rossi et al., 2019; Filippini et al., 2024). Our dependent variable, *ESG*, is a binary variable taking the value 1 if respondents take into account ESG criteria when investing their savings, or would consider them if they had savings to invest; 0 otherwise. Thus, our survey question is designed to capture both actual investment behaviour and hypothetical scenarios.

Individual investors aim to maximise their utility using the information available at the time of their decisions. Investors who value ESG factors in their utility functions are more likely to invest in high-ESG stocks, even with lower returns, while expecting greater return incentives to consider low-ESG stocks. This interplay highlights the inherent tension between ESG preferences and financial returns. Giglio et al. (2021) report how 45% of surveyed investors see no justification for investing in ESG products, 25% invest for ethical reasons, and only 7% are motivated by potential returns.

Recent literature distinguishes between two types of sustainable investors: those motivated by *value* (financial reasons) and those driven by *values* (social impact) (Starks, 2023). While the survey does not precisely adopt this terminology, respondents who answered affirmatively can still be grouped into two main categories of investors or potential investors. The first category includes those who consider (or would consider) ESG criteria in their investment decisions. These respondents selected: “Yes, and I normally take them into account when deciding how to invest savings (or would do so if I had any savings

to invest)” or “Yes, and I would take them into account if there were more ESG financial instruments to invest in (and I had resources to invest)”. The second category includes individuals who do not consider (or would not consider) ESG factors in their investment decisions. These respondents selected: “Yes, but I don’t normally take them into account when deciding how to invest savings (or wouldn’t take them into account if I had savings to invest)”.

2.1.2 Literacy and awareness measures

FL is widely recognised as a key factor influencing consumer participation in financial markets and services (Lusardi and Mitchell, 2014). Building on existing literature, we also consider SFL. Moreover, in today’s financial landscape, digital skills have become essential for individuals seeking to invest.

Building on the “Big Five” framework (Lusardi and Mitchell, 2007), we construct a measure of FL based on five questions from the survey: compound interest rates, inflation, risk diversification, the relationship between risk and return, and knowledge of mortgages. Additionally, as a robustness check, we calculate three alternative measures of financial literacy. The first follows Lamboglia et al. (2024) and consists of five questions, differing from our measure by including a question on simple interest rates while excluding the one on risk-return. The second measure consists of six questions, adding the simple interest rate question to our original measure. Finally, the third measure comprises eight questions, incorporating additional questions on stock market predictability and whether a bank account protects against inflation, as in Marinucci et al. (2023). Our findings yield qualitatively similar results.

Figure I.1 in Appendix I illustrates the various components of FL. The most widely recognised concept is the risk-return relationship. Among the “Big Five” questions, the most familiar concept is the mortgage costs, with over 70% correct answers. Topics such as inflation, risk diversification, and simple interest rates are understood on average by around 64% of respondents, while the concept of compound interest stands as the most difficult with only 40% of correct answers. For the remaining questions, approximately half

of the respondents think that keeping savings in a current account always protects them from inflation, and a similar number believe that experts can accurately predict stock performance.

Recent studies demonstrate that financial literacy and digital skills are closely linked (Prete, 2022). Digital literacy is a crucial factor in determining households' financial resilience and overall well-being (Kass-Hanna et al., 2022; Choung et al., 2023). Marconi et al. (2024) focus on two waves of surveys conducted on the Italian adult population, one before and one two years after the outbreak of the COVID-19 pandemic. They demonstrate that digital skills are crucial in shaping financial behaviours and attitudes, including those toward digital financial services, but they appear irrelevant to investment decisions. According to the 2022 Index of Digitization of the Economy and Society (DESI)³ developed by Eurostat, which uses indicators related to technological advancement, Italy lags behind the EU average in terms of more advanced digital skills. DFL is a multifaceted concept that combines elements of both financial literacy and digital skills, along with aspects specific to the access and use of digital financial services (Lyons and Kass-Hanna, 2021). It is defined as "a combination of knowledge, skills, attitudes and behaviours necessary for individuals to be aware of and safely use digital financial services and digital technologies" (OECD, 2022). Following the existing literature (Luo et al., 2021; Lamboglia et al., 2024), we construct the DFL variable as an index ranging from 0 to 7. Respondents receive a score of 1 for each of the seven questions in which they answer "Very" or "Quite" regarding their use of digital devices for various financial activities.

For private investors to make well-informed decisions about financial products with sustainable characteristics, they must have a solid understanding of both general financial literacy and sustainable finance concepts. SFL measures an individual's understanding of financial products designed to support sustainable development (Filippini et al., 2024). We define *SFL* as a binary variable which takes value 1 if people know about ESG products, 0 otherwise. Building on Filippini et al. (2024), we assess the role of sustainable finance in highlighting environmental concerns by defining Sustainable Finance Awareness (SFA)

³https://digital-agendadata.eu/datasets/digital_agenda_scoreboard_key_indicators/indicators

as a binary variable which takes the value of 1 if respondents answer “Yes” to the question “Have you ever heard of sustainable finance?” and 0 otherwise.⁴ Notably, SFA is quite low, with approximately 68% of respondents having never heard of sustainable finance.

Following Heeb et al. (2023) and Filippini et al. (2024), we include *Climate Awareness*, constructed as a dummy equal to 1 if respondents answer “Protecting the environment and fighting climate change” to the question “Which of the following goals do you consider most urgent at this time?” and 0 otherwise.

2.1.3 Demographic and psychographic variables

We control for various socio-demographic factors and psychographic characteristics. *Female*, is a dummy equal to 1 if the respondent is female, and 0 otherwise. *Age* is a continuous variable representing the respondent’s age. We also include the marital status, as a categorical variable that classifies respondents into three groups: *Married*, *Single*, *Separated/divorced/widowed*. Following Lamboglia et al. (2024), we construct the variable *University degree*, which takes the value 1 if the respondent holds at least a university degree.

The respondents’ occupational status is a categorical variable that classifies individuals into four groups: *Employed*, *Student*, *Jobseeker*, and *None of these conditions*, a residual category for those who do not fit into any of the preceding classifications.

We define the variable *Perceived living standards* as a binary indicator, taking the value 1 if respondents rate their standard of living compared to their peers as “High” or “Very high”, and 0 otherwise.⁵

We construct a dummy variable, *Managing HH income*, to indicate respondents who are responsible for managing the household budget, either alone or with others. *Living with children* is a dummy taking value 1 if respondents live with children, and 0 otherwise.

We control for a series of non-cognitive abilities. Financial decisions often involve a conflict between short-term rewards (short-horizon doers) and long-term gains (long-

⁴Filippini et al. (2024) use an open ended question.

⁵The survey provides a hypothetical measure of the net monthly income respondents consider necessary to live decently. However, we argue that the question regarding their standard of living offers a more accurate reflection of their actual circumstances.

horizon planners) (Shefrin and Thaler, 1988). A person’s ability to control impulses and plan for the future influences their financial behaviour (such as saving, debt management, and seeking financial advice). When self-control fails, individuals tend to make non-optimal decisions. Following Conte et al. (2024b), we consider a set of variables that signal a “virtuous” or “vicious” behaviour based on their potential to predict favourable or adverse outcomes in financial decision-making.

To represent “virtuous” cognitive abilities, we use the following variables. A dummy variable is assigned a value of 1 for participants who report engaging in the following behaviours “Always” or “Often”: *Long-term goals*, setting long-term financial goals and strive to achieve them; *Tracking expenditure*, monitoring their expenses refers to keeping track of deadlines for recurring expenses to avoid missing them; *Affordable*, considering whether they can afford to buy something; *Comparing prices*, comparing prices even for small amounts.

The variable *Buying on impulse* captures “vicious” cognitive abilities and it is defined as a dummy equals to 1 if respondents indicate they “Always” or “Often” engage in the following behaviour: ‘ Making a purchase that turned out to be superfluous at a later date’.

Financial advisor is a dummy variable which takes value 1 if respondents keep updated on economic and financial issues talking with a financial advisor, and 0 otherwise.

Savings and *Pension*, are two dummy variables equal to 1 if if participants normally save money and plan to save for pension, even small amounts, as soon as possible, both providing protection against financial difficulties.

The survey also includes a self-reported measure of risk attitude, recorded on a 10-point Likert scale, based on responses to the following question: “In your approach to making financial decisions, including financial investments, how risk-averse are you?”. A score of 1 indicates a person who is not at all inclined to take risks, while a score of 10 represents someone who is extremely risk tolerant. We construct the variable *Risk-tolerance* equal to 1 for people who choose a value greater than four, the median value.⁶ We expect that

⁶Lamboglia et al. (2024) defines the same variable for values greater than six. As a robustness check, we find that using their measure does not change our results.

the attitude towards risk affects not only the investments but also the perceptions of the risks and dangers related to climate change. Villacis et al. (2021) show with a lab-in-the-field experiment conducted with one of the most vulnerable groups to climate change in Latin America that risk preferences are significantly associated with risk perceptions in the context of climate change.⁷

We also include a dummy variable, *Vote*, which equals 1 if a person votes, or would have voted if they had been eighteen at the time of the last polls, and 0 otherwise. The literature documents a positive correlation between political party ideologies regarding human-caused climate change and the perceived importance of the issue. Empirical evidence shows a relationship between political conservatism and climate change denial in different countries (Krange et al., 2019; McCright and Dunlap, 2011). Although the survey does not ask for respondents' political views, it does capture voting behaviour (or hypothetical voting behaviour if given the opportunity). This reveals the underplaying of civic engagement, as there is not a direct economic payoff for voting. This measure indicates the willingness of people in a community to bear a personal cost to improve the common good (Putnam, 1993; Guiso et al., 2011).

We construct the variable *Voluntary*, which equals 1 if a person has ever done any kind of voluntary work, and 0 otherwise. We use this variable as a proxy for donation. In fact, donations, as well as electoral participation, are two outcome-based measures of social capital, as there are no legal or economic incentives to either donate or vote. These decisions are motivated solely by social pressure and internal norms, which are the essential elements of social capital (Guiso et al., 2004).

Finally, we control for geographical area of residence using three dummy variables: North (1 for North-West or North-East, 0 otherwise), Centre (1 for Centre, 0 otherwise), and South and Islands (1 for South or Islands, 0 otherwise).

⁷Although the question explicitly asks about the willingness to bear financial risk, literature shows that a stable trait determines risk-taking across different domains of life. Individuals have an underlying risk preference that affects their willingness to take risks in all contexts (Dohmen et al., 2011).

3 Econometric model

Our objective is to analyse the determinants of individual demand for ESG (Environmental, Social, and Governance) investment products, while accounting for the roles of financial literacy, awareness of sustainable finance, and other individual-level characteristics.

However, an important feature of our data is that a portion of respondents report having never heard of ESG investments. These individuals form a distinct group, potentially differing in meaningful ways—such as knowledge, socio-demographic background, or attitudes toward finance—from those who are aware of ESG products. Simply excluding this group or treating them as missing could lead to selection bias, as the sample of “aware” individuals is likely non-random.

To address this issue, we adopt a sample selection model using a Heckman probit approach. This method accounts for the possibility that the observable outcome (demand for ESG products) is only defined for a selected subpopulation (those aware of ESG investments). Identification of the model requires an exclusion restriction—that is, a variable that affects the likelihood of being in the selected sample but does not directly influence the outcome of interest (ESG investment behaviour). We use Sustainable Financial Awareness (SFA) for this purpose. It is reasonable to assume that while SFA influences whether someone has heard of ESG investments, it does not directly affect their level of sustainable financial literacy (SFL), conditional on other covariates.

Given the binary nature of the dependent variable and the potential for selection bias, we specify the model in two stages:

$$\begin{cases} SFL_i^* = \alpha_1 SFA_i + z_i' \alpha_2 + u_i & (\text{selection equation}) \\ ESG_i^* = \beta_1 FL_i + \beta_2 DFL_i + x_i' \beta_3 + \epsilon_i & (\text{response equation}) \end{cases}$$

$$\begin{cases} SFL_i = 1, ESG_i = 1 & \text{if } SFL_i^* > 0 \text{ and } ESG_i^* > 0 \\ SFL_i = 1, ESG_i = 0 & \text{if } SFL_i^* > 0 \text{ and } ESG_i^* \leq 0 \\ SFL_i = 0, ESG_i = . & \text{if } SFL_i^* \leq 0 \end{cases} \quad (\text{observational rule}) \quad (4.1)$$

$$\begin{pmatrix} u_i \\ \epsilon_i \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{u\epsilon} \\ \rho_{u\epsilon} & 1 \end{pmatrix} \right] \quad (\text{error component})$$

The selection equation (ESG awareness process) models the propensity for individual i to be aware of ESG products. The observed selection indicator SFL_i equals 1 if the latent awareness $SFL_i^* > 0$, and 0 otherwise.

The outcome equation (ESG demand process) models the individual's latent demand for ESG investments. We observe actual demand $ESG_i = 1$ if $ESG_i^* > 0$, and 0 otherwise—but only for those with $SFL_i = 1$.

We do not observe the latent variables. Instead, we observe: ESG_i , a binary dependent variable equal to 1 if the respondent invests in, or expresses interest in investing in, ESG products, and 0 otherwise; FL_i and DFL_i , which denote individual i 's levels of *financial literacy* and *digital financial literacy*, respectively. The vectors $\mathbf{z}_i$ and $\mathbf{x}_i$ include a series of control variables such as age, gender, income, education, and other socio-demographic characteristics.

From an empirical standpoint, the literature suggests that both FL and DFL may be *endogenous* to financial decision-making behaviour (e.g., Lyons and Kass-Hanna, 2021; Aristei et al., 2024). While this raises concerns about potential endogeneity in our model, we conduct appropriate statistical tests and find *no evidence of endogeneity*. The model that treats these variables as endogenous, along with its results, is reported in Appendix K.

4 Results

Table 4.1 shows the results of the extended probit model.

Starting with the selection equation, we observe that the coefficient on the exclusion restriction SFA is positive and highly significant. This supports the validity of our identification strategy, suggesting that individuals with higher sustainable financial awareness also tend to have greater SFL.

Our main variables of interest are climate awareness and the measures of literacy. The coefficient on *Climate awareness* is negative and statistically significant for SFL, but

positive and statistically significant for ESG investments. This means that individuals who are more concerned about climate issues do not necessarily have greater knowledge of sustainable finance. However, when they do have such knowledge, they are more likely to invest in ESG products. As far as FL and DFL are concerned, we do not find any effect of these literacies on ESG investments. This result is in line with part of the literature that does not find any effect and this might probably due to the fact that ESG investments may be perceived as less remunerative with respect to other types of investments.

As for the socio-demographics we find the following results. The coefficient on *Female* is negative and statistically significant in the selection equation, indicating that women are generally less knowledgeable about sustainable finance. However, once they are aware of ESG products, they tend to choose them more than men. Emotional involvement, as the ability to have an emotional reaction when confronted with environmental degradation, plays a crucial role in shaping our beliefs, values, and attitudes toward the environment Chawla (1998, 1999). Extensive research documents how women tend to react more emotionally to environmental problems making them more inclined to engage in pro-environmental behaviour. Literature shows that women are more concerned than men about climate change (O'Connor et al., 1999; Brody et al., 2008; McCright and Dunlap, 2011; Leiserowitz et al., 2013).

As for the age of the respondent, we find a U-shaped relationship for SFL, meaning that younger people are less sustainable finance literate with respect to older. On the contrary, we observe an inverse U-shaped relationship for ESG, suggesting that ESG investments are higher among younger individuals and declines as they grow older. The literature finds mixed results about climate change concerns and age. Younger individuals are expected to exhibit greater concern than older generations, as they have grown up during a period when media coverage of climate change has steadily increased (Franzen and Vogl, 2013).

Considering *Married* as the reference category, our results show that single individuals exhibit a lesser degree of knowledge about SFL. The opposite is true for people that are separated, divorced, or widowed.

The coefficient on *University degree* is positive and statistically significant for SFL. This

results indicates that the higher the education, the higher the knowledge about sustainable finance, but not the investments in ESG products.

With respect to *Employed* that is our reference category, we have that students, unemployed, and people who do not fall into those three categories have a lower degree of SFL, as they are probably more concerned about other issues. As for the ESG investments, we find that jobless individuals invest less in ESG.

Individuals responsible for managing household income tend to be more knowledgeable about sustainable finance. However, this does not influence their investment in ESG products.

TABLE 4.1
Determinants of ESG investments

	SFL		ESG	
	Coeff.	St. Error	Coeff.	St. Error
SFA	1.769***	(0.013)		
Climate awareness	−0.250***	(0.039)	0.245***	(0.026)
FL			−0.086	(0.034)
DFL			0.006	(0.007)
Female	−0.296***	(0.034)	0.077***	(0.029)
Age	−0.111 * *	(0.053)	0.103*	(0.052)
Age2	0.002 * *	(0.001)	−0.002***	(0.001)
Single	−0.060 * *	(0.029)	−0.025	(0.112)
Separated/widower/divorced	0.362 * *	(0.147)	0.188	(0.254)
University degree	0.259***	(0.061)	0.077	(0.124)
Student	−0.127*	(0.065)	−0.027	(0.087)
Jobseeker	−0.252*	(0.145)	−0.214 * *	(0.101)
None of these conditions	−0.548***	(0.110)	0.169	(0.399)
Managing HH income	0.206***	(0.070)	0.016	(0.016)
Living with children	0.088	(0.066)	0.085*	(0.048)
Savings	0.278***	(0.031)	0.076	(0.100)
Pension	0.068	(0.071)	−0.154***	(0.040)
Financial advisor	0.304***	(0.049)	0.100 * *	(0.040)
Perceived living standards	0.246***	(0.083)	0.057	(0.044)
Risk tolerance	0.314***	(0.015)	0.095	(0.075)
Vote			0.032	(0.084)
Voluntary			0.186***	(0.041)
Affordable			0.084***	(0.023)
Comparing prices			−0.380***	(0.109)
Tracking expenditure			0.158 * *	(0.066)
Long-term financial goal			−0.067	(0.088)

Table 4.1 continued from previous page

Buying on impulse			−0.088***	(0.005)
Constant	0.356	(0.771)	−0.123	(0.884)
Area dummies	Yes		Yes	
ρ_{ue}	−0.276	(0.020)		
Log pseudolikelihood			−3464.7466	
Observations			5,364	
Selected			2,262	
Nonselected			3,102	

Note: The table shows the estimation results for the model in Eq. (4.1). Robust standard errors clustered at geographical areas level are reported in parenthesis. *, ** and *** denote statistical significance at 10%, 5% and 1%, respectively. Sampling weights are used.

The coefficient on *Living with children* is positive and statistically significant solely on investments in ESG products, likely because it encourages a more forward-looking perspective when taking into account future generations' needs.

Individuals who declare to consistently save money tend to have higher levels of SFL, although there is no effect on ESG investments.

Those who start saving for retirement early, tend to invest less in ESG products, as indicated by the negative and statistically significant coefficient on *Pension*.

Those who consult a financial advisor for investments tend to invest more in ESG products compared to those who do not. This finding aligns with that part of the literature suggesting that investing in sustainable products does not yield lower returns than traditional investments (see the meta-analysis by Hornuf and Yüksel, 2024).

Moreover, there is evidence in the literature that financial advisors play a significant educational role by improving the financial literacy of their clients (Migliavacca, 2021). In addition, the introduction of EU Regulation 2021/2616 mandates that, starting in 2022, financial institutions must inform their clients about ESG investments and elicit their sustainability preferences. As shown by Seifert et al. (2024), many potential ESG investors remain unaware of the existence of sustainable investment options. When provided with information regarding financial returns or the positive impact of sustainable investments, these investors are more likely to invest in ESG products. Our results support the emerging literature highlighting the important role financial advisors play in guiding investors toward green alternatives.

There is a series of factors that the literature has found to influence environmental attitude and pro-environmental behaviour. It is widely agreed that concern about climate change tends to grow as income and education levels rise (Lee et al., 2015; Meyer, 2015; Franzen and Vogl, 2013; Whitmarsh and Capstick, 2018). It is intuitive that those with lower incomes are more focused on immediate issues and tend to give less attention to challenges with medium- to long-term consequences. In our case, we do not have a proper income measure; however, we use the variable *Perceived living standard* as its proxy. The results show a positive and strongly significant effect for SFL, confirming the idea that higher income are associated with higher attention towards the environment. However, we do not find any effect for the ESG investments.

Individuals with higher risk tolerance tend to have greater knowledge of sustainable finance, although this does not influence their investments in ESG products.

For the remaining variables that influence only ESG investments, we find that while the variable *Vote* does not have any effect, the coefficient on the variable *Voluntary* is positive and strongly significant. This captures the fact that more pro-social people tend to invest more in ESG products.

Additionally, we control for certain behavioural traits and habits that may influence investment choices. Among virtuous behaviours, engaging in volunteer work, being mindful of spending, and budgeting—associated with more deliberate, value-driven consumption—increase the likelihood of choosing ESG products. Interestingly, price comparison—usually seen as a smart consumer habit—does not show the same positive link. This might suggest that ESG products, often priced higher, could be overlooked when consumers focus mainly on price. On the other hand, detrimental behaviours, like impulsive buying, which involve less reflection and consideration, are negatively associated with ESG purchases, likely because such purchases require more thought and value alignment. Therefore, in general, virtuous behaviours tend to have a positive impact, while detrimental behaviours have a negative impact on the consumption of ESG products.

5 Conclusion

This paper has made a contribution to the growing literature on sustainable finance by empirically exploring the complex interplay between climate awareness, financial literacy, and digital financial literacy in shaping young adults' preferences for ESG investment products.

This study has shown that going green in investment decisions is not just about caring for the planet—it is about knowing how. While climate awareness is widespread among young adults, it does not automatically translate into sustainable investing. The real game-changer? Sustainable financial literacy, particularly when paired with sustainable finance awareness, trusted guidance from financial advisors, and a forward-looking risk attitude.

Our findings have revealed a clear awareness–action gap: young people care deeply about climate issues but often lack the financial tools to back that concern with investment choices. Interestingly, digital financial literacy does not significantly affect ESG investments, suggesting that ESG options may still be under-represented or under-explained on digital platforms.

Women, risk-takers, and civic-minded individuals have emerged as especially receptive to ESG investing when properly informed, hinting at powerful behavioural levers. But without targeted education and access, even the most climate-conscious individuals may remain on the sidelines.

To truly make *green the new black*, we need more than good intentions—we need action powered by knowledge, platforms that make ESG accessible, and intermediaries who can bridge the gap. Our results have suggested that financial advisors can play a crucial role in this process, both by educating clients and by aligning sustainability preferences with investment choices.

The future of sustainable investing lies not only in raising awareness but in equipping the next generation with the tools and confidence to invest in line with their values.

Chapter 5

Final Remarks

This thesis has explored the complex interplay of cognitive, psychological, and contextual factors in economic decision-making, focusing on financial and environmental choices. By integrating experimental methods, large-scale surveys, and behavioral analysis, this research provides novel insights into deviations from rational economic models and highlights the mechanisms underlying individual decision processes.

The first major contribution of this work lies in the analysis of decision time under ambiguity. The findings reveal that cognitive effort and processing fluency significantly influence the speed of decision-making. Individuals classified under different decision models exhibit distinct response times, with variations driven by complexity, similarity, and uncertainty in decision tasks. These results underscore the role of cognitive processing in shaping economic behavior beyond traditional choice outcomes.

The second key contribution examines the impact of financial literacy and economic conditions on intertemporal preferences. The study demonstrates that financial knowledge plays a crucial role in shaping individuals' patience and long-term planning, particularly in times of economic uncertainty. The analysis of the COVID-19 pandemic highlights how macroeconomic shocks influence discount rates, revealing the vulnerability of financial decision-making under crisis conditions.

The third major finding focuses on risk attitudes toward climate change, exploring the interaction between emotions, knowledge, and environmental decision-making. By

leveraging facial emotion recognition and self-reported measures, the research quantifies the influence of affective states on climate-related choices. The results suggest that emotional responses can either amplify or mitigate risk aversion, depending on individual cognitive appraisals and prior knowledge of climate issues.

The final contribution investigates the relationship between financial literacy, digital financial literacy, and sustainable investing behaviour. The study finds that while climate awareness significantly increases the likelihood of choosing ESG products, financial and digital literacy do not have a direct effect on sustainable investment choices. This suggests that being financially or digitally literate is not enough to bridge the awareness–action gap. Instead, sustainable financial literacy and sustainable finance awareness emerge as critical enablers. The results highlight key barriers that prevent environmentally conscious individuals from translating their values into investment behaviour, underscoring the importance of targeted educational initiatives and the crucial role of financial advisors in guiding investors toward green alternatives.

Overall, this thesis advances the understanding of economic decision-making by integrating behavioral insights with empirical evidence from both controlled experiments and large-scale surveys. The findings have practical implications for policymakers, financial educators, and institutions seeking to enhance financial literacy, promote sustainable investing, and improve decision-making under uncertainty. Future research could further investigate the intersection of digital transformation, financial behavior, and environmental consciousness, ensuring that individuals are better equipped to navigate an increasingly complex economic landscape.

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A Choice Tasks

TABLE A.1
THE 49 DECISION TASKS FACED BY THE PARTICIPANTS

task	unchanging	changing	average							
	$(m_1, \dots, m_M; m)$	$(n_1, \dots, n_N; n)$	$\#balls$	$\#priors$	$ \Delta(\#priors) $	$ \Delta(\#win-balls) $	$ \Delta_{EU} $	$ \Delta_{SM} $	$ \Delta_{RD} $	$ \Delta_{AM} $
1	1,2;3	0,1,2,3;3	13.5	4.5	1	1.70	.153	.183	.158	.158
2	0,1,2,3;3	0,1,2,3;3	19.5	6.5	1.5	2.13	.152	.155	.157	.149
3	0,1,2,3,4;4	0,1,2,3;3	27.5	7.5	2.5	6.31	.146	.153	.151	.138
4	0,3;3	0,1,2,3,4;4	18	5	1.4	3.68	.132	.170	.138	.129
5	1,2;3	0,1,2,3,4;4	18	5	1.4	3.47	.134	.161	.139	.138
6	0,1,2,3;3	0,1,2,3,4;4	24	7	1.4	2.81	.133	.143	.138	.126
7	0,1,2,3,4;4	0,1,2,3,4;4	32	8	2	3.85	.143	.149	.148	.140
8	0,1,2,3,4,5;5	0,1,2,3,4;4	42	9	3	9.04	.132	.140	.137	.126
9	0,3;3	0,1,2,3,4,5;5	23.5	5.5	1.8	6.06	.118	.150	.124	.108
10	1,2;3	0,1,2,3,4,5;5	23.5	5.5	1.8	6.18	.126	.145	.131	.127
11	0,1,2,3,4;4	0,1,2,3,4,5;5	37.5	8.5	1.8	4.26	.123	.124	.129	.113
12	0,3;3	0,1,2,3,4,5,6;6	30	6	2.3	9.33	.114	.155	.121	.105
13	0,1,2,3,4,5;5	0,1,2,3,4,5,6;6	54	10	2.3	5.85	.117	.120	.123	.107
14	0,1,3,4;4	0,1,2,3;3	23.5	6.5	1.5	4.26	.149	.157	.153	.145
15	0,4;4	0,1,2,3,4;4	20	5	1.4	3.10	.131	.166	.136	.126
16	0,4;4	0,1,2,3,4,5;5	25.5	5.5	1.8	5.42	.126	.157	.132	.116
17	0,4;4	0,1,2,3,4,5,6;6	32	6	2.3	8.50	.110	.152	.116	.103
18	2,3;5	0,1,2,3;3	17.5	4.5	1	1.88	.153	.185	.159	.160
19	0,2,3,5;5	0,1,2,3;3	27.5	6.5	1.5	6.25	.148	.153	.153	.142
20	0,5;5	0,1,2,3,4;4	22	5	1.4	2.88	.138	.167	.144	.131
21	2,3;5	0,1,2,3,4;4	22	5	1.4	2.88	.135	.162	.141	.141
22	0,2,3,5;5	0,1,2,3,4;4	32	7	1.4	4.05	.134	.140	.139	.127
23	0,5;5	0,1,2,3,4,5;5	27.5	5.5	1.8	4.94	.121	.162	.127	.116
24	2,3;5	0,1,2,3,4,5;5	27.5	5.5	1.8	4.91	.123	.143	.129	.127
25	0,2,3,5;5	0,1,2,3,4,5;5	37.5	7.5	1.5	4.14	.121	.124	.127	.110
26	0,5;5	0,1,2,3,4,5,6;6	34	6	2.3	7.62	.114	.146	.121	.105
27	2,3;5	0,1,2,3,4,5,6;6	34	6	2.8	7.69	.116	.142	.122	.119
28	0,1,5;6	0,1,2,3;3	25.5	5.5	1	6.93	.226	.228	.236	.186
29	2,3,4;6	0,1,2,3;3	25.5	5.5	1	5.27	.158	.191	.163	.163
30	0,2,4,6;6	0,1,2,3;3	31.5	6.5	1.5	8.22	.159	.163	.164	.154
31	0,1,3,5,6;6	0,1,2,3;3	37.5	7.5	2.5	11.28	.148	.156	.153	.142
32	0,2,3,4,6;6	0,1,2,3;3	37.5	7.5	2.5	11.33	.158	.168	.163	.151
33	2,3,4,5,6;6	0,1,2,3;3	37.5	7.5	2.5	13.79	.235	.252	.243	.238
34	0,1,2,4,5,6;6	0,1,2,3;3	43.5	8.5	3.5	14.24	.157	.161	.161	.152
35	0,1,2,3,4,5,6;6	0,1,2,3;3	49.5	9.5	4.5	17.23	.149	.158	.153	.143
36	0,6;6	0,1,2,3,4;4	24	5	1.4	2.68	.136	.167	.142	.131
37	2,4;6	0,1,2,3,4;4	24	5	1.4	2.72	.128	.148	.133	.131
38	0,1,5;6	0,1,2,3,4;4	30	6	1.2	5.55	.227	.217	.240	.169
39	0,3,6;6	0,1,2,3,4;4	30	6	1.2	3.66	.132	.145	.138	.125
40	0,1,2,6;6	0,1,2,3,4;4	36	7	1.4	7.46	.179	.170	.199	.122
41	0,2,4,6;6	0,1,2,3,4;4	36	7	1.4	6.04	.132	.140	.137	.125
42	0,1,2,4,5,6;6	0,1,2,3,4;4	48	9	3	12.17	.132	.139	.137	.122
43	0,6;6	0,1,2,3,4,5;5	29.5	5.5	1.8	4.61	.126	.156	.132	.113
44	2,4;6	0,1,2,3,4,5;5	29.5	5.5	1.8	4.61	.123	.141	.129	.125
45	2,3,4;6	0,1,2,3,4,5;5	35.5	6.5	1.5	3.94	.118	.136	.123	.119
46	0,1,2,5;6	0,1,2,3,4,5;5	41.5	7.5	1.5	6.71	.206	.198	.220	.150
47	0,1,2,3,5;6	0,1,2,3,4,5;5	47.5	8.5	1.8	8.37	.182	.182	.192	.153
48	0,1,2,4,5,6;6	0,1,2,3,4,5;5	53.5	9.5	2.5	9.27	.126	.130	.133	.115
49	0,6;6	0,1,2,3,4,5,6;6	36	6	2.3	7.14	.118	.151	.126	.108

Note: Each task is made of two two-stage lotteries, an unchanging lottery and a changing lottery. The unchanging lottery is composed of M one-stage lotteries, each made of m balls, with the k 'th containing m_k blue balls. The changing lottery is composed of N one-stage lotteries, each made of n balls, with the j 'th containing n_j blue balls. In the tasks above, it is assumed that the blue is the winning colour. The average value assumed by some task-specific variables used in Table 1.6 is reported. Note that, while the variables $\#balls$, $\#priors$ and $|\Delta(\#priors)|$ change within task (depend only on the round) but not between subjects, the variables $|\Delta(\#win-balls)|$ and $|\hat{\Delta}_\tau|$, $\tau \in \{EU, SM, RD, AM\}$, depend on the elimination sequence and, consequently, change between subjects. The calculation of $|\hat{\Delta}_\tau|$, $\tau \in \{EU, SM, RD, AM\}$, is based on the expectation of the parameter of interest characterising the type's functional, calculated individually for each subject conditional on being of that particular type (see Conte and Hey, 2013).

B Comprehensive literature review on decision time

The main paradigm used to model binary decisions is the *drift-diffusion model* (Ratcliff, 1978). The model jointly accounts for both the choice and response time, and suggests that a decision is driven by accumulation of information over time, until accumulated evidence reaches a positive or negative response boundary. The decision time is the time required to reach one of the two boundaries and depends on the average amount of information collected per unit of time, namely drift rate. Moreover, the accumulation of evidence is not constant over time but it varies following a normal distribution. This is the reason why the process can end up at the wrong boundary, meaning that the model can also account for errors in decisions. Drift-diffusion models (DDM) are a powerful tool to explain how correct and incorrect decisions are made. They apply over different paradigms and can predict the most accuracy and response time measures for decision processes in many two-choice tasks. Ratcliff and Rouder (1998) uses a DDM to explore the relationship between decision times for correct decisions and incorrect decisions showing that two of the parameters of the model (across-trial variability in drift rate for nominally equivalent stimuli and variability in the starting point) can explain slow and fast errors in decisions. An outstanding work that summarises how well DDM can jointly model choice and process when applied to binary choice datasets is the one of Clithero (2018).

An important aspect to be highlighted for the purpose of our work is the efficacy of DDM in predicting many decision-time phenomena observed in economic literature, at least to some extent. Among the effects captured by DDM and similar models, there are *sequential effects* that occur when the decision time of subjects becomes faster due to familiarisation with the task (Luce, 1986; Kocher and Sutter, 2006; Achtziger and Alós-Ferrer, 2014) and *option discriminability* effects predicting the existence of an inverse relationship between stimuli dissimilarity and decision time (Thurstone, 1927; Busemeyer and Townsend, 1993; Moffatt, 2005; Milosavljevic et al., 2010). Those two effects are particularly relevant to compare our findings with the current evidence in the literature. Then, DDM includes other parameters to take into account other characteristics of the decision process that affect response time. An increase in the decision thresholds leads

to an increase in expected decision time, *ceteris paribus*. It is possible to exogenously influence subjects' thresholds by imposing a time limit to answer, inducing time pressure and so reducing the thresholds, or increasing incentives (penalties) for correct (incorrect) responses to expand them. Our experimental design focuses on the latter approach to incentivise more deliberate decisions from subjects and to reduce noise in the data.

We already mentioned how DDM can account for the *speed-accuracy tradeoff* and make predictions about speed of mistakes. The negative relationship between decision time and errors in decisions can be as well interpreted as a measure of attention (Caplin and Martin, 2012). In addition, subjects tend to spend more time on a choice immediately after an error in judgment. This *post-error slowing effect* (PES) (Rabbitt and Rodgers, 1977; Laming, 1979) can be explained by increased caution from the subject that requires additional information accumulation (increasing the thresholds) before taking a decision.

Although DDM can predict most of those regularities observed in empirical data, they only focus on binary choices while the dimension of the choice set seems to affect decision process. Reutskaja et al. (2011) suggest that cognitive constraints as attention and memory are becoming more relevant in the decision process when the choice set increases. Moreover, DDM do not take into account the idea that subjects might use different decision processes. With respect to this, our suggestion is that different decision processes account for differences in response times, and this is exactly what we want to explore with our analysis.

C How the Different Preference Functionals were Fitted

Here we describe how C&H used the data – using only the data on the decisions for all 149 subjects for all 49 tasks, consisting of a total of 256 decision problems for each subject,¹ giving a grand total of 19,668 observations; the mixture estimation was based in these 19,668 observations. The crucial point is that we are interested in knowing whether there are different types of decision-makers in the population for the type of problem considered here. This was assessed in C&H by fitting a *Finite Mixture Model* (henceforth, mixture model or, more simply, mixture) from choice data.

A mixture model is a representation of the heterogeneity of the population. There are different types of decision-makers and types differ in the decision rules, or more technically, in the functional that describes their choice process. In the case of our experiment, “type” refers to a subject’s choice process that is recognised as being compatible with one of the four theories of decision-making under ambiguity. We will describe these theories later. The crucial point here is that a mixture model enables us to estimate *jointly* the parameters of the preference functionals which characterise our types and the proportions of types in the population, namely the “mixing proportions”. Put differently, the parameters of each type’s functional are automatically estimated only from those subjects who appear to be “statistically” compatible with that type.² Note that, in the experiment, subjects can either win or not win, therefore the utility function, $u(\cdot)$, is normalised such that $u(\text{win}) = 1$ and $u(\text{not win}) = 0$ and there is no attitude to risk parameter to estimate.

In a finite mixture model, the mixing proportion of a type represents the probability of a randomly chosen subject being of that particular type. The larger the mixing proportion of a type, the higher the probability of the subject being of that particular type. C&H assign subjects to types following a majority rule: a subject is assigned to a specific type if her posterior probability of that type is the highest.³

¹The number of questions in each task depended upon the initial number of one-stage lotteries in the changing task: to be precise if there were N such one-stage lotteries then there would be N decision-problems in that task. N varied across task.

²This is what differentiates a mixture from a pooled estimation procedure assuming a single type at a time.

³The power of a mixture model is higher, the neater its capacity to assign subjects to types with high probability. As shown in Conte and Hey (2013, Figure 4), in 88.58% of subjects are assigned to type with posterior probability higher than 90%.

Using the parameter estimates and the assignment of subjects to types of the mixture model, we can isolate and investigate the effect of decision type on decision time.

C.1 Expected Utility Theory (EU)

According to the Expected Utility Theory, the valuation of a two-stage lottery used in this experiment is

$$V_{EU}[\mathcal{R}(r_1, \dots, r_k, \dots, r_R; r)] = \left[\frac{r_1}{r} + \dots + \frac{r_k}{r} + \dots + \frac{r_R}{r} \right] \frac{1}{R} \quad (\text{C.1})$$

This valuation follows by the property of *EU* of being linear in the probabilities and by the fact that each one-stage lottery is equally likely. It is worth noting that the *EU* preference functional in this formulation does not require any parameter estimation.

As an example, let us consider the choice problem depicted in Figure ??, where the two-stage lotteries A (left lottery) and B (right lottery) include five and two one-stage lotteries, respectively. Assuming that red is the winning colour, the valuations of these lotteries according to Expected Utility Theory are

$$\begin{aligned} V_{EU}[A(0, 1, 2, 3, 4; 4)] &= \left[\frac{0}{4} + \frac{1}{4} + \frac{2}{4} + \frac{3}{4} + \frac{4}{4} \right] \cdot \frac{1}{5} = 0.5 \\ V_{EU}[B(0, 3; 3)] &= \left[\frac{0}{3} + \frac{3}{3} \right] \cdot \frac{1}{2} = 0.5 \end{aligned}$$

Under *EU*, the two lotteries have the same valuation.⁴

C.2 Smooth Model (SM)

Smooth Model evaluates a two-stage lottery of our experiment as follows:

$$V_{SM}[\mathcal{R}(r_1, \dots, r_k, \dots, r_R; r)] = \left[\phi\left(\frac{r_1}{r}\right) + \dots + \phi\left(\frac{r_k}{r}\right) + \dots + \phi\left(\frac{r_R}{r}\right) \right] \frac{1}{R} \quad (\text{C.2})$$

Here, $\phi(x) = (1 - e^{-sx}) / (1 - e^{-s})$, where $-\infty < s < +\infty$ is the only characterising parameter to be estimated. *SM* reduces to *EU* when $s \rightarrow 0$.

⁴This valuation is deterministic and does not include any error terms.

Now, let us consider how the Smooth Model evaluates the lotteries of the decision problem depicted in Figure ?? . As a value for s we use the mean of the normal distribution assumed for it whose moments are estimated in C&H. This is $s = 1.377$.

$$\begin{aligned}
V_{SM} [A(0, 1, 2, 3, 4; 4)] &= \left[\phi\left(\frac{0}{4}\right) + \phi\left(\frac{1}{4}\right) + \phi\left(\frac{2}{4}\right) + \phi\left(\frac{3}{4}\right) + \phi\left(\frac{4}{4}\right) \right] \cdot \frac{1}{5} \\
&= [0 + 0.39 + 0.67 + 0.86 + 1] / 5 = 0.583 \\
V_{SM} [B(0, 3; 3)] &= \left[\phi\left(\frac{0}{3}\right) + \phi\left(\frac{3}{3}\right) \right] \cdot \frac{1}{2} = [0 + 1] \cdot \frac{1}{2} = 0.5
\end{aligned}$$

We conclude that the average *SM* subject gives a higher valuation to lottery A than to lottery B.

C.3 Rank Dependent Expected Utility (*RD*)

Given that $r_1 < \dots < r_k < \dots < r_R$, a two-stage lottery of our experiment is evaluated as follows:

$$V_{RD} [\mathcal{R}(r_1, \dots, r_k, \dots, r_R; r)] = \sum_{k=1}^R h\left(\frac{r_k}{r}\right) \left[h\left(\frac{R-k+1}{R}\right) - h\left(\frac{R-k}{R}\right) \right] \quad (C.3)$$

Here, $h(p) = p^g / [p^g + (1-p)^g]^{1/g}$, with $h(0) = 0$ and $h(1) = 1$. The only parameter to be estimated is $g > 0$. When $g = 1$, *RD* reduces to *EU*.

The Rank Dependent Expected Utility evaluates the lotteries of the decision problem depicted in Figure ??, using as a value of g the mean of the lognormal distribution as estimated in C&H, which is $g = 1.139$, as follows.

$$\begin{aligned}
V_{RD} [A(0, 1, 2, 3, 4; 4)] &= 0 + h\left(\frac{1}{4}\right) \left[h\left(\frac{4}{5}\right) - h\left(\frac{3}{5}\right) \right] + h\left(\frac{2}{4}\right) \left[h\left(\frac{3}{5}\right) - h\left(\frac{2}{5}\right) \right] \\
&\quad + h\left(\frac{3}{4}\right) \left[h\left(\frac{2}{5}\right) - h\left(\frac{1}{5}\right) \right] + h(1) \cdot \left[h\left(\frac{1}{5}\right) - 0 \right] = 0.492 \\
V_{RD} [B(0, 3; 3)] &= 0 + 1 \cdot \left[h\left(\frac{1}{2}\right) - 0 \right] = 0.494
\end{aligned}$$

Here, lottery B receives a higher valuation than lottery A by the average *RD* subject.

C.4 Alpha Expected Utility Model (AM)

According to the Alpha Expected Utility Model, the valuation of a generic two-stage lottery is a weighted average of the value of the worst and the best one-stage lotteries within the two-stage lottery:

$$V_{AM} [\mathcal{R}(r_1, \dots, r_k, \dots, r_R; r)] = a \frac{r_1}{r} + (1 - a) \frac{r_R}{r} \quad (\text{C.4})$$

The only parameter to be estimated is the weight $0 \leq a \leq 1$.

The Alpha Expected Utility Model evaluates the lotteries of the decision problem depicted in Figure ?? as follows. As a value for the parameter a we use the mean of the beta distribution estimated in C&H, which is $a = 0.542$.

$$\begin{aligned} V_{AM} [A(0, 1, 2, 3, 4; 4)] &= a \frac{0}{4} + (1 - a) \frac{4}{4} = 0.458 \\ V_{AM} [B(0, 3; 3)] &= a \frac{0}{3} + (1 - a) \frac{3}{3} = 0.458 \end{aligned}$$

Again, we see that the two lotteries are equally evaluated by the average AM subject, as for EU , but here only the extreme priors of each lottery are used in the calculation.

C.5 Stochastic and Distributional assumptions

C&H assume that subjects make mistakes in their choices, more specifically, that they make errors when calculating the difference in the valuations of the two lotteries: $V_\tau(A) - V_\tau(B) + u_\tau$, with $\tau \in \{EU, SM, RD, AM\}$; $u_\tau \sim N(0, \sigma_\tau^2)$ is an additive error term, independent across questions. They further consider a probabilistic tremble of magnitude w and estimate the parameters of the models in consideration (s in the SM , g in the RD , and a in the AM) together with σ_τ^2 and w . Finally, they estimate the mixing proportions of types, that is the proportions of the population who are of each of the considered types, where a type is described by one of the four above-mentioned models.

For all the details concerning the estimation of the mixture model and the computation of posterior probabilities not directly relevant to the present paper, we refer the reader to C&H.

D Summary statistics

TABLE D.1
Summary statistics

Data code	Variable	Definition	Mean	std.~err.
SEX	Female	=1 if female; 0 otherwise	0.424	0.010
ETA	Age	Year of birth	59.368	0.339
STUDIO	<i>Education</i> Upper secondary school diploma University degree and higher	Categorical: education levels	0.267	0.009
STUMCF	Mother's education	=1 if upper secondary school diploma and higher	0.162 0.1206	0.006 0.006
QTASSO	<i>Financial literacy</i> Compound interest	=1 if correct answer; 0 otherwise	.518	0.010
QINT	Inflation	=1 if correct answer; 0 otherwise	0.613	0.010
QRISK1	Risk diversification	=1 if correct answer; 0 otherwise	0.575	0.010
STACIV	<i>Civil status</i> Married/in civil partnership Single Separated/divorced Widow/er	Categorical: status category	0.528 0.201 0.010 0.094 0.177	0.010 0.010 0.006 0.006 0.008
APQUAL2	<i>Employment status</i> Unemployed Employed	=1 if unemployed; 0 otherwise =1 if employed (employee and self-employed)	0.129 0.480	0.007 0.010
CONDGEN	<i>HH income assessment</i> Insufficient HH income	=1 if insufficient income through the end of the month; 0 otherwise	0.547	0.010
RITBOL	Behind in paying utility bills	=1 if late with payment; 0 otherwise	0.068	0.005
B25	<i>Income support measures</i> Non-COVID-19-related financial assistance	=1 if received financial assistance; 0 otherwise	0.097	0.006
MISCOVID	COVID-19 personal income support measures	=1 if received income support; 0 otherwise	0.090	0.006
IMPCOVID	COVID-19 HH income support measures	=1 if HH received income support; 0 otherwise	0.167	0.008
EMERG	<i>Financial resilience and life satisfaction</i> Borrow in an emergency	=1 if able to borrow; 0 otherwise	0.562	0.010
HAPPY	Happiness	=1 if happy; 0 otherwise	0.535	0.010
RISMOTBIS	<i>Reasons for saving</i> Major purchases Provision for unexpected events Old-age provision Education/economic support/legacy to children, grandchildren Travel, vacations Other	Categorical: saving reasons	0.097 0.393 0.282 0.186 0.016 0.027	0.006 0.010 0.009 0.008 0.002 0.003
CILY2	<i>HH income quintile</i> I II III IV V	Categorical: income quintiles	0.200 0.200 0.200 0.200 0.200	0.009 0.008 0.008 0.008 0.008
CILW2	<i>HH wealth quintile</i> I II III IV V	Categorical: wealth quintiles	0.200 0.200 0.200 0.200 0.200	0.008 0.009 0.008 0.008 0.007

E Alternative specifications of the financial literacy indicator

TABLE E.1
Interval regression with alternative specification of the financial literacy indicator

	Coefficient	std.err.	p-value
Female	0.135	0.100	0.176
Age	0.020	0.010	0.041
<i>Education</i>			
Upper secondary school diploma	-0.134	0.112	0.233
University degree and higher	-0.165	0.137	0.229
Mother's education	-0.301	0.126	0.017
Financial Literacy	-0.122	0.101	0.224
<i>Civil status</i> (base case = married/in civil partnership)			
Single	-0.088	0.137	0.520
Separated/divorced	-0.065	0.158	0.678
Widow/er	0.207	0.151	0.170
<i>Employment status</i>			
Unemployed	0.007	0.184	0.971
Employed	0.202	0.167	0.227
<i>HH income assessment</i>			
Insufficient HH income	0.312	0.105	0.003
Behind in paying utility bills	0.386	0.180	0.032
<i>Income support measures</i>			
Non-COVID-19-related financial assistance	-0.054	0.165	0.745
COVID-19 personal income support measures	0.244	0.151	0.107
COVID-19 HH income support measures	0.236	0.121	0.051
<i>Financial resilience and life satisfaction</i>			
Borrow in an emergency	-0.001	0.094	0.994
Happiness	-0.257	0.091	0.005
<i>Reasons for saving</i> (base case = major purchases, investments, paying off debts)			
Provision for unexpected events	-0.435	0.145	0.003
Old-age provision	-0.692	0.155	0.000
Education/economic support/legacy to children, grandchildren	-0.437	0.156	0.005
Travel, vacations	-0.207	0.308	0.501
Other	-0.295	0.308	0.338
<i>HH income quintile</i> (base case = I)			
II	0.101	0.156	0.516
III	-0.066	0.167	0.693
IV	-0.334	0.184	0.069
V	-0.467	0.200	0.020
<i>HH wealth quintile</i> (base case = I)			
II	-0.473	0.151	0.002
III	-0.377	0.146	0.010
IV	-0.513	0.149	0.001
V	-0.557	0.1630	0.001
Intercept	1.788	0.844	0.034
σ	1.896	0.049	0.000
# Observations		6,239	
Left-censored obs.		1,785	
Right-censored obs.		1,711	
Log-likelihood		-9224.8044	

F Incentivized Questionnaire on SL and SFL

F.1 Sustainability Literacy Questions

1. Which of the following topics are included in the United Nations (UN) Sustainable Development Goals Development? (Multiple options possible)

- Economic growth
- Social participation
- Environmental protection

Correct answer: a + b + c

2. Which of the following definitions do you think best describes sustainable development?

- Ensure universal access to education, health, and social services
- Meeting today's needs by minimizing the impact on the environment
- Meeting today's needs without limiting future generations
- I don't know

Correct answer: c

3. What is the most common cause of pollution of streams and rivers worldwide?

- Waste disposal by cities
- Industrial waste and landfills
- Draining surface water flowing from roads, paved areas and fields
- Waste in the immediate vicinity of streams and rivers
- I don't know

Correct answer: c

4. Which of the following options is the main reason for the decline in fish stocks in the Atlantic Ocean?

- Fisheries strive to maximise their catch
- Global climate change
- Lower fertility of fish
- Marine pollution
- I don't know

Correct answer: a

5. In Italy, in 2022, the poverty threshold for an individual was an income of €690 per month, while for a family of four, it was an income of €1,874.50 per month. What percentage of the Italian population was below the poverty line that year?

- 1-5%
- 6-10%
- 11-15%
- more than 15%
- I don't know

Correct answer: b

6. What was the average annual GDP growth rate in Italy between 2015 and 2022?

- less than 1%
- 1-1.9%

- 2-3%
- more than 3%
- I don't know

Correct answer: b

F.2 Sustainable Finance Literacy Questions

1. In the context of sustainable financial investments, the (english) acronym “ESG” is often used. What do you think the abbreviation “ESG” stands for?

- Environmental and Social Goals
- Environmental and Sustainable Goals
- Environmental, Social and Governance
- Environmental, Sustainable and Governance
- I don't know

Correct answer: c

2. Does a product advertised in Italy as a “sustainable financial product” have to meet uniform criteria, set by the state regulatory authorities?

- Yes
- No
- I don't know

Correct answer: b

3. Are you aware of a label (or certificate, or proof) that certifies a sustainable financial product (from governmental or non-governmental organizations)?

- Yes
- No

Correct answer: a

4. Let's say a company has a low environmental footprint but has poor social and employee practices. Would it be possible to call the shares of this company a "sustainable" financial product in the financial markets?

- Yes
- No
- I don't know

Correct answer: a

5. In how many of the 3 ESG components (Environment, Social, Corporate Governance) does a company have to be sustainable in order to be considered a sustainable company on the financial markets?

- Only one of the elements
- 2 elements
- All 3 elements
- I don't know

Correct answer: a

6. An investment in a sustainable fund that includes companies with a low CO2 footprint directly reduces global CO2 emissions.

- Yes
- No

- I don't know

Correct answer: b

7. Do financial institutions that offer sustainable products always proactively influence the sustainability behavior of the invested companies (e.g., by participating in the annual shareholders' meeting)?

- Yes
- No
- I don't know

Correct answer: b

8. Is there a difference between “sustainable investing” and “impact investing?”

- Yes
- No
- I don't know

Correct answer: a

G Testing the treatment effect on emotions via the ICOprobit

We are primarily interested in estimating the difference in self-reported emotions between two time points—before and after watching a videoclip. The emotions are measured as Y_{before} and Y_{after} , respectively, each taking five possible values (1 to 5) that indicate the intensity of the emotion elicited, following the classification described in Section 4.1:

$$Y_T = \begin{cases} 1 & \text{very low intensity of the emotion} \\ 2 & \text{low intensity of the emotion} \\ 3 & \text{moderate intensity of the emotion ,} \\ 4 & \text{high intensity of the emotion} \\ 5 & \text{very high intensity of the emotion} \end{cases} \quad T \in \{\text{before, after}\}$$

To test the effect of the treatment on individual’s emotions, we shall use the Ordered Probit Model with Implicit Censoring (ICOprobit) proposed by Conte et al. 2025b.

Let ΔY denote the difference between these two measurements, which can take three possible values: -1 if $Y_{\text{after}} < Y_{\text{before}}$; 0 if $Y_{\text{after}} = Y_{\text{before}}$; and 1 if $Y_{\text{after}} > Y_{\text{before}}$. This classification accounts for potential changes in emotional intensity due to the videoclip exposure. When $\Delta Y = 0$, we must consider an implicit form of censoring, wherein individuals who already reported either the minimum ($Y_{\text{before}} = 1$) or maximum ($Y_{\text{before}} = 5$) emotional intensity cannot exhibit a further decrease or increase, respectively. Since our data does not provide additional information on this matter, we acknowledge the possibility of censoring and adjust the classification accordingly. Specifically, when a subject chooses $Y_{\text{before}} = Y_{\text{after}} = 1$, we interpret this as either their emotional intensity remaining unchanged or decreasing ($\Delta Y = \{-1, 0\}$). Similarly, when they choose $Y_{\text{before}} = Y_{\text{after}} = 5$, we construct the choice as indicating either an unchanged emotional intensity or an increase ($\Delta Y = \{0, 1\}$).

Let $\Delta Y_i^* (-\infty < \Delta Y_i^* < \infty)$ be the underlying latent variable representing respondent i ’s change in emotional response before and after watching the videoclip.⁵ The only explanatory variable is a dummy variable d_i , which takes the value 1 if the subject watched the environment-related videoclip and 0 otherwise.

The model assumes that the latent change in emotional intensity depends linearly on d_i :

$$\begin{aligned} \Delta Y_i^* &= d_i \gamma + e_i, \\ e_i &\sim N(0, 1), \quad i = 1, \dots, n \end{aligned} \tag{G.1}$$

⁵While this indicator captures the direction of change, it does not correspond directly to the difference in latent variables, $\Delta y^* = y_{i\text{after}}^* - y_{i\text{before}}^*$, where y_{iT}^* represents latent emotional intensity. However, since the observed response Y_{iT} is influenced by the cutoffs τ_k that are generally assumed to remain unchanged between time periods and individuals, a sufficiently large change in y_i^* will be reflected as a categorical shift.

Here, γ represents the effect of watching the environment-related videoclip on the change in latent emotional intensity.⁶ The stochastic error term e_i follows a standard normal distribution, with the normalisation of the variance required to set the otherwise arbitrary scale of the latent variable ΔY_i^* . The latent variable ΔY_i^* is linked to the observed variable ΔY_i through a set of two cut-points, η_l and η_u , which are estimated along with the other parameters of the model. The rule that links the observed variable ΔY_i to the latent variable ΔY_i^* is:

$$\begin{cases} -\infty < \Delta Y_i^* < \eta_l & \text{if } \Delta Y_i = -1 \\ \eta_l < \Delta Y_i^* < \eta_u & \text{if } \Delta Y_i = 0 \text{ \& } Y_{\text{before}} = Y_{\text{after}} \neq \{1, 5\} \\ -\infty < \Delta Y_i^* < \eta_u & \text{if } \Delta Y_i = 0 \text{ \& } Y_{\text{before}} = Y_{\text{after}} = 1 \\ \eta_l < \Delta Y_i^* < \infty & \text{if } \Delta Y_i = 0 \text{ \& } Y_{\text{before}} = Y_{\text{after}} = 5 \\ \eta_u < \Delta Y_i^* < \infty & \text{if } \Delta Y_i = 1 \end{cases} \quad (\text{G.2})$$

The corresponding individual likelihood contributions are:

$$\Pr(\Delta Y_i) = \begin{cases} \Pr(\Delta Y_i = -1) = \Phi(\eta_l - d_i \gamma) \\ \Pr(\Delta Y_i = 0 \text{ \& } Y_{\text{before}} = Y_{\text{after}} \neq \{1, 5\}) = \Phi(\eta_u - d_i \gamma) - \Phi(\eta_l - d_i \gamma) \\ \Pr(\Delta Y_i = 0 \text{ \& } Y_{\text{before}} = Y_{\text{after}} = 1) = \Phi(\eta_u - d_i \gamma) \\ \Pr(\Delta Y_i = 0 \text{ \& } Y_{\text{before}} = Y_{\text{after}} = 5) = 1 - \Phi(\eta_l - d_i \gamma) \\ \Pr(\Delta Y_i = 1) = 1 - \Phi(\eta_u - d_i \gamma) \end{cases} \quad (\text{G.3})$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function. The estimated coefficient γ represents the effect of the treatment (watching the environment-related videoclip) on the change in latent emotional intensity. This model extends the standard ordered probit model to address potential censoring issues arising from the limited number of response categories. It is important to note that the latent dependent variable represents the change in emotional intensity between two time points. The censoring issue arises because individuals who reported an extreme emotional state in the initial period cannot express an even more extreme state in the later period due to the constraints of the response scale.

Notably, this specification is equivalent to a Difference-in-Differences (DiD) model for ordinal variables, where the change in self-reported emotions serves as the dependent variable and the treatment dummy captures the effect on the latent emotional intensity of the environment-related videoclip exposure with respect to the neutral one. Given that Likert-scale data is widely used in surveys and experiments, the ICOprobit model provides a straightforward and intuitive estimator for analysing changes in ordinal outcomes across different conditions or treatments.

The full-sample log-likelihood for the sample of individuals is:

⁶The model can be extended to include a vector of individual characteristics, allowing for the estimation of their coefficients alongside the treatment effect.

$$\text{Log-Likelihood} = \sum_{i=1}^n \log \Pr(\Delta Y_i) \quad (\text{G.4})$$

The model is estimated using the Maximum Likelihood technique.

H Estimating preference functional parameters via the Bivariate Heterogeneous Preference (BHP) estimator for switching multiple price list Data

To evaluate the impact of our treatment and the connected emotions this may have raised, we use an experimental design similar to Tanaka et al. (2010). Each subject encounters two sMPLs, each presenting a choice between two alternative lotteries. Each list consists of 14 rows. While probabilities and outcomes remain constant across both lists, the higher payoff in lottery B varies. As subjects progress through the rows, the better outcome in lottery B gradually increases, making it increasingly attractive in terms of expected payoff.

Each subject presented with the two sMPLs will identify a single switch-point for each list. This switch-point represents the specific row where the subject transitions from preferring lottery A to lottery B, assuming a monotonic preference structure.

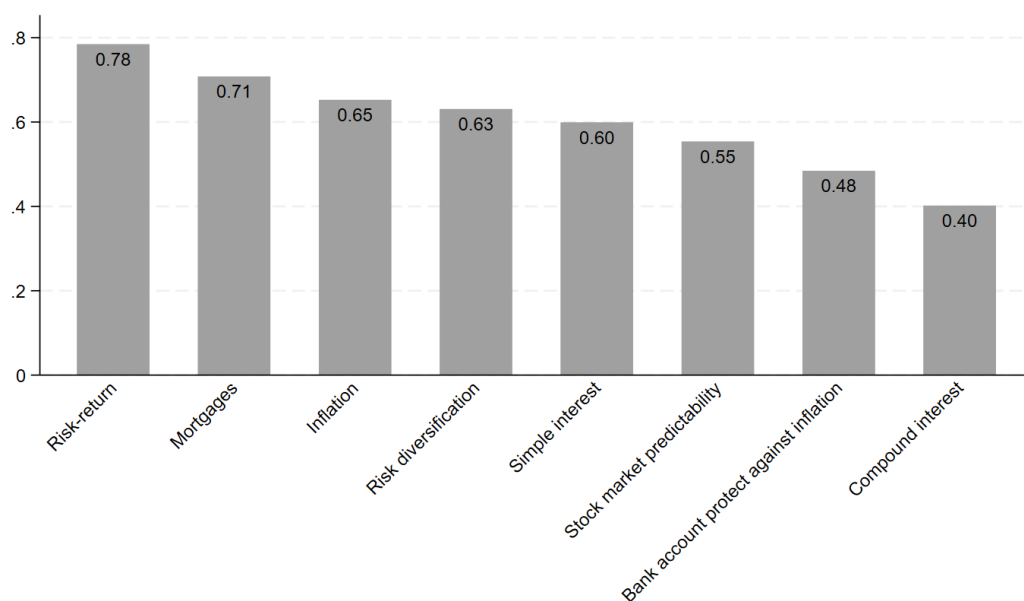
We use a power utility function defined as $u_i(z; \alpha_i) = z^{\alpha_i}$. The power parameter $\alpha_i > 0$ characterises risk preferences: it is less than 1 for risk-averse individuals, equal to 1 for risk-neutral individuals, and greater than 1 for risk-seeking individuals. The probability-weighting function, $w_i(p; \gamma_i)$, where p represents the true probability of the higher outcome, follows the one-parameter functional form introduced by Prelec (1998): $w_i(p; \gamma_i) = \exp[-(-\ln(p))^{\gamma_i}]$. The parameter $\gamma_i > 0$ determines the shape of the probability-weighting function. When $\gamma_i = 1$, there is no probability distortion, and the model simplifies to Expected Utility (EU). If $0 < \gamma_i < 1$, the function exhibits an inverse-S shape, meaning subject i overweights low-probability high outcomes relative to an EU decision-maker. Conversely, when $\gamma_i > 1$, the function takes an S-shape, leading subject i to undervalue low-probability high outcomes.

The two key parameters, α_i and γ_i , are jointly distributed, with their moments potentially varying based on subject characteristics. Since both parameters must be strictly positive, we assume they follow a bivariate lognormal distribution:

$$\begin{pmatrix} \alpha_i \\ \gamma_i \end{pmatrix} \sim \text{Lognormal} \left(\begin{pmatrix} \mu_\alpha \\ \mu_\gamma \end{pmatrix}, \begin{pmatrix} \sigma_\alpha^2 & \rho\sigma_\alpha\sigma_\gamma \\ \rho\sigma_\alpha\sigma_\gamma & \sigma_\gamma^2 \end{pmatrix} \right).$$

Here, μ represents the mean, σ denotes the standard deviation, and ρ is the correlation coefficient of the underlying bivariate normal distribution. The bivariate lognormal density function evaluated at (α_i, γ_i) is denoted as $f(\alpha_i, \gamma_i; \mu_\alpha, \sigma_\alpha, \mu_\gamma, \sigma_\gamma, \rho)$. The Bivariate Heterogeneous Preference (BHP) model, developed by Conte et al. (2025a), is used to estimate the parameters of this bivariate (between-subject) distribution of risk aversion and probability weighting.

I Summary statistics



Note: The figure shows the percentage of correct answers to the question used to assess financial knowledge. N= 5,364. Sampling weights are used.

FIGURE I.1
Components of Financial Knowledge

TABLE I.1
Summary statistics

Variable	Description	Mean	St. Dev.
<i>Literacy and awareness measures</i>			
ESG	= 1 if considering ESG when investing, 0 otherwise	0.323	0.467
FL	Index ranging from 0 to 5	3.255	1.289
DFL	Index ranging from 0 to 7	4.588	1.957
SFL	= 1 if knowledgeable about ESG criteria, 0 otherwise	0.422	0.494
SFA	= 1 if heard of sustainable finance, 0 otherwise	0.321	0.467
Climate Awareness	= 1 if fighting climate change is an urgent goal, 0 otherwise	0.546	0.498
<i>Socio-demographics</i>			
Gender	= 1 if Female, 0 if Male		
Female		0.511	0.500
Male		0.489	0.500
Age	Continuous variable	26.593	4.838
Marital status	Categorical variable: 3 categories		
Married		0.427	0.495
Single		0.557	0.497
Separated/divorced/widowed		0.016	0.124
University degree	= 1 if has a university degree, 0 otherwise	0.306	0.461
Economics degree	= 1 if has a university degree in economic subjects, 0 otherwise	0.050	0.217
Education parents	= 1 if at least one parent has university degree or higher, 0 otherwise	0.707	0.455
Occupational status	Categorical variable: 4 categories		
Employed		0.552	0.497
Student		0.270	0.444
Jobseeker		0.150	0.357
None of the above		0.028	0.164
Perceived living standards	= 1 if higher than peers, 0 otherwise	0.182	0.386
Managing HH income	= 1 if in charge of managing HH budget	0.613	0.487
Living with children	= 1 if living with children, 0 otherwise	0.163	0.370
Affordable	= 1 if considering whether they can afford to buy something, 0 otherwise	0.901	0.299
Comparing prices	= 1 if comparing prices, 0 otherwise	0.888	0.315
Tracking expenditure	= 1 if monitoring expenses, 0 otherwise	0.537	0.499
Long-term financial goal	= 1 if long-term financial goals, 0 otherwise	0.645	0.479
Buying on impulse	= 1 if buying on impulse, 0 otherwise	0.793	0.857
Financial advisor	= 1 if consulting financial advisor, 0 otherwise	0.153	0.360
Savings	= 1 if saving money, 0 otherwise	0.464	0.499
Pension	= 1 if planning to save for pension as soon as possible, 0 otherwise	0.549	0.498
Risk tolerance	= 1 if self-reported risk attitude greater than four, 0 otherwise	0.489	0.500
Vote	= 1 if votes or would have voted if they had been eighteen, 0 otherwise	0.705	0.456
Voluntary	= 1 if ever done any kind of voluntary work, 0 otherwise	0.502	0.500
High Digital Skills	= 1 if confident in performing digital activities, 0 otherwise	0.471	0.499
Geographical Area	Categorical variable: 3 categories		
North		0.441	0.496
Centre		0.193	0.395
South and Islands		0.366	0.482

Notes: The table displays the mean (Mean) and the standard deviation (St. Dev.) for all the variables. The total sample size is N=5,364. The statistics are generated using sampling weights.

J The questionnaire and the computation of indicators

ESG

Do you know what environmental, social and corporate governance sustainability criteria are in relation to financial investment decisions (the ESG criteria)? [single answer].

1. Yes, and I normally take them into account when deciding how to invest savings (or would do so if I had any savings to invest)
2. Yes, and I would take them into account if there were more ESG financial instruments to invest in (and I had resources to invest)
3. Yes, but I don't normally take them into account when deciding how to invest savings (or wouldn't take them into account if I had savings to invest)
4. No, I've never heard of them

Financial Literacy

Inflation: Five siblings receive a total of 1,000 euros as a gift but have to wait one year before they can access their share. When that year has passed, if the annual inflation rate is 8 per cent, each sibling will be able to use their share to buy [single answer]:

1. More than what they could buy today
2. The same things
3. Less than what they could buy today
4. I don't know

Interest rate: Suppose you deposit 100 euros into a new deposit account that guarantees a net annual interest rate of 2 per cent and has no fees. No other deposits or withdrawals are made on this account. How much will there be in the account at the end of the first year after interest is paid? [single answer]

1. More than 102 euros
2. 102 euros
3. Less than 102 euros
4. It is impossible to answer with the available information
5. I don't know

Interest compounding: ... and after 5 years, how much will the available amount be if no further deposits nor withdrawals are made on this account, there are no fees and it continues to bear interest at a guaranteed annual rate of 2 per cent? [single answer]

1. More than 110 euros

2. 110 euros
3. Less than 110 euros
4. It is impossible to answer with the information available
5. I don't know

Risk diversification: Can investment risk usually be reduced by purchasing different types of bonds and stocks?

1. True
2. False

Mortgages: Usually, for the same amount, a fifteen-year mortgage has a higher monthly installment compared to a thirty-year mortgage, but the overall interest paid over the mortgage's duration is lower

1. True
2. False

Digital financial literacy

How comfortable are you using a PC or other digital devices to...

1. transfer money/make payments
2. manage a current account
3. inquire about requesting a loan
4. take out an insurance policy
5. make a payment by card
6. protect sensitive data when purchasing financial services or making online payments
7. buying financial instruments through online trading platforms or roboadvisors

Digital Skills

How confident do you feel (or would you feel, if necessary) with the following activities?

1. Recognizing common computer fraud attempts (hacking, phishing, etc.)
2. Managing and protecting your personal data
3. Browsing and finding information on the Internet (e.g., about products, subscriptions, etc.)
4. Using e-mail or instant messaging, participating in video calls or social platforms

5. Reading online books/magazines
6. Participating in online training courses
7. Creating, editing, transferring document files
8. Installing software/changing software settings
9. Activating and using digital identity systems

Sustainable Finance Awareness

Have you ever heard of sustainable finance?

1. Yes
2. No

Climate Awareness

Which of the following goals do you consider most urgent at this time?

1. Protecting the environment and fighting climate change
2. Improving access to education and training
3. Fighting poverty
4. Fighting unemployment and joblessness
5. Addressing the challenges of immigration
6. Countering financial and political corruption
7. Countering gender discrimination
8. Promoting Italian talents more
9. Countering the social and economic repercussions of war

K Structural model with sample selection and endogenous regressors

Following the existing literature we include a series of variables that have proved to influence sustainable investments. Among these variables, financial and digital literacy are suspected to be endogenous. When an explanatory variable is endogenous, the standard econometric approach is to use instrumental variable (IV) methods to obtain consistent estimates of its causal effect. However, in our case, both the dependent variable and the suspected endogenous variable are binary, which can lead to biases in standard IV techniques. Thus, we apply an extended probit with two endogenous equations and a selection one.

The selection and the response equations are the same of those in Equation 4.1. The suspected endogeneity of FL is modelled with two exclusions. The literature shows a strong association between parents' education levels and children's financial literacy (Lusardi et al., 2010). Accounting for the educational level of the respondent's parents serves as a proxy for assessing the family environment. The idea is that an intellectually and culturally enriched environment can enhance the inclination to learn various subjects, including economic and financial topics, thereby improving comfort with money-related matters. Thus, we instrument financial literacy with a dummy indicating whether at least one of the parents hold a university degree or higher qualification (*Education parents*). Additionally, we include a dummy equal to 1 if the respondent holds an degree in Economics (*Economics degree*). Both coefficients of the exclusion restrictions are positive and highly significant, indicating their appropriateness.

Similarly to Marinucci et al. (2023), we construct the binary variable *High digital skills* taking value 1 when respondents answer "Very" or "Quite" to at least eight (the median value) out of the nine questions assessing their confidence in performing various digital activities⁷. We also check for the possible endogeneity of digital financial literacy instrumenting the variable with *High Digital Skills*.

$$\begin{cases} SFL_i^* = x_i' \alpha_1 + y_{1i}' \alpha_2 + u_i & (\text{selection equation}) \\ ESG_i^* = \beta_1 FL_i + \beta_2 DFL_i + x_i' \beta_3 + \epsilon_i > 0 & (\text{response equation}) \\ FL_i = x_i' \delta_1 + z_{1i}' \delta_2 + v_i & (\text{endogenous regressor equation}) \\ DFL_i = x_i' \gamma_1 + z_{2i}' w_2 + \eta_i & (\text{endogenous regressor equation}) \end{cases}$$

⁷Following Marconi et al. (2024), we also tested an alternative approach using a self-assessed measure of digital literacy on a 10-point Likert scale, where 1 indicates "very low" and 10 indicates "very high". We transform this measure into a dummy assigning value 1 if the response is 7 or higher and 0 otherwise

$$\begin{cases} SFL_i = 1, ESG_i = 1 & \text{if } SFL_i^* > 0 \text{ and } ESG_i^* > 0 \\ SFL_i = 1, ESG_i = 0 & \text{if } SFL_i^* > 0 \text{ and } ESG_i^* \leq 0 \\ SFL_i = 0, ESG_i = . & \text{if } SFL_i^* \leq 0 \end{cases} \quad (\text{observational rule}) \quad (\text{K.1})$$

$$\begin{pmatrix} u_i \\ \epsilon_i \\ v_i \\ \eta_i \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{u\epsilon} & \rho_{uv}\sigma_v & \rho_{u\eta}\sigma_\eta \\ \rho_{u\epsilon} & 1 & \rho_{\epsilon v} & \rho_{\epsilon\eta}\sigma_\eta \\ \rho_{uv}\sigma_v & \rho_{\epsilon v}\sigma_v & \sigma_v^2 & \rho_{v\eta}\sigma_v\sigma_\eta \\ \rho_{u\eta}\sigma_\eta & \rho_{\epsilon\eta}\sigma_\eta & \rho_{v\eta}\sigma_v\sigma_\eta & \sigma_\eta^2 \end{pmatrix} \right] \quad (\text{error component})$$

The model consists of four interrelated equations and is constructed around two latent variables: SFL_i^* , representing the respondent i 's unobserved knowledge of sustainable finance and investment attitude. This equation selects in or out those who do (do not) know anything about ESG in relation to financial investment decisions. For those knowledgeable in ESG, ESG_i^* is the latent propensity to invest in ESG financial instruments. These are not directly observed and are related to the observed variables SFL and ESG as described by the observational rule.

As for the observable outcomes, ESG outcomes are only observed for those who are aware of the ESG criteria in relation to financial investment decisions. This structure introduces non-random sample selection, as the estimation of ESG outcomes is conditional on passing the selection threshold.

Both financial literacy (FL_i) and digital financial literacy (DFL_i) are treated as endogenous regressors in the ESG response equation. Their potential correlation with unobserved determinants of ESG behaviour justifies the inclusion of first-stage equations (labelled as *endogenous regressor equation*), each with their own exclusion restrictions (z_{1i} and z_{2i} , respectively) that are needed as a matter of identification.

The model assumes that the structural errors follow a multivariate normal distribution. These distributional assumptions are crucial for identifying the model and for implementing full information maximum likelihood estimation. The correlations between errors across equations (*e.g.*, $\rho_{u\epsilon}$, $\rho_{\epsilon v}$) allow for both selection bias and endogeneity to be explicitly modelled.

This is a classic example of a recursive system involving: a Heckman-style binary selection equation that accounts for a non-random sample, as ESG outcomes are only observed for a subset of firms; a structural equation with endogenous regressors.

The full model captures both the individual's knowledge of sustainable finance and the subsequent adoption of ESG practices, correcting for biases due to unobserved heterogeneity and endogenous regressors. The estimation approaches is Full Information Maximum Likelihood (FIML). The model is estimated in STATA using the "eprobbit" command.

TABLE K.1
Determinants of ESG investments

	SFL	ESG	FL	DFL
SFA	1.750*** (0.037)			
Education parents			0.110*** (0.026)	
Economics degree			0.341 * * (0.140)	
High digital skills				1.355*** (0.112)
Female	-0.305*** (0.030)	0.155 (0.090)	-0.267*** (0.041)	-0.344*** (0.056)
Age	-0.117 * * (0.048)	0.082*** (0.031)	0.046 (0.062)	0.079*** (0.004)
Age2	0.002*** (0.001)	-0.002*** (0.001)	0.000 (0.001)	-0.001*** (0.000)
Single	-0.054 * * (0.024)	-0.081 (0.083)	0.179*** (0.047)	-0.064 (0.073)
Divorced/separated/widowed	0.425*** (0.151)	0.407 (0.432)	-0.728*** (0.083)	-0.801*** (0.170)
Degree	0.261*** (0.059)	0.002 (0.057)	0.130* (0.068)	-0.049 (0.073)
Student	-0.151 * * (0.067)	-0.116 * * (0.051)	0.289*** (0.050)	-0.100 (0.176)
Jobseeker	-0.245* (0.145)	-0.176 * * (0.086)	-0.070 * * (0.034)	-0.499 * * (0.205)
None of these conditions	-0.528*** (0.121)	0.309 (0.415)	-0.451*** (0.041)	-1.205*** (0.351)
Managing HH income	0.202*** (0.068)	-0.051 (0.074)	0.201*** (0.036)	0.631*** (0.079)
Living with children	0.113 (0.071)	0.098*** (0.021)	-0.052 (0.070)	0.215 * * (0.101)
Savings	0.271*** (0.027)	0.044 (0.074)	0.084 (0.060)	0.238*** (0.053)
Pension	0.037 (0.071)	-0.254*** (0.062)	0.351*** (0.043)	0.448*** (0.058)
Financial advisor	0.302*** (0.035)	0.093 * * (0.040)		
Perceived living standards	0.226 * * (0.090)	0.057 (0.038)		
Risk-tolerance	0.294*** (0.003)	0.090 (0.075)		
Climate awareness		0.199*** (0.041)		
FL		0.240 (0.281)		
DFL		0.005 (0.046)		
Vote		0.029 (0.087)		
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Table K.1 – continued from previous page

	SFL	ESG	FL	DFL
Voluntary		0.171*** (0.065)		
Affordable		0.078 * * (0.030)		
Comparing prices		−0.351*** (0.093)		
Tracking expenditure		0.146*** (0.039)		
Long-term financial goals		−0.059 (0.088)		
Buying on impulse		−0.083*** (0.006)		
Constant	0.368 (0.714)	−0.775 (1.547)	1.937 * * (0.966)	2.408*** (0.156)
Area dummies	Yes	Yes	Yes	Yes
σ_v^2			1.504 (0.024)	
σ_η^2			2.989 (0.181)	
$\rho_{u\epsilon}$			−0.188* (0.103)	
$\rho_{v\epsilon}$			−0.376 (0.315)	
$\rho_{\eta\epsilon}$			−0.038 (0.137)	
ρ_{vu}			−0.151*** (0.016)	
$\rho_{u\eta}$			0.010 (0.055)	
$\rho_{v\eta}$			0.091*** (0.005)	
Observations			5,364	
Selected			2,262	
Nonselected			3,102	
Log pseudolikelihood			−22689.553	

Note: The table shows the estimation results for the model in Eq. (K.1). Robust standard errors clustered at geographical areas level are reported in parenthesis. *, ** and *** denote statistical significance at 10%, 5% and 1%, respectively. Sampling weights are used.