The Role of Intuition and Reasoning in Driving Aversion to Risk and Ambiguity

Jeffrey V. Butler
EIEF

Luigi Guiso
EIEF

Tullio Jappelli
University of Naples Federico II and CSEF

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Abstract

Using a large sample of retail investors as well as experimental data we find that risk and ambiguity aversion are positively correlated. We provide evidence that a common link is decision mode: intuitive thinkers tolerate more risk and ambiguity than effortful reasoners. One interpretation is that intuitive thinking confers an advantage in risky or ambiguous situations. We present supporting lab and field evidence that intuitive thinkers outperform others in uncertain environments. Finally, we find that risk and ambiguity aversion vary with individual characteristics and wealth. The wealthy are less risk averse but more ambiguity averse, which has implications for financial puzzles.

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1. Introduction

In many situations individuals behave as if they are able to estimate the probabilities associated with specific outcomes and to calculate the expected payoff of their decisions. In other situations the probabilities of outcomes are unknown. Economists define as risk averse individuals who prefer a certain payment rather than a gamble with the same expected payoff, and as ambiguity averse individuals who would rather choose an option with fewer unknown elements than one with many unknown elements.[1] Individuals' attitudes towards risk and ambiguity are prime candidates to explain behavior in financial markets. For instance, aversion to risk and to ambiguity can explain why people are reluctant to invest in stocks and therefore demand an equity premium (Epstein and Schneider, 2010).

In this paper we undertake a systematic study of risk and ambiguity aversion, how they correlate with observable characteristics and how they correlate with each other. To make the two concepts operational, we use measures of attitudes towards risk and ambiguity from a sample of retail investors as well as from experimental evidence. We complement survey data drawn from a representative sample of Unicredit retail investors (the Unicredit Client Survey, or UCS) with corroborating experimental data.[2] The UCS survey contains detailed demographic and financial information as well as a section devoted explicitly to obtaining measures of attitudes towards risk and ambiguity. We find that individuals are heterogeneous along both dimensions and that their attitudes towards risk and ambiguity exhibit a common pattern: those who dislike financial risk are also more likely to dislike ambiguity.

While this correlation has been documented before, we go further to show that attitudes toward risk and ambiguity can be traced back to the way individuals approach decisions. Research in psychology suggests that people rely on two modes of thinking when making decisions.[3] In the terminology of Stanovich and West (2000), the first mode of decision

[1] Ellsberg (1961) was the first to show that individuals tend to prefer prospects whose probabilities are known over the same prospects with unknown probabilities.

[2] See Alvarez et al. (2011) for details about the survey.

[3] See Sloman (1996), Evans and Over (1996), Hammond (1996), Stanovich and West (2000), Gilovich et al. (2002), Kahneman (2003) and Slovic (2003). Much of the literature, most notably regards intuitive (System 1) thinking as a source of mistakes and biases, while a handful of researchers disagree (see, e.g., Gigrenzer and Todd, 1999; Klein, 2003; Dijksterhuis, 2004)

making (System 1) is intuitive thinking, while the second mode (System 2) is based on effortful reasoning and systematic processing of information. System 2 is calculative, analytical and controlled and involves systematic conscious comparisons of different alternatives. While such deliberative reasoning is slow, System 1 is quick, automatic and can even be unconscious.[4]

In the UCS we obtain information on individuals' predispositions to rely on both decision modes. This allows us to classify respondents into three groups: those who rely mostly on intuition, those who use both intuition and reasoning and those who rely predominantly on deliberative reasoning. We find that attitudes towards risk and ambiguity vary significantly with the way individuals make decisions. The survey shows that, relative to individuals who use both modes, those who decide predominantly using intuition are less likely to be averse to risk and ambiguity. We replicate this finding in two separate experiments involving over 1300 participants from universities in Rome, using incentive compatible measures of risk and ambiguity aversion and an alternative behavioral measure of decision mode suggested by previous research (Rubinstein, 2007; Achtziger and Alós–Ferrer, 2012).

One interpretation of our results is that intuitive thinkers have a comparative advantage in dealing with situations involving risk and uncertainty, as they can reach decisions more promptly and on the basis of less information—two factors which may be crucial for performance in many ambiguous situations. This conjecture was raised by Klein (1998, 2003) and indirectly supported by a handful of studies providing evidence across various types of decisions that effortful, deliberative, decision-making processes often yield lower quality decisions or predictions than intuition or its close cousins (see, e.g., Dijksterhuis, 2004; Lee, Amir and Ariely, 2009; Pham, Lee and Stephen, *forthcoming*). We contribute to this burgeoning literature by providing field-based and experimental evidence in the specific context of decision-making in highly ambiguous environments of the comparative performance advantage that reliance on intuition provides. For experimental evidence on this

[4] Recent research comparing how fraternal and paternal twins make decisions suggests that reliance on these decision modes has a genetic component and is a stable, individual, trait, see Bouchard and Hur (1998). Our experiment shows that decision mode is stable across contexts, and that participants who take longer to reach decisions involving uncertain monetary outcomes also took longer to make choices in decisions free of monetary consequences (see Table A2 in the Appendix).

performance advantage, we invited a randomly chosen subset of participants in our first two experiments to participate in an Iowa Gambling Task (Bechara et al., 1994) involving 100 sequential choices under uncertainty. We found that participants who relied more on intuition performed significantly better in the task. For field-based evidence, we follow the trading strategies of our UCS sample of investors around the time of the 2008 stock market crash and show that investors who rely mainly on intuition were better able to time the market, exiting at a faster pace before the stock market crashed than deliberative thinkers.

The remainder of the paper proceeds as follows. Section 2 describes our two main data sources: the UCS survey and corroborating experiments. Sections 3 and 4 focus on the UCS survey, describing our measures of risk and ambiguity aversion as well as decision mode before presenting our main empirical evidence of the effect of intuition and reasoning on preferences for risk and uncertainty. Section 5 discusses our experimental evidence corroborating the correlation between decision mode and risk and ambiguity preferences found in the survey data. Section 6 presents evidence on the performance advantage of intuitive thinking in the form of, first, results from an Iowa Gambling Task experiment and, second, behavior of investors around the time of the 2008 stock market crash. In Section 7 we relate our findings to the existing literature. Section 8 concludes.

2. The survey and experimental data

We use two sources of data. The first source is the second wave of the Unicredit Clients' Survey (UCS) which was run between June and September 2007. The survey is comprised of interviews with a sample of 1,686 Italian customers of Unicredit, one of the largest European Banking groups. The sample was stratified according to three criteria: geographical area, city size, and financial wealth. To be included in the survey, customers must have had at least 10,000 euro worth of assets with Unicredit at the end of 2006. The survey is described in greater detail in the Appendix or in Alvarez, Guiso and Lippi (2011).

Besides collecting detailed demographic information and data on investors' financial investments, the survey collected data on the way respondents handle decisions—whether by reliance on intuition or by effortful reasoning—as well as indicators of various attitudes that have a bearing on financial decisions and, more generally, on decisions under risk and uncertainty. Here we focus on two prominent attitudes that have been cited to characterize decisions under risk and uncertainty: risk aversion and ambiguity aversion.

Our second source of data is two experiments we conducted on-line in 2009 and 2010. Participants in both experiments were recruited from among college students attending one of two universities in Rome, Italy: LUISS Guido Carli or La Sapienza. In total, we have data for 1,306 students. Each participant completed exactly one of the two experiments. The experiments allow us to construct incentive-compatible measures of risk and ambiguity preferences as well as an alternative, more objective, measure of participants' primary decision modes.[5] Details on the design of the experiments, the measures of preferences for risk and ambiguity as well as the measures of decision mode that we collected appear in the Appendix.

The survey and experimental data should be viewed as complementary. The main advantage of the survey is the heterogeneity of the sample which involves true investors and comes close to being representative of the population of Italian investors (see Alvarez et. al, 2011). The main drawback of the survey data is that because of time and space limitations the questions that can be asked in a general purpose survey are limited and normally involve only self-assessed descriptions when measuring decision mode or hypothetical situations when eliciting risk and ambiguity preferences. Hence, the measures of aversion to risk and

[5] Conducting the experiment on-line rather than in a more traditional laboratory setting has pros and cons, of course. The primary benefit in this case was scalability: to have enough observations to examine primarily intuitive thinkers we anticipated it would be necessary to collect more observations than would be practical using in-lab sessions. An additional benefit is to lessen the salience of the experimenters, ameliorating common concerns about experimenter demand effects. The primary downside of conducting the experiments on-line is the limited interaction opportunities between experimenters and participants that make it difficult to directly address individual's specific concerns or doubts. For example, individuals who doubt the veracity of the instructions and suspect that the experimenters strategically rig outcomes may have a preference for options involving less ambiguity for reasons having nothing to do with ambiguity preferences (see, e.g., Schneeweiss, 1973; Kadane 1992). To allay such concerns, decision situations were described clearly and thoroughly; randomness was (accurately) described as being resolved impartially and not being contingent on participant's choices–e.g., "…the computer will draw a chip … each chip has the same probability of being drawn…." Finally, to lessen participants' more general concerns about the possibility of being deceived, the invitation to participate originated from a trusted institution (EIEF) and was signed by a faculty member (Butler), whose contact information was provided in the e-mail and who promptly replied to individuals' questions concerning the experiment.

ambiguity may not be incentive compatible. The main advantage of the experiment is its narrow focus making it possible to dig deeper and obtain measures of intuitive thinking using different methodologies. Additionally, monetary incentives in the experiments were designed to make truthful revelation of risk and ambiguity preferences optimal. The main drawback of the experiment is that participants are students, which limits the study of the relationship between wealth and attitudes toward risk and uncertainty.[6]

3. Decision mode and attitudes towards risk in the survey data

3.1. Measuring decision mode: intuition and reasoning

Even though the dual system is a feature of all individuals, people differ in the prevalence of one system or another when making decisions (Stanovich and West, 2000; Klein, 2003). Some individuals make decisions only after a thorough processing of all available information and a systematic comparison of the potential alternatives, even at the cost of possibly losing an opportunity by waiting to make a decision. Others decide quickly, even (or perhaps even more) when faced with complex problems, processing at glance the little information at hand and coming up with a choice. Thus, to establish whether decision mode affects attitudes towards risk we can use variation in the reliance on the two systems across individuals. To understand how people make decisions and who relies more on System 1 or 2, UCS respondents were asked the following question: [7]

"Think of when you make a decision. Generally speaking, do you tend to decide rather quickly relying mostly on your intuition or rather do you tend to think accurately about all possible alternatives and consequences of your choice, taking as much time as needed before reaching a final decision?"

[6] All raw experimental data and statistical code are available on request. Data from the UCS are also available upon request but may require permission from Unicredit.

[7] The question on the decision mode could have been framed in the context of a financial decision, for instance "Think of when you make a decision about financial matters." Specific focus on a financial decision would have increased our confidence that the decision mode applies to financial decision rather than to other contexts.

Respondents can answer in three ways: (1) *I decide very rapidly on the basis of my intuition;* (2) *I partly ponder and partly rely on intuition*; (3) *I ponder accurately, reasoning carefully about my choice.”*

This question allows us to define two dummy variables, classifying survey participants into groups that differ in the prevalence of intuitive thinking versus reasoning. Table 1 shows that the fraction of intuitive thinkers is 15 percent, while the fraction of those who use predominantly deliberative reasoning is 43 percent (the residual fraction relying on both intuition and reasoning is 42 percent.

For this indicator to be a valid measure of the decision mode, two conditions must hold. First, since the indicator is based on self-reported information, one has to trust that people are consciously aware of how they typically approach decisions. Second, since we rely on cross-sectional differences on how individuals make decisions, the underlying assumption is that there are systematic differences in the mode of thinking across individuals and that, even if all people clearly use both intuition and reasoning, in some individuals intuitive thinking is more prevalent than in others. That is, reliance on intuition versus reasoning must be, at least to some extent, an individual trait. Evidence from twins studies points to a strong genetic component in the way people make decisions, suggesting that decision mode is indeed a stable trait (Bouchard and Hur, 1998).[8] That individuals are consciously aware of this trait is supported by the evidence in our experiments which shows that the self-reported measure is significantly correlated with objective measures of decision mode (Section 6).

3.2. Measuring risk and ambiguity aversion

We measure risk attitudes in two ways. First, the survey has a qualitative indicator of risk tolerance patterned after the US Survey of Consumer Finance:

[8] Stanovich and West (2000) also provide evidence supporting this assumption. They argue that the systematic differences in performance along a large variety of tasks that they document in a sample of individuals can be traced to differences in the prevalence of one of the two systems of thinking, System 1 (based on intuition) or 2 (based on reasoning). Similarly, Klein (2003) offers many examples consistent with the idea that individuals differ systematically in their willingness to rely on intuition to make decisions.

Which of the following statements comes closest to the amount of financial risk that you are willing to take when you make your financial investment: (1) a very high return, with a very high risk of losing money; (2) high return and high risk; (3) moderate return and moderate risk; (4) low return and no risk.

From this question we construct a categorical variable ranging from 1 to 4 with larger values corresponding to greater dislike for risk. Only 1.8 percent chooses "a very high return, with a very high risk"; 28 percent choose "high return and high risk;" most are moderately risk or strongly risk averse (52 and 19 percent, respectively).[9]

The question allows us to classify risk attitudes but not to distinguish absolute and relative attitudes towards risk. Since we observe income and wealth in the data, we could purge the risk aversion indicator from differences in endowments. However, we also use a second measure that allows us to classify individuals according to their relative risk aversion. This relies on questions similar to those analyzed by Barsky et al. (1997) in the Panel Study of Income Dynamics, where individuals are asked to choose among different lifetime earnings profiles. In particular, the UCS asks:

Suppose you are the only income earner in your family and must change jobs. You can choose between two options:

A. With firm A you will make the same wage that you make today for sure;
B. With firm B you have a 50% chance of making twice as much as in your current job and a 50% chance of seeing it reduced by 1/3.

Which of the two opportunities do you choose?

If they chose A they are then asked*: If by choosing firm B you had as before a 50% chance of doubling your wage but with probability 50% you could see it reduced by ¼ (instead of 1/3), would you still choose firm A? (Yes, No)*

If they chose B then they are asked*: If by choosing firm B you had as before a 50% chance of doubling your wage but a 50% probability of seeing it reduced by 50% (instead of 1/3), would you still choose firm B? (Yes, No)*

[9] A recent literature on eliciting preferences from survey data shows that qualitative questions on risk aversion are informative and have predictive power on behavior, see Barsky et al. (1997), Guiso and Paiella (2008), Dohmen et. al. (2011).

From the answers to this question we obtain a second categorical variable, also taking values from 1 to 4 and increasing in the degree of relative risk aversion.

While risk averse individuals prefer a certain payment rather than a gamble with same expected payoff, ambiguity averse individuals are those who would rather choose an option with fewer unknown elements than one with many unknown elements. In recent years several studies have provided a theoretical basis for ambiguity aversion and have characterized preferences that distinguish ambiguity aversion from risk aversion, see for example Maccheroni et al. (2005) and Ghirardato et. al. (2004). We construct a dummy variable indicating whether individuals are averse to ambiguity using a question in the UCS based on the original Ellsberg (1961) thought experiment:

Suppose you face two urns each with 100 balls. The first urn has 100 balls, some are red some are black but you do not know how many are red and how many are black. The second urn has 100 balls: 50 red and 50 black. One ball is drawn from the urn that you choose and you will win 1,000 Euros if the ball is of the color that you choose. Choose the color. Now tell me whether you prefer to have the ball drawn from the first of the second urn. Choose one of the following options:

1. *A strong preference for the first urn.*
2. *A slight preference for the first urn.*
3. *Indifferent between the two urns.*
4. *A slight preference for the second urn.*
5. *A strong preference for the second urn.*

We term the urn where the number of red or white balls is unknown as the "ambiguous urn" and classify those who answer 4 or 5 as ambiguity averse. The majority (52 percent) is averse to ambiguity either strongly (32 percent) or slightly (19.5 percent). One fourth is indifferent between the two urns. Only 13 percent prefers the ambiguous urn. However, without knowing *why* they prefer this urn, we cannot classify these individuals' ambiguity preferences.[10]

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[10] These individuals could simply believe that the ambiguous urn has a more favorable distribution, for whatever reason. While such unwarranted optimism with respect to the ambiguous urn seems akin to ambiguity loving, it

The pattern of responses is similar to that obtained in experiments where individuals face a choice between risky and ambiguous prospects. In particular, it is common to find that some individuals have a preference for ambiguous lotteries.[11] For instance Halevy (2007) finds that in an experiment involving 104 individuals who are asked to choose between an ambiguous urn and a risky urn, 61 percent are ambiguity averse, 22 percent are ambiguity neutral and 17 percent prefer the ambiguous urn. The UCS is the first survey to ask Ellsberg-type questions in a large sample of heterogeneous individuals and thus the first to allow correlating attitudes towards ambiguity with observable characteristics and other attitudes towards risk.

4. Results from survey data

To show the link between risk attitudes and decision mode we construct two dummies, one for intuitive thinking (equal to 1 for those who rely mostly on intuition, and zero otherwise) and one for deliberative reasoning (equal to 1 for those who rely mostly on reasoning, and zero otherwise). The comparison group includes respondents who rely on both intuition and reasoning. For each attitude we run a regression on the two dummies for decision mode and a set of additional variables that capture observable heterogeneity that may be relevant for that attitude. In particular, we control for age, gender, marital status, education and region of residence. We also construct a measure of each household's total wealth and include its log as a further control (see the Appendix for details and Table 1 for summary statistics).

4.1. Risk aversion

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does not fit with any theoretical definition of ambiguity-loving that we know of and hence we do not classify it as such.

[11] There are several alternatives to obtaining an index of ambiguity aversion. One is to ask individuals, as we do, to choose between a risky lottery and an ambiguous lottery; an alternative, followed for example by Guiso et al (2007) and Halevy (2007), is to ask the willingness to pay for lotteries involving risk and involving ambiguity and then back out a measure of ambiguity aversion from the reported prices. A third, recently developed methodology (Bossaerts et al, 2006; Ahn et al, 2007; Choi et al, 2007) faces individuals in lab experiments with a large number of simple portfolio choices involving risky but non-ambiguous and ambiguous assets with varying prices. Individual preference parameters are then retrieved from these choices. Each of these approaches has pros and cons discussed in Section 6.

Table 2 reports the coefficients and standard errors of an ordered probit model for the qualitative indicator of risk aversion. The first column presents a regression of risk aversion on the two dummies of intuitive thinking and reasoning. Reliance on intuition is associated with lower risk aversion compared to individuals who use both intuition and reasoning, but the effect is not statistically different from zero. On the other hand, a predominant reliance on reasoning is associated with significantly higher levels of risk aversion.

To give a sense of the economic importance of decision mode we compute the marginal effects of relying on intuition and reasoning. Our estimates imply that individuals who rely mostly on reasoning are 5.8 percentage points more likely to be in the most risk-averse group (those preferring low return and no risk) than those who use both reasoning and intuition, which is about one third of the unconditional proportion of individuals in this group.

Column 2 adds demographic variables to the baseline specification. As in previous studies risk aversion increases with age and is significantly lower for males and more educated individuals (e.g. Barsky et al, 1997; Guiso and Paiella, 2008; Dohmen et al, 2011). However, the size and significance of the coefficients of decision mode are not affected. In the third column we add the log of total wealth as an additional control. Higher wealth is associated with lower risk aversion, as suggested by plausible representations of attitudes towards risk, but again the effect of the decision mode dummies is unaffected.

Table 3 reports the results of an ordered probit model with relative risk aversion as the dependent variable. The results are similar to Table 2: deliberative respondents (those who rely mostly on reasoning) are significantly more risk averse than those who rely both on reasoning and intuition. Demographic variables also induce similar effects except that here, wealth has no predictive power on relative risk aversion which is consistent with preferences exhibiting constant relative risk aversion. Turning our attention to economic significance, we see again that a deliberative decision mode has a substantial impact, raising the probability of being in the highest relative risk aversion group by 8 percentage points (15 percent of the sample mean).

A possible concern with our findings is that decision mode indicator captures cognitive ability, which has been found to be *positively* correlated with risk tolerance (Frederick, 2005;

Benjamin et al., 2007; Burks et. al (2009), Dohmen et al (2010). We have several answers to this concern. First, in the same literature cognitive ability is identified with reasoning ability. For instance, Benjamin et al. (2007) find that mathematical ability is strongly negatively correlated with risk aversion. Insofar as being better at reasoning implies relying more on it, we should find a *negative* effect of our reasoning dummy on risk aversion, not positive.

Second, if our measure of decision mode was capturing cognitive ability one would expect to find a positive correlation between reliance on reasoning and education if only because IQ test scores are highly correlated with educational attainment. Instead we find a small and negative correlation (-0.054).

Third, if our measure of decision mode reflects cognitive ability we should find a correlation of this measure with individual time discounts. In fact, Frederick (2005), Benjamin et al. (2006), Burks et al (2009) and Dohmen et al (2010) find that people with better cognitive ability, besides being less risk averse, are also more patient. However, when we use a measure of subjective time discounting present in the UCS we find no statistically significant effect of intuition and reasoning.[12] For all of these reasons, we conclude that our measure of decision mode reflects the way individuals approach decisions rather than their cognitive ability.

4.2. Ambiguity aversion

Table 4 reports estimates of the probability of being ambiguity averse. We estimate a probit model using the dummy for ambiguity aversion as the dependent variable. The dummy takes the value of one if a respondent is classified as ambiguity averse and zero otherwise. Column 1 shows that decision mode has a strong and statistically significant effect on the probability of being ambiguity averse. Intuitive thinkers are much less likely to be averse to

[12] The UCS asked survey participants to choose between €100,000 one year from the interview and an immediate sum M<100,000. The initial value of M is set at €95,000. If the respondent accepts (turns down) 95,000 now she is asked whether she would accept 90,000 now (respectively 97,000); if she accepts 90,000 (turns down 97,000) she is further asked whether she would accept 80,000 now (respectively 98,000). If she turns down 80,000 her discount rate is above 20%; if she turns down 98,000 the alternative offered is to wait one year and get 100,000. This allows classifying respondents into 6 categories with increasing subjective discount rates. In an ordered probit regression of this indicator of subjective discount the dummy for intuition has a small positive coefficient and that for reasoning small and negative but none of them is statistically significant (t-stat of 0.61 and -1.02, respectively).

ambiguity than people who decide using both intuition and reasoning. On the other hand, deliberative thinkers are much more likely to be ambiguity averse. These patterns are unchanged when we control for demographic variables (column 2) or wealth (column 3). The marginal effects of decision mode are again large: reliance on intuition lowers the probability of being ambiguity averse by about 13 percentage points, which is about one third of the sample proportion of ambiguity averse respondents.

One interpretation of the positive correlation between intuition and ambiguity tolerance is that intuitive thinking proxies for impulsivity and, at the same time, impulsive individuals are more likely to make mistakes, as shown in Frederick (2005). Following this argument, one could argue that intuitive individuals choose the ambiguous lottery more often by mistake, because, being less patient, they make decisions too fast and are thus more exposed to mistakes. If this were the case we should find a strong correlation between our decision mode indicator and subjective discount. Contrary to this argument, we find no correlation as was shown at the end of Section 5.1.

The correlation between ambiguity aversion, demographic variables and wealth is interesting in its own right. As far as we know, most existing evidence on aversion to ambiguity has been obtained from experiments with little variation in individual characteristics and, so far, no evidence is available on the relationship between ambiguity aversion and wealth. Differently from attitudes towards risk, we find in Table 4 that age and gender are unrelated with ambiguity aversion (columns 2 and 3). We find a mild effect of education and marital status: more educated individuals are more likely to be averse to ambiguity, as are married people (column 2). Only the effect of marital status survives when we control for wealth, however (column 3).

Interestingly, the effect of wealth on the probability of being ambiguity averse is positive (column 3). Neither theory nor introspection provides hints about how attitudes toward Knightian uncertainty should vary with wealth, making it difficult to interpret this correlation. However, it may not be unreasonable that it is the wealthy that are particularly afraid of unknown outcome probabilities: after all, a wrong decision when probabilities are unknown may transform a rich man into a poor man, but can only transform a poor man into a (still) poor man.

The positive correlation between wealth and ambiguity aversion could have important implications for portfolio choice and assets pricing. First, since the wealthy hold a substantial portion of assets, it is their preferences that mostly matter for the pricing of risk. If ambiguity aversion and wealth are positively correlated, the correlation may help account for a large equity premium, even if relative risk aversion does not vary with wealth. Secondly, it may explain why, even at high levels of wealth, in many countries people fail to participate in the stock market. This fact is hard to rationalize with a fixed cost of participation (Guiso et al. 2008), but is not inconsistent with ambiguity aversion, as shown by Dow et al. (1992), Bewley (1998) and Epstein and Schneider (2010).

5. Corroborating evidence on correlation: Experiments 1 and 2

Like most experiments, our pool of participants lacks the heterogeneity in individual characteristics necessary to uncover many of the interesting relationships we found using the UCS data. There is little variation in age or education level, and the variation we observe in income is not participants' income but rather their parents' income. Nevertheless, data from experiments 1 and 2 allow us to provide evidence that the phenomenon at the center of our current inquiry—that differences across individuals in their predominant mode of thinking lead to predictable variation in risk and ambiguity preferences—is robust. We find a significant relationship between risk and ambiguity aversion and decision mode even in this vastly different (experimental) population, and even though decisions are not purely hypothetical. Below we describe our experimental measures of decision mode and risk and ambiguity preferences. For details on the experimental designs see the Appendix. Instructions are provided in the Instructions Appendix.

5.1 Measures of decision mode in the experiments

From Experiments 1 and 2 we obtain one main behavioral measure of decision mode, exploiting a fundamental difference between the intuitive and deliberative systems: since the intuitive system in the brain is relatively fast, individuals who rely more on intuition than on effortful, deliberative, reasoning should reach decisions more quickly than their deliberative counterparts. This is consistent with Rubinstein (2007), where the author documents variation in decision time across *types of decisions*: decisions which involve cognitive reasoning take longer than decisions that are primarily instinctive or intuitive. In our study, we *fix the type* of decision and use variation in response time as a measure of how much an individual is relying on his or her deliberative, versus intuitive, facilities. For further evidence on this fundamental distinction between decision modes, see Achtziger and Alós–Ferrer (2012) as well as the discussion therein.

Specifically, we record the amount of time in seconds that each participant takes to reach decisions in choices involving risk and uncertainty.[13] We measure the time participants spend on the two questions used in our ambiguity preferences elicitation procedure. These two questions involve real monetary stakes in the context of risk and ambiguity. For details of the exact questions used, see the Appendix. From the time it takes participants to complete these two questions we construct a 3-category behavioral decision mode classification analogous to the self-reported measure in the UCS by labeling subjects according to how relatively quickly they answered. A participant is labeled "intuitive" if his or her decision time was in the bottom quartile of response times—i.e., if he or she made decisions relatively quickly. We label those in the top quartile "deliberative." To create a comparison group, all other participants are labeled "partially deliberative."[14]

To provide evidence that this behavioral measure of decision mode is measuring what we claim it is, we construct two additional, alternative, decision mode measures. First of all, we collect the same self-reported 3-category measure of decision mode as in the UCS.

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[13] We collect decision time data for all sections of each experiment. In our analysis, we focus on decisions involving real monetary stakes and which involve risk and uncertainty. We focus on these questions because they are central to our investigation. However, the patterns in decision time and thinking mode are present in other sections of the experiment that do not involve monetary stakes, risk or uncertainty providing some reassurance that decision time is a stable individual trait. In particular, Table A2 in the Appendix shows that individuals who decide quickly (slowly) when monetary stakes are involved also complete the REI, which does not involve any monetary stakes, quickly (slowly).

[14] Comparisons are strictly within-experiment as the questions used to elicit ambiguity aversion, and hence construct our decision mode measure, differ across experiments. That is to say, an Experiment 1 (2) participant's response time is only compared to the response times of other Experiment 1 (2) participants.

Secondly, we collect a widely-used psychological measure of intuitive and deliberative thinking: the 40-item Rational Experiential Inventory (REI in Pacini and Epstein, 1999). We do not use these latter two measures directly in our analyses as we have concerns about their validity in the specific context of our experiments, which involve only students, as we feel that students are generally encouraged to think of themselves as deliberative, effortful reasoners which may color self-assessments. Our preferred behavioral measure of decision mode should suffer to a lesser extent, if at all, from such self-image biases.

However, to provide some reassurance that our more novel behavioral measure of decision mode is indeed capturing variation in reliance on intuition, we report in the Appendix (Table A3) a series of ordered probit estimates using our behavioral decision mode measure as the dependent variable, and these alternative, more transparent, decision mode measures as explanatory variables. The estimates show that the alternative decision mode measures are highly statistically significantly related to our preferred behavioral decision mode measure, suggesting that all three measures capture a common and prevalent phenomenon.

5.2 Measures of risk and ambiguity aversion

To measure risk aversion, in both Experiments 1 and 2 we use a procedure due to Holt and Laury (2002). Briefly, participants face a sequence of ten choices between two binary lotteries: lottery A—featuring a high maximum payoff (€38.50) but a low minimum payoff (€1.00)—and lottery B featuring less extreme payoffs (max €20, min €16). For each choice in the sequence there is a known probability, *p,* of the high payoff which is common to both lotteries and increases from 0.1 to 1 in steps of 0.1 as the sequence progresses. The choice number in this sequence where an individual switches from preferring the less extreme lottery B to preferring lottery A is our measure of risk aversion, which takes values from 1 to 10 and is increasing in risk aversion.[15]

[15] Such "multiple price lists" (MPL) have become commonly used tools in experimental economics owing largely to their simplicity. The potential drawbacks of common MPLs are also well-recognized and include susceptibility to framing operating through, e.g., a propensity to pick middle rows and a more general weak incentives/hypothetical bias problem as typically only one row is chosen by experimenters to determine earnings. Another recurring issue is how to interpret inconsistent response patterns (multiple switch points). These issues are discussed in more detail in Andersen, et al. (2006). To address the first two concerns, in Experiment 1 we

Because measuring ambiguity aversion is trickier than measuring risk aversion, we use two different elicitation procedures. In Experiment 1 we use an urn-valuation procedure pioneered by Halevy (2007). In Experiment 2, we measure ambiguity preferences more directly by letting participants choose between lotteries involving either risk or ambiguity. This second procedure has two main advantages: it is simpler to implement and, at the same time, allows identification of ambiguity-loving behavior which is not possible with the Halevy procedure.

The ambiguity preference elicitation procedure used in Experiment 1 proceeds in two-phases. In the first phase, two urns are described to participants: one urn contains 5 red balls and 5 white balls; the other urn contains exactly 10 balls, each of which is either red or white, but the number of red or white balls is unknown (the ambiguous urn). It is explained that the computer will choose one ball at random from each of the two urns, and that the participant must guess which color ball will be drawn from each of the two urns. Each correct guess pays €20, while incorrect guesses pay nothing. In the second phase of the procedure participants state the minimum amount of money they would accept in exchange for the right to collect the earnings from each of their two bets, separately. This "minimum willingness-to-accept" is elicited using a Becker-DeGroot-Marschak (1964) mechanism which provides incentives for

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implement a one-row-at-a-time version of the mechanism used in Holt and Laury (2002). Specifically, on each of a sequence of ten separate screens participants choose between Lottery A or Lottery B as described above for one value of x, as x ranges from 0.1 to 1.0 in steps of 0.1. I.e., a typical screen would ask only one question: choose between "Option A: [x] probability of receiving 20 euro; [1-x] probability of receiving 16 euro;" or "Option B: [x] probability of receiving 38.50 euro; [1-x] probability of receiving 1 euro." The positions of Options A and B (i.e., which comes first) are randomized on each screen. This procedure serves to make each separate decision as salient as possible, thereby ameliorating the weak incentives/hypothetical bias problem. Furthermore, presenting each decision separately and randomizing the order options are presented order plausibly lessens the impact of heuristics thought to be particularly relevant when choices are presented in a more standard ordered table format—heuristics such as picking the middle row, picking the middle option, or picking the first option. The main drawback of this particular mechanism is the possibility of multiple switching points. There is no consensus on how to handle such inconsistent observations—we balance a concern for preserving data against a concern about added noise by classifying individuals only with respect to their first switching point. In Experiment 2, we implement a simpler mechanism that has the advantage of not permitting multiple switching points—the "switching MPL" first used by Harrison et al., 2005. Here, all ten choices between Option A and Option B are presented in an ordered table format as in Holt and Laury (2002), but participants are asked only to specify the first row where they switch from preferring Option A to Option B. This downside of this simpler MPL is that it may be susceptible to the types of framing effects mentioned above. Although previous research finds negligible framing effects overall in these MPLs (e.g., Andersen, et al., 2006), one might *a priori* worry about their influence on the intuitive decisionmakers studied herein.

truthful reporting.[16] The *difference* between a participant's valuation of their bet on the ambiguous urn and their value for their bet on the risky urn is an indicator of ambiguity aversion. Those who value the bet related to the ambiguous urn strictly less are labeled ambiguity averse.[17]

In Experiment 2, we describe to participants the same two urns used in Experiment 1. They are then told that one ball will be drawn from one of the two urns. They must choose which of the two urns the ball is extracted from and will win €20 if the extracted ball is red. Participants are then asked to consider *exactly the same* two urns and given a second, nearly identical, choice: they must choose one of the two urns to extract a ball from and will win €20 if the color of the extracted ball is white.[18] We label those who choose the non-ambiguous urn both times ambiguity averse and those who choose the ambiguous urn both times ambiguity-loving. All other participants are labeled ambiguity neutral.

Table 5 gives descriptive statistics for our decision mode measures as well as participant demographics.

5.3. Results from Experiments 1 and 2

[16] Theoretically, truth-telling is a dominant strategy in the Becker-DeGroot-Marschak (BDM) mechanism. Whether the BDM mechanism reliably elicits truth-telling in practice, however, has been questioned by several researchers (see inter alia, Harrison, 1992; Plott and Zeiler, 2005; and Harrison and Rutström 2008). The mechanism has been criticized as being difficult for participants to understand and therefore susceptible to participant's misconceptions or confusion about the incentives the mechanism provides. It also has been criticized for providing weak incentives for exact truth-telling—i.e., losses from misreporting just a little can be quite minimal depending on how the BDM is implemented. To partially address these concerns, our implementation of the BDM mechanism incorporates features suggested by Plott and Zeiler (2005) as effective at reducing participant misconceptions. We provide a limited form of training through a detailed numerical example demonstrating the optimality of truth-telling, followed by a mandatory quiz on how the mechanism works. We also stress to participants at the beginning of the experiment that their responses are anonymous—individuals are identified only by an experiment code. Finally, to provide adequate incentives for truth-telling, we use a lottery/asset with high variance (binary outcomes: €0 or €20) and participants are told that buying prices may range from the lowest prize to the highest prize (i.e., from € 0.00 to € 20.00) as suggested in Harrison and Rutström (2008).

[17] While it is tempting to label as "ambiguity-seeking" those who value the bet related to the ambiguous urn strictly more, this is not possible. For example, an individual could simply believe that there is a larger proportion of red balls in the ambiguous urn, and therefore value a bet of "red from the ambiguous urn" more highly than a bet on either color ball from the non-ambiguous urn. This is a perfectly valid subjective belief that would be consistent with strictly valuing a bet on the ambiguous urn more. We thank David K. Levine for disabusing us of this common misperception.

[18] We implement a procedure to ensure stated preferences are strict (see the Appendix for details).

Results from both Experiments 1 and 2 confirm the main findings in the survey data. Participants labeled more intuitive by our behavioral measure of decision mode are both less risk averse and less likely to be ambiguity averse than partially deliberative individuals. Furthermore, in Experiment 2 where ambiguity-loving can be identified, the results suggest that being an intuitive thinker both significantly reduces ambiguity aversion and significantly increases ambiguity-loving.[19] These patterns prove robust to controlling for relevant demographic determinants of risk and ambiguity aversion such as gender and parents' income and, as in the survey, when controlling for a measure of cognitive ability.[20]Also, it should be noted that although we present results for each experiment separately for transparency nothing changes qualitatively if we conduct our analyses on the pooled data from both experiments. In particular, the significance patterns remain virtually the same.

Table 6 presents regressions of risk aversion on decision mode for both experiments separately. Negative and significant coefficients on the dummy for intuitive thinkers indicate that intuitive thinkers are significantly less risk averse than partially deliberative thinkers (the excluded category), while positive and significant coefficients on our deliberative indicator imply deliberative thinkers are more risk averse than those who rely on both deliberative and intuitive thinking.

Similarly, Table 7 demonstrates that being an intuitive thinker significantly reduces the likelihood of being ambiguity averse and increases one's chances of being ambiguity loving relative to partially deliberative thinkers. Computing the marginal effects of decision mode on ambiguity preferences reveals an impact strikingly similar to the analogous estimates in our survey results: controlling for demographics, being an intuitive thinker reduces the probability

[19] As in the survey, one may be concerned that our intuitive thinkers are simply more prone to make mistakes and this is why they appear more risk tolerant and less ambiguity averse in our data. As detailed in the Appendix, we implement our risk aversion elicitation procedure in two slightly different ways, so that mistakes should manifest themselves differently across experiments. For example, making a mistake in the risk preferences elicitation procedure used in Experiment 2 is equally likely to misclassify an individual as risk loving as it is to mis-classify an individual as risk averse. Also note that the idea of intuitive thinkers being simply more prone to mistakes is not consistent with our findings in the Iowa Gambling Task experiment (Section 8), where we show that intuitive thinkers *perform better* than deliberative and partially deliberative thinkers.

[20] Here our cognitive ability measure is a participant's score on a standardized mathematics exam given in the final year of high school in Italy. The correlation between cognitive ability and our main thinking mode variable is non-significant in both experiments: 0.017 ($p > 0.7$) in Experiment 1 and -0.034 ($p > 0.35$) in Experiment 2. This suggests that our behavioral decision mode measure is not simply a proxy for cognitive ability.

of being ambiguity averse by 9.2 percentage points in Experiment 1 and 11.7 percentage points in Experiment 2. Furthermore, in Experiment 2 where constructing an indicator of ambiguity loving is possible, we find that the marginal effect of being an intuitive thinker is to increase the probability of being ambiguity loving by 11.4 percentage points.

6. Performance in uncertain environments

So far, our analysis with survey and experimental data shows that decision mode and attitudes toward risk and ambiguity are correlated. One reason this may occur is that intuitive thinkers are more comfortable in situations involving risk and uncertainty because reliance on intuition provides a comparative advantage. If this is the case, we should find that intuitive thinkers perform better in uncertain situations. In this section we provide evidence confirming this prediction. Our first source of evidence is experimental, while our second source comes from data collected about actual investment decisions.

To obtain an experimental measure of performance, we invited a random sub-sample of participants in Experiments 1 and 2 to come to the laboratory at the Einaudi Institute for Economics and Finance and participate in an experiment. In total, 170 students participated in our Iowa Gambling Task (Bechara, et al., 1994) experiment. To begin, each participant was given an endowment of 10 euros and presented with four card decks on his or her computer screen.[21] Each participant selected cards, one at a time, from any of the four decks by clicking.[22] Participants knew nothing about the card decks, i.e. they operated in an ambiguous environment. Unbeknownst to participants: (i) two of the four card decks were programmed to yield a positive expected return; (ii) the other two decks yielded a negative expected return; and (iii) each participant would get a total of 100 draws from the four card decks. All participants were actually paid their earnings from this experiment. To classify participants in terms of primary decision mode, in our analysis we associate to each Iowa Gambling Task

[21] The Iowa Gambling Task experiment was programmed and conducted with the software z-Tree (Fischbacher 2007).

[22] The decks were pre-programmed to be identical to the decks used in the original Iowa Gambling Task (Bechara et al., 1994).

participant their behavioral decision mode measure from Experiment 1 or 2.[23] For further details on our Iowa Gambling Task experiment, see the Appendix; screenshots appear in the Instructions Appendix.

Figure 1 plots, for each decision mode, the average proportion of draws from good decks in each block of 10 card draws. For example, intuitive thinkers drew, on average, about 52 percent of their first 10 cards from good decks, while the analogous proportion for deliberative thinkers is only about 46 percent. From Figure 1 it is evident that intuitive thinkers generally outperformed deliberative thinkers in this ambiguity-laden task. Table 8 makes this comparison more formal: even controlling for demographics, in all 10-draw blocks intuitive thinkers selected cards from good decks more often than partially deliberative thinkers who, in turn, performed no differently than deliberative participants. Moreover, in the majority of 10-draw blocks intuitive thinkers' performance advantage was statistically significant.[24] Overall, intuitive thinkers took about 7 percentage points more of their draws from good decks than partially deliberative thinkers—a highly statistically significant performance gap. At the same time—consistent with appearances in Figure 1—there was no evidence of a performance difference between deliberative and partially deliberative thinkers.

Our second source of evidence combines the UCS survey data with a panel of administrative data having detailed information on respondents' financial portfolios. Data are available at a monthly frequency starting in December 2006 until October 2009. Thus, they cross the Great Recession. Specifically, for each of 26 asset classes we know the value of each individual's holdings at the end of each month and the net flow in each month. Because we observe the net assets flows we can identify net trades.

[23] It is worth noting that there is evidence of persistence in decision mode. Regressing the total time spent on all 100 card draws on dummies for our behavioral decision mode measure from Experiments 1 and 2 reveals that intuitive thinkers took about 45 fewer seconds to complete all 100 draws than partially deliberative thinkers ($p = 0.009$) and about 80 fewer seconds than deliberative thinkers ($p = 0.000$). This pattern is robust to controlling for demographics and/or clustering standard errors by session. Not conditioning on decision mode, the average time spent to complete all 100 draws was about 395 seconds.

[24] We lose a few observations by controlling for demographics as is evident from the number of observations in the table. However, the results and significance patterns are the same with or without demographic controls, so we report them with these controls.

We consider market timing in the months preceding the collapse of Lehman Brothers, a situation involving substantial Knightian uncertainty (Caballero, 2009; Caballero and Simsek, 2011). If in situations rife with ambiguity intuitive stockholders elaborate an effective decision more quickly than deliberative investors, we expect them to make good use of this ability and exit the market before the collapse of Lehman Brothers at a faster pace than deliberative stockholders. That is, conditional on selling stocks they should rather sell at a faster rate before the collapse than after. Figure 2 gives a graphical illustration of this phenomenon. It plots the differences in the fractions of intuitive and deliberative stockholders who held stocks in December 2006 and who sold stocks in subsequent months. The vertical bar identifies the collapse of Lehman. The figure shows that intuitive thinkers are more likely to have sold stocks before the collapse of the stock market than deliberative investors: in 17 of the 21 months before the Lehman collapse intuitive investors were strictly more likely to have sold stocks. After Lehman there is no difference between the two groups. Table 9 shows this more formally. It reports estimates of the following linear probability model:

$$s_{it} = \alpha(\text{before}_t \times \text{intuitive}_{it}) + \beta\left[(1-\text{before}_t)\times\text{intuitive}_{it}\right] + \gamma\text{before}_t + \delta(1-\text{before}_t) + \lambda Z_{it} + u_{it}$$

where s_{it} is a dummy equal to one if investor *i* sells stocks in month *t*; sell *before* equals one before the Lehmann shock, *intuitive* equals one for intuitive investors, and *Z* is a vector of additional control variables. The coefficient α measures any extra tendency to sell stocks by intuitive investors before the collapse of the market relative to the mean rate at which stockholders were selling stocks, measured by γ. The parameter β measures this tendency, but after the collapse, relative to the mean rate at which investors were selling, measured by δ. A positive value of α and a zero value of β would be evidence that intuitive investors perform better at timing the market than deliberative ones.

The estimates in column (1) of Table 9 are consistent with this hypothesis. Intuitive investors are 1.4 percentage points more likely to sell stocks before Lehman's collapse than the average (5.7 percent). After the collapse they sell at the same rate as deliberative investors.

This result holds if we add demographic variables and investors' wealth (column 2) and it is not due to the intuitive dummy capturing some other dimensions of ability, or greater financial information. In the remaining columns we add interaction terms between the *before* and (1-*before*) dummies with a measure of education (column 3) and proxies for financial literacy (column 4); a self-reported measure for financial capability (column 5); and the time spent gathering financial information (column 6). None of these variables gives an advantage in timing the market, while the effect of intuitive thinking before Lehman is always significant.

One final point to notice is that our estimates in columns (1)-(6) suggesting that intuitive investors were more likely to sell stocks before Lehman's collapse might be criticized because our definition of stockholding in the UCS dataset refers only to stocks held at one institution (Unicredit). As with all administrative data, this definition excludes stocks held in accounts at other institutions. In principle, intuitive investors might have offset stock selling before Lehman brothers by purchasing stocks held in different accounts. To take this criticism into account, we replicate our baseline regression restricting the sample to those who have accounts only at Unicredit. The estimated coefficient is 0.025, in line with the full sample estimates.

7. Relation to the literature

Our results are related to several strands of recent literature. There is an emerging literature eliciting individual risk preference parameters and characterizing their heterogeneity, either by relying on experiments (Holt and Laury, 2002), or by using large-scale surveys (Barsky et al. 1997; Guiso and Paiella, 2008; Dohmen et al., 2011; Donkers et. al., 2001) or large scale field experiments (Harrison, Lau and Rutström, 2007; Andersen et al., 2008; Bombardini and Trebbi, 2011). Most of this literature characterizes risk aversion, but a handful of papers investigate how risk aversion correlates with various other preference traits, such as loss aversion, see von Gaudecker et al. (2011). Instead, we focus on preferences for risk and ambiguity and study whether and why these traits are related.

A related literature uses theory-guided laboratory experiments presenting individuals with a large number of simple portfolio choices involving risky but non-ambiguous assets and ambiguous assets with varying prices. Given a specification for preferences under ambiguity, observed choices permit the recovery of preference parameters identifying the model that best characterizes these choices, as in Bossaerts et al. (2006), Ahn et al. (2007), and Choi et al. (2007), Chakravarty and Roy (2006) and Hsu et. al. (2005). Like us, some of these papers study whether aversion to risk and to ambiguity are related (Cohen et al., 2011; Chakravarty and Roy, 2006, 2009); but differently from them we are also interested in understanding the *mechanism* that links these traits, and in particular whether the architecture of the cognitive system plays a role in shaping attitudes towards risk and uncertainty.

Several recent papers look at the effect of cognitive ability on risk taking. These papers find that higher cognitive ability is associated with a higher propensity to take risk (Frederick, 2005; Dohmen et. al, 2010) and a lower incidence of behavioral anomalies such as aversion to small-stakes risks (Benjamin et. al. 2006). In contrast to these papers which examine how differences in ability to reason are related to risk aversion, we focus on how the decision mode - intuition or reasoning - affects individual attitudes towards risk and uncertainty.

Our study also relates to a strand of research in psychology arguing that human cognitive architecture is based on a dual system—two ways of thinking and approaching decisions (Kahneman, 2003). The first system, which Stanovich and West (2000) term System 1, corresponds to what is commonly called intuition. System 2, on the other hand, handles effortful reasoning. Individuals who rely on effortful, deliberative, reasoning carry out systematic comparisons of relevant alternatives and assess the pros and cons of each based on available information. In contrast, when decisions are based on intuition there is no systematic comparison of alternatives: a decision is taken at glance, by rapidly evaluating the main features of the problem at hand and achieving a conclusion. Klein (1998; 2003) conjectures a direct link between decision mode and attitudes towards risk and uncertainty by observing that intuitive thinking is uniquely suited to adventurous behavior and risk taking. The key point is that intuition can handle severe uncertainty so that individuals who are better at using System 1 may also feel more comfortable dealing with uncertainty and risk (though no distinction is made between the two) and thus develop higher tolerance for both. It is this feeling of comfort with *detection* and *learning* about risks that could make intuitive thinkers more tolerant to risk and uncertainty. We provide the first evidence consistent with this conjecture.

Most directly related to the current study, a handful of papers in the psychological dual-systems vein provide evidence, across various decision contexts, of the relatively poor quality of decisions that deliberative (System 2) processes often deliver compared to the more intuitive or automatic System 1 decision processes. In a series of non-incentivized experiments, Dijksterhuis (2004) studies the performance advantages of "unconscious thought" in complex decisions by putting some participants under cognitive load and thereby limiting participants' ability to use their deliberative facilities, while other participants were not put under such cognitive load. The main finding was that "when making complex decisions, conscious thought is inferior relative to unconscious thought." Using a different manipulation, Pham, Lee and Stephen (*forthcoming*) implement experimental treatments which either reinforce or undermine participant's reliance on emotion in decision-making and then have participants predict various outcomes, finding enhanced reliance on emotion when forecasting outcomes significantly increases predictive accuracy across a wide array of situations and time horizons. Interpreting emotion as the opposite of deliberation, Lee, Amir and Ariely (2009) manipulate experimental participants' reliance on emotion by, in one treatment, placing some subjects under cognitive load and some not, finding reliance on emotion enhances transitivity—a precursor to rationality. Similarly, Gigerenzer and Todd (1999) argue, and provide suggestive empirical, that individuals use "fast and frugal" (System 1) heuristics as an optimal response to the severe knowledge and computation constraints characterizing real-world decision environments. More tangentially related, Inbar, Cone and Gilovich (2010) investigate what features of a decision problem cue deliberative processes versus intuitive processes, finding evidence that more precisely-stated questions tend to cue rationality.[25] Differently from these papers, we focus on how reliance on intuition affects

[25] It is worth noting that, while the authors of this last study claim to find evidence that more rationality is associated with less ambiguity aversion, and more intuitive processes with more ambiguity aversion—i.e., the opposite of what we find—their results are actually not clear on this point. This is primarily because what they describe as an ambiguous urn in one of their treatments is actually non-ambiguous. The urn in question contained "`…at least two' red marbles out of the 100, adding that `any number of red marbles from exactly two all the way up to 100 is equally likely.'" This urn, while certainly relatively complex and representing a two-stage lottery, is

preferences for both risk and ambiguity simultaneously, providing a combination of large- and small-scale experimental and survey evidence.

8. Concluding remarks

In this paper, we document substantial individual heterogeneity in the two attitudes that have been used to characterize choice under uncertainty. Most individuals dislike risk as well as ambiguity, but the intensity varies with observable characteristics. Most importantly, the two attitudes are not independent. Empirically, individuals who dislike risk more are also more likely to be averse to ambiguity, as also documented by Hsu et al. (2005) and Bossaerts et al. (2006). Expanding these latter results, we present three independent sources of evidence—correlational, experimental and survey-based—that a common factor linking these attitudes is the predominant way in which people handle decisions: whether by intuitive thinking or through deliberative, effortful, reasoning.[26]

We find that predominant decision mode is systematically related to how much people dislike risk and whether they are averse to ambiguity. Intuitive thinkers are more willing to tolerate risk and ambiguity than people who handle decisions by effortful reasoning. We argue that one plausible interpretation of our findings is that intuitive thinking is particularly adept at dealing with complex situations involving substantial uncertainty and many alternatives, as implied by Damasio et al. (1991) and Bechara et al. (1997). That intuitive thinking can be a powerful mode of achieving conclusions should not be surprising: many problems in mathematics find first an intuitive solution (a conjecture) and only later, through laborious reasoning, receive an analytic proof. Sometimes the time gap between conjecture and proof can be as long as a century, as with Poincaré's conjectures. Sometimes even after centuries and many attempts by excellent mathematicians the proof is still elusive (e.g., Coldbach's conjecture). The length of these gaps is a good measure of the power of intuitive thinking and

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non-ambiguous because the number of red marbles in it is known to participants to be uniformly distributed from 2 to 100.

[26] In Butler, Guiso and Japelli (2013) we further explore this link between preferences for risk and uncertainty and decision mode by experimentally manipulating participants' willingness to rely on intuition, finding results largely consistent with those presented herein.

suggests that intuition is particularly valuable when problems are analytically hard as those involving substantial uncertainty. This is consistent with our evidence from an Iowa Gambling Task experiment as well as our novel evidence on investors' market timing during the financial crisis, both of which suggest that intuitive thinkers perform better when choices are made under substantial risk and ambiguity.

Finally, exploiting individual heterogeneity in the UCS survey data we show that, though attitudes towards risk and ambiguity have as a common root individual decision mode, these preferences also vary with important observable variables: age, gender and, most importantly, wealth. While risk aversion is negatively related to wealth, the correlation between ambiguity aversion and wealth is positive. Correlation across these attitudes as well as their correlation with individual wealth can have important consequences for financial portfolio decisions and for the possibility of reconciling some of the puzzles in finance by allowing for more complex preference representations.[27] The positive correlation between ambiguity aversion and wealth that we document may, if confirmed, provide an explanation for the stockholding puzzle (the fact that many do not invest in stocks in spite of the large equity premium) at high wealth levels.[28] In addition, if the wealthy are increasingly ambiguity averse this may contribute to reconcile the historical level of the equity premium with the level predicted by the standard portfolio model (based on expected utility maximization) using reasonable values of risk aversion. Since ambiguity aversion commands an additional "ambiguity premium" on uncertain assets (Epstein and Schneider, 2010), the finding that many investors tend to be both risk and ambiguity averse implies that it may be possible to find reasonable parameter configurations of risk and ambiguity aversion that produce enough risk intolerance to account for the historical equity premium.

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[27] As pointed out by Bossaerts et. al (2006) a positive correlation between risk and ambiguity aversion can help explain the "value effect."

[28] Gollier (2006) shows conditions under which aversion to ambiguity reinforces risk aversion in the sense that it induces investors to invest less in stocks – the risky and ambiguous asset. See also Hansen et al. (1999), Chen and Epstein (2002), Klibanoff et al. (2005), Mukerji et al. (2005), Gollier and Salanié (2006) and Epstein and Schneider (2010).

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Table 1. Sample statistics, UCS survey

The table reports sample statistics for the variables used in the estimation based on the UCS survey. The sample includes 1686 individuals.

Variable	*Mean*	*Standard deviation*	*Minimum*	*Maximum*
Intuitive	0.15	0.35	0	1
Deliberative	0.43	0.49	0	1
Qualitative indicator of risk aversion	2.87	0.72	1	4
Relative risk aversion	3.18	1.05	1	4
Ambiguity averse	0.52	0.50	0	1
Age	54.81	12.26	25	89
Male	0.70	0.46	0	1
Education (years)	12.73	4.25	0	21
Married	0.68	0.46	0	1
Resident in the North	0.51	0.50	0	1
Resident in the Center	0.24	0.43	0	1
Large city	0.01	0.12	0	1
Financial literacy	4.63	1.15	1	8
Financial ability	3.20	0.85	1	5
Financial information	2.36	1.62	1	7

Table 2: Determinants of the qualitative indicator of risk aversion.

The table shows ordered probit estimates of the probability that the investor is risk averse. The left hand side is a categorical variable taking values from 1 to 4, with higher values corresponding to a higher degree of risk aversion measured from self-reported preferences for risk and return combinations. *Only Intuitive* is a dummy equal to 1 if the investor relies mostly on intuition when making decisions (zero otherwise); *Deliberative* is a dummy equal to 1 if he relies mostly on reasoning (zero otherwise). The excluded group is those who partly rely on intuition partly on reasoning. Standard errors are reported in parenthesis. *** significant at 1%; *** significant at 5%.

	(1)	*(2)*	*(3)*
Intuitive	-0.063	-0.077	-0.099
	(0.081)	(0.082)	(0.082)
Deliberative	0.236**	0.213**	0.217**
	(0.058)	(0.059)	(0.059)
Age		0.004	0.006*
		(0.002)	(0.002)
Male		-0.324**	-0.308**
		(0.061)	(0.061)
Education		-0.041**	-0.035**
		(0.007)	(0.007)
Married		-0.045	-0.035
		(0.060)	(0.060)
North		-0.031	-0.016
		(0.068)	(0.068)
Centre		-0.029	-0.016
		(0.077)	(0.078)
City size		-0.330	-0.340
		(0.234)	(0.234)
Log Household Wealth			-0.099**
			(0.028)
Observations	1,686	1,686	1,686

Table 3: Determinants of the indicator of relative risk aversion.

The table shows ordered probit estimates of the probability that the investor is relative risk averse. The left hand side is a categorical variable taking values from 1 to 4, with higher values corresponding to a higher degree of relative risk aversion. *Intuitive* is a dummy equal to 1 if the investor relies mostly on intuition when making decisions (zero otherwise); *Deliberative* is a dummy equal to 1 if he relies mostly on reasoning (zero otherwise). The excluded group is those who partly rely on intuition partly on reasoning. Standard errors are reported in parenthesis. *** significant at 1%; ** significant at 5%.

	(1)	*(2)*	*(3)*
Intuitive	-0.060	-0.077	-0.076
	(0.083)	(0.084)	(0.084)
Deliberative	0.203**	0.194**	0.197**
	(0.061)	(0.062)	(0.062)
Age		0.006*	0.006**
		(0.002)	(0.002)
Male		-0.305**	-0.310**
		(0.064)	(0.064)
Education		-0.029**	-0.026**
		(0.007)	(0.007)
Married		-0.036	-0.028
		(0.063)	(0.063)
North		0.120	0.129
		(0.069)	(0.070)
Centre		0.105	0.119
		(0.080)	(0.080)
City size		-0.158	-0.164
		(0.235)	(0.235)
Log Household Wealth			-0.036
			(0.028)
Observations	1686	1686	1686

Table 4. Determinants of ambiguity aversion.

The table shows probit estimates of the probability that the investor is ambiguity averse. *Intuitive* is a dummy equal to 1 if the investor relies mostly on intuition when making decisions (zero otherwise); *Deliberative* is a dummy equal to 1 if he relies mostly on reasoning (zero otherwise). The excluded group is those who partly rely on intuition partly on reasoning. Standard errors are reported in parenthesis. *** significant at 1%; ** significant at 5%.

	(1)	*(2)*	*(3)*
Intuitive	-0.348**	-0.354**	-0.342**
	(0.094)	(0.095)	(0.096)
Deliberative	0.221**	0.233**	0.230**
	(0.066)	(0.067)	(0.068)
Age		-0.000	-0.003
		(0.003)	(0.003)
Male		0.122	0.104
		(0.069)	(0.070)
Education		0.016*	0.009
		(0.008)	(0.008)
Married		0.180**	0.161*
		(0.069)	(0.069)
North		0.104	0.091
		(0.078)	(0.078)
Centre		0.214*	0.201*
		(0.089)	(0.090)
City size		0.254	0.266
		(0.274)	(0.274)
Log Household Wealth			0.134**
			(0.033)
Observations	1,686	1,686	1,686

Table 5. Sample statistics, experimental data

	Experiment 1	*Experiment 2*	*Iowa Gambling Task*
Behavioral decision mode (in seconds)			
Intuitive	17.17	40.48	28.59
Partially deliberative	28.64	74.39	60.31
Deliberative	75.24	177.19	180.02
Self-reported decision mode			
Mainly intuition (dummy)	0.06	0.05	0.05
Both intuition and reasoning (dummy)	0.60	0.59	0.61
Mainly reasoning (dummy)	0.34	0.35	0.35
Risk aversion	4.98	6.17	6.11
Ambiguity aversion (dummy)	0.26	0.43	0.50
Ambiguity loving (dummy)	n.a.	0.17	0.36
REI-Experiential engagement	3.23	3.05	3.06
Male	0.49	0.47	0.51
Age	22.76	24.97	24.62
Math Score	7.76	7.47	7.58
Family Income (in thousand euro)	70.32	44.47	49.33
Observations	534	772	168

Table 6. Behavioral decision mode and risk aversion

Columns 1-4 present ordered probit estimates using the measures of risk preferences described in the text as the dependent variable. These measures are increasing in risk aversion. "Intuitive" and "Deliberative" are dummy variables for our main behavioral decision mode measure (described in the text), the excluded category being "Partially deliberative." "Math Score" is each participant's self-reported score on a standardized math exam given in the final year of high school in Italy. The score theoretically ranges from 0 to 10. The income measure is the participant's family's total annual net income from all sources, in thousands of euros. "Experimental design controls" include dummies for the order in which the two versions of each risk and ambiguity elicitation method were presented to subjects (in experiment 2 they were always presented in the same order). Robust standard errors, clustered at the session level in appear in parentheses.

Dependent variable = Risk preferences measure				
	Experiment 1		Experiment 2	
	(1)	(2)	(3)	(4)
Intuitive	-0.110**	-0.111***	-0.048**	-0.042
	(0.029)	(0.032)	(0.023)	(0.052)
Deliberative	0.163***	0.084**	0.283***	0.307***
	(0.023)	(0.033)	(0.049)	(0.065)
Age		-0.003		-0.002
		(0.024)		(0.005)
Male		-0.046		0.032*
		(0.063)		(0.019)
Math score		-0.006		-0.029
		(0.026)		(0.034)
30 ≤Income< 45		-0.194		-0.130
		(0.337)		(0.115)
45≤ Income< 70		0.078		0.019
		(0.368)		(0.035)
70 ≤ Income< 120		-0.184		-0.094**
		(0.293)		(0.047)
Income ≥ 120		-0.425**		0.052
		(0.186)		(0.119)
Experiment design controls	Yes	Yes	n/a	n/a
Observations	534	486	772	692

Table 7. Behavioral decision mode and attitude toward ambiguity

Columns 1 and 2 estimate a probit model with a dummy for ambiguity aversion in the first experiment as the dependent variable. Columns 3-6 use data from the second experiment and estimate probit models using dummies for ambiguity-aversion (col. 3-4) or ambiguity loving (col. 5-6) as the dependent variable. “Intuitive” and “Deliberative” are dummy variables for our main behavioral decision mode measure (described in the text), the excluded category being “Partially deliberative.” “Math Score” is each participant’s self-reported score on a standardized math exam given in the final year of high school in Italy. The score theoretically ranges from 0 to 10. The income measure is the participant’s family’s total annual net income from all sources, in thousands of euros. “Experimental design controls” include dummies for the order in which the two versions of each risk and ambiguity elicitation method were presented to subjects (in experiment 2 they were always presented in the same order). Robust standard errors, clustered at the session level in appear in parentheses.

	Experiment 1		*Experiment 2*			
	Ambiguity Aversion		Ambiguity Aversion		Ambiguity Loving	
	(1)	(2)	(3)	(4)	(5)	(6)
Intuitive	-0.373**	-0.288*	-0.246***	-0.304***	0.433***	0.454***
	(0.152)	(0.153)	(0.057)	(0.040)	(0.071)	(0.059)
Deliberative	0.147*	0.131	0.065	-0.036	-0.115*	-0.108
	(0.084)	(0.115)	(0.128)	(0.143)	(0.062)	(0.074)
Age		-0.027***		-0.005**		-0.005
		(0.008)		(0.002)		(0.005)
Male		-0.072		0.237***		-0.031
		(0.226)		(0.078)		(0.070)
Math score		-0.021		-0.026		0.013
		(0.042)		(0.026)		(0.049)
30 ≤Inc< 45		0.155		-0.013		0.315
		(0.135)		(0.165)		(0.223)
45≤ Inc< 70		0.100		-0.222*		0.157***
		(0.136)		(0.126)		(0.056)
70 ≤ Inc< 120		-0.016		-0.337***		0.079
		(0.126)		(0.096)		(0.064)
Income ≥ 120		-0.176		-0.846		0.521***
		(0.172)		(0.534)		(0.054)
Constant		0.351	-0.123***	-0.082	-1.039***	0.055
		(0.301)	(0.029)	(0.073)	(0.053)	(0.068)
Experiment design controls?	Yes	Yes	n.a.	n.a.	n.a.	n.a.
Observations	534	486	772	692	772	692

Table 8. Regressions for proportion of cards from "good decks"

Each column presents OLS estimates. The dependent variable in columns 1-10 is the proportion of cards in the 10-card block in the column heading that an individual drew from a "good deck," i.e., one with a positive expected return. The dependent variable in the last column is the proportion of all 100 draws from good decks. The main explanatory variables are dummies for being Intuitive or Deliberative, as measured in Experiments 1 or 2. The excluded category is "partially deliberative." Robust standard errors, clustered at the session level, are in parentheses.

	Block of 10 Draws										
	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	All 100
Intuitive	0.08*	0.05	0.06	0.05	0.10**	0.08*	0.05	0.11***	0.12**	0.03	0.07***
	(0.04)	(0.07)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)	(0.02)
Deliberative	-0.00	-0.01	0.03	-0.05	-0.02	0.02	0.03	-0.05	0.04	0.06*	0.01
	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.02)
Age	0.00	-0.00	0.00	0.00	0.00	-0.01	-0.01	-0.00	-0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Male	0.00	0.08**	-0.03	-0.04	-0.02	-0.01	0.01	0.02	-0.07	-0.04	-0.01
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.02)
Math score	0.01	0.02**	-0.01	0.00	-0.01	0.00	0.01	-0.00	-0.01	-0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
30 ≤Inc< 45	-0.01	0.01	0.02	-0.01	-0.03	0.07	0.02	0.06	0.09***	0.06	0.03
	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.06)	(0.05)	(0.03)	(0.05)	(0.03)
45 ≤Inc<70	-0.09	-0.02	0.06	-0.03	0.01	0.04	0.02	0.05	0.08*	0.05	0.02
	(0.06)	(0.05)	(0.04)	(0.04)	(0.03)	(0.04)	(0.08)	(0.06)	(0.04)	(0.04)	(0.03)
70 ≤Inc<120	-0.03	0.11**	0.01	0.04	0.01	0.07*	-0.03	0.07	0.11**	0.11**	0.05
	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.03)
Inc ≥ 120	-0.12	0.03	0.01	-0.01	-0.04	-0.08**	-0.02	-0.11	-0.09**	0.01	-0.04
	(0.12)	(0.06)	(0.08)	(0.06)	(0.06)	(0.03)	(0.12)	(0.10)	(0.04)	(0.15)	(0.04)
Constant	0.44***	0.30**	0.51**	0.51***	0.62**	0.59***	0.56***	0.59***	0.68**	0.56***	0.54***
	(0.13)	(0.12)	(0.19)	(0.11)	(0.24)	(0.17)	(0.12)	(0.18)	(0.24)	(0.16)	(0.13)
Observations	143	143	143	143	143	143	143	143	143	143	143
R-squared	0.05	0.10	0.03	0.07	0.04	0.10	0.04	0.07	0.10	0.05	0.08

Table 9. Intuitive thinking and market timing

The table shows estimates of the linear probability that the investor sells stocks in month *t*. *Before* is a dummy=1 if *t* precedes the collapse of Lehman Brothers; *Intuitive* is a dummy equal to 1 if the investor relies mostly on intuition when making decisions (zero otherwise). *Education* is years of completed education; *Financial literacy* is an index of financial literacy based on answers to a set of quizzes posed to UVCS respondents; *Financial ability* is a self-reported index of ability to make financial decisions (see Guiso and Jappelli, 2010 for a description of the last two indicators); *Financial information* is a measure of the time investors spend collecting financial information. Standard errors are reported in parenthesis. Column (7) restricts the sample to investors with assets only at Unicredit. *** significant at 1%; ** significant at 5%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Before *intuitive	0.014**	0.017**	0.017**	0.017**	0.027**	0.026**	0.025**
	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)
(1-*Before*) *intuitive	0.002	0.004	0.004	0.004	0.012	0.011	0.007
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.010)
Before	0.057**	0.018	0.005	0.025	0.022	0.032	-0.108
	(0.002)	(0.035)	(0.036)	(0.036)	(0.042)	(0.040)	(0.061)
(1-*Before*)	0.039**	0.002	-0.003	-0.005	-0.003	0.014	-0.125*
	(0.003)	(0.035)	(0.036)	(0.037)	(0.042)	(0.040)	(0.062)
Male		-0.010**	-0.009*	-0.010**	-0.014**	-0.013**	-0.005
		(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)
Age		0.000**	0.000*	0.000**	0.000**	0.000**	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log net wealth 2007		0.001	0.005	0.001	0.001	0.001	0.012*
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)
*Before**educ.			-0.002**				
			(0.000)				
(1-*Before*) * educ.			-0.002**				
			(0.001)				
*Before**fin. literacy				-0.002			
				(0.002)			
(1-*Before*) *fin. lit.				0.001			
				(0.002)			
Before * fin. abil.					0.002		
					(0.003)		
(1-*Before*) * fin. abil.					0.005		
					(0.003)		
Before * fin.inf.						-0.002	
						(0.001)	
(1-*Before*) * fin. inf.						-0.002	
						(0.002)	
R-squared	0.05	0.05	0.06	0.05	0.06	0.06	0.06
Observations	609	609	609	609	609	512	342

Figure 1
Proportion of cards from "good decks," Iowa Gambling Task experiment

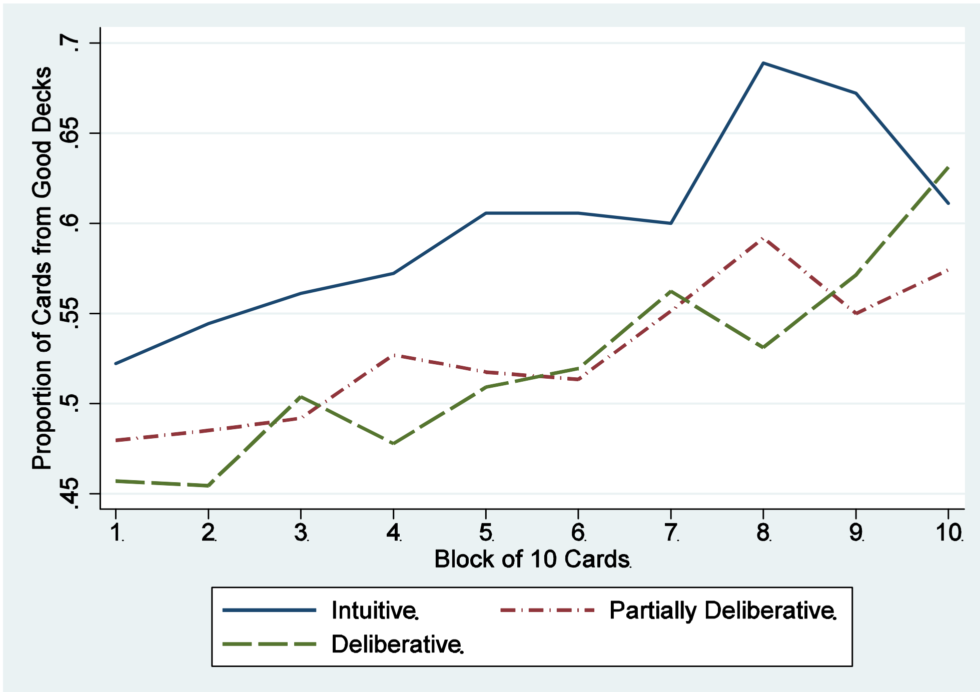

Figure 2
Probability of selling before and after the crisis