The role of intuition and reasoning in driving aversion to risk and ambiguity

Jeffrey V. Butler
EIEF - Einaudi Institute for Economics and Finance

Luigi Guiso
European University Institute and EIEF

Tullio Jappelli
University of Naples Federico II and CSEF

October 25, 2011

Abstract

Using a large sample of retail investors as well as experimental data we find that risk and ambiguity aversion are positively correlated. We show the common link is decision style: 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.

JEL classification: **D81; D83.**
Keywords: Risk Aversion, Risk Ambiguity, Decision Theory, Dual Systems, Intuitive Thinking.

1. Introduction

In many situations individuals take decisions with clear estimates of the probabilities associated with specific outcomes. In other situations people don't know the probabilistic structure of the events. Economists refer to the first situation as risk, and the second as ambiguity.[1] These attitudes towards risk and ambiguity are prime candidates to explain behavior in financial markets. For instance, since financial assets' returns tend to be risky and (at least at times) ambiguous, 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 an experimental study with survey data drawn from a representative sample of Unicredit retail investors (the Unicredit Client Survey, or UCS).[2] The 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 attitudes towards risk and ambiguity exhibit a common pattern: those who dislike financial risk are also more likely to dislike ambiguity.

Most interestingly, we show that the 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 making (System 1) is intuitive thinking, while the second mode (System 2) is based on effortful reasoning and systematic processing of

[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] For details about the survey see also Alvarez, Guiso and Lippi (2011).
[3] See Sloman (1996), Evans and Over (1996), Hammond (1996), Stanovich and West (2000), Gilovich et al. (2002), Kahneman (2003) and Slovic (2003).

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 style suggested by previous research (Rubinstein, 2007).

One interpretation of our results is that intuitive thinkers have a comparative advantage in dealing with situations involving risk and uncertainty, as they can react more promptly to the limited information available in ambiguous situations. In the last section of the paper we provide field-based and experimental evidence supporting this view. For experimental evidence, we invited a randomly chosen subset of participants in our main experiments to participate in an Iowa Card Task (described below) involving 100 sequential choices under uncertainty. We found that participants who relied more on intuition performed significantly better in the card task. For corroborating empirical evidence from the field, we follow the trading strategies of our 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 by exiting from stocks at a faster pace than deliberative thinkers before the stock market crashed.

The remainder of the paper proceeds as follows. In Section 2 we describe closely related literature. In Section 3 we describe our two data sources, the survey data and experimental

[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).

data. Section 4 presents our indicators of risk aversion, ambiguity aversion and thinking mode in the survey. Section 5 shows regressions of the effect of intuition and reasoning on these behavioral traits. Section 6 discusses the results of the experiments, confirming the relationship between decision style and risk and ambiguity aversion. Section 7 presents the results from the Iowa card task and the behavior of investors around the stock market crash. Section 8 concludes.

2. Related Literature

Our paper is 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, as in Holt and Laury (2002), or by using large-scale surveys, as Barsky et al. (1997), Guiso and Paiella (2008), Dohmen et al. (2011), and Donkers et. al. (2001) or large scale field experiments as in 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 paper is also related to a recent and burgeoning literature in neuroscience and neuroeconomics that studies how people's brains handle decisions under risk and uncertainty. In a famous contribution Bechara et al. (1997) show that individuals with normal IQ and reasoning ability, but whose capacity to feel emotions is diminished because of damage to their prefrontal cortex, cannot handle uncertainty effectively. Substantial involvement of intuitive thinking in decisions involving risk and uncertainty is also consistent with functional magnetic resonance studies showing that the orbitofrontal cortex and the amygdala are the areas of the brain that are most active when individuals face ambiguous choices (Hsu et. al.,2005; Rustichini, 2005). These findings suggest that our results may reflect a comparative advantage that intuitive thinkers have in dealing with risk and uncertainty, and that such advantage translates into greater tolerance for both. We contribute to this literature by providing new direct evidence on the comparative advantage intuition confers in situations involving uncertainty in larger and more representative samples than previous studies.

Finally, a recent strand of research in psychology argues 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 thinking 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.

3. 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 euros worth of assets with Unicredit at the end of 2006. The survey is described in greater detail in the Appendix 1 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 aversion as well as alternative, more objective, measures of participants' primary decision modes and favorability towards relying on intuition. 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. Experimental instructions are available from the authors upon request.

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 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.

4. Thinking mode and attitudes towards risk in the survey data

4.1. 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 thinking 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:

"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?"

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).[5] 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 style (Section 6).

4.2. Measuring attitudes towards risk and ambiguity

[5] 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.

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:

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).[6]

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)*

[6] 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).

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)*

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.

Ambiguity aversion reflects a dislike for situations where individuals are uncertain about the probabilities of outcomes rather than, or in addition to, the aversion they may have to the variability in outcomes. In recent years several studies have provided a theoretical basis for aversion to ambiguity and have characterized preferences that separate ambiguity aversion from risk aversion. For example Maccheroni et al. (2005) and Ghirardato et. al. (2004) study preference representations where aversion to ambiguity is identified by a single parameter that is distinguished from risk aversion. 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 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 suggesting that they are ambiguity neutral. Only 13 percent prefers the ambiguous urn. However, without knowing *why* they prefer this urn, we cannot classify these individuals' ambiguity preferences.[7].

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.[8] 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 ambiguity are 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.

5. Results from survey data

To show the link between risk attitudes and decision style 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 thinking 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 Appendix for details and Table 1, panel D for summary statistics).

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

[8] 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.

5.1. Risk aversion

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 thinking 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 thinking mode are not affected. In fact, thinking mode is poorly correlated with demographic characteristics (age or gender), despite the somewhat popular idea that women are more "intuitive" than men. 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 thinking 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 thinking 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 thinking 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 thinking 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.[9] For all of these reasons, we conclude that our measure of thinking mode reflects the way individuals approach decisions rather than their cognitive ability.

5.2. Ambiguity aversion

[9] 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).

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 thinking 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 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 thinking 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 thinking 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 aversion to ambiguity and wealth are positively correlated, the correlation may help account for a large equity premium if equity happens to be ambiguous, 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 aversion to ambiguity, as shown by Dow et al. (1992), Bewley (1998) and Epstein and Schneider (2010).

6. The experiments

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, our experimental data allow us to provide evidence that the phenomenon at the center of our current inquiry—that differences across individuals in their predominant mode of think lead to predictable variation in risk and ambiguity aversion—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 thinking mode and risk and ambiguity aversion. For details on the experimental designs see the Appendix.

6.1 Measures of thinking mode in the experiments

In the experiment we use one main measure of thinking mode but collect data on two other measures to validate the first. As our main measure we exploit 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 engaging his or her deliberative versus intuitive facilities.

In particular, we record the amount of time in seconds that each participant takes to reach decisions in choices involving risk and uncertainty.[10] We measure the time participants spent on 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 thinking 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."[11]

To validate this behavioral measure of thinking mode we construct two additional thinking mode measures. First of all, we collect the same self-reported 3-category measure of

[10] 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 (see, e.g., Section 7, below) providing some reassurance that decision time is a stable individual trait.

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

thinking mode as in the UCS. 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 focus on the most relevant 10-item subscale which measures an individual's favorability towards relying on intuition. Using these subscales, we classify participants as "high-intuitive" if they score in the top 25th percentile on this subscale relative to other participants in the same experiment (i.e., Experiment 1 or 2), and "low-intuitive" if their scores are in the bottom 25th percentile.

We do not use these latter two measures directly as we have concerns about their validity in the context of our experiments which involves only students. Specifically, we feel that students are generally encouraged to think of themselves as deliberative, effortful reasoners which may color self-assessments. On the other hand, our behavioral decision-time measure of thinking mode should suffer to a lesser extent, if at all, from such self-image biases. Still, it is worth noting that both the self-reported 3-category measure of thinking mode and the thinking mode measure we construct from the REI are highly significant predictors of our behavioral decision style measure.[12] This suggests all three measures are capturing a common and prevalent phenomenon.

6.2 Measures of risk and ambiguity aversion

To measure risk aversion, in both experiments we use a procedure due to Holt and Laury (2002). Briefly, participants face a sequence of choices between two binary lotteries: lottery A and lottery B. Lottery A features a high maximum payoff (€38.50) but a low minimum payoff (€0.10), while lottery B features a lower maximum payoff but a higher minimum payoff (€20 and €16, respectively). There is a known probability p of the high payoff in both lotteries. Participants choose between lotteries A and B in each of a sequence of 10 decisions where the probability of the high payoff, p, is increased from 0.1 to 1 in steps of 0.1. The decision in this

[12] We ran several ordered probit regressions featuring our main thinking mode measure on the left hand side and, on the right hand side, sets of dummies for either or both of these other two thinking mode measures. With or without controlling for demographics, the results show that each of these other two measures of thinking mode is a significant predictor of our main thinking mode measure. This is true whether controlling for both of the other thinking mode measures simultaneously, or whether they enter one at a time into the regressions. These estimates are not reported, but are available upon request.

sequence where an individual switches from preferring 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.[13]

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 (non-ambiguous) urn contains 5 red balls and 5 white balls; the other (ambiguous) urn contains exactly 10 balls, each of which is either red or white, but the number of red or white balls is unknown. 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 truthful reporting.[14] The *difference* in a participant's valuations of their

[13] In Experiment 1, participants were asked to decide on each of the separate lotteries separately, where the order in which lotteries was presented was randomized. If there are multiple switching points, we follow much of the literature in characterizing an individual's risk preferences by the *first* switch point (i.e., the lowest p for which lottery A is preferred to lottery B). In Experiment 2 participants were presented one table containing all 10 lotteries—ordered increasing in p—and asked to indicate the lowest *p* at which they preferred lottery A to lottery B. Both of these procedures are common in the literature and using both here provides an extra robustness check on our results.

[14] For each of the two urn-guesses, separately, the procedure is as follows: the computer draws a number between 0 and 20 which can be thought of as a "price." If this price is higher than the participant's stated minimum willingness-to-accept, the participant receives a payment equal (in euros) to the price but gives up his or her right to the earnings from the urn-guess. Otherwise the participant retains the right to the earnings from his or her urn-guess. This mechanism provides incentives for participants to truthfully state their values for each of the bets irrespective of risk preferences. Since the main concern with this mechanism is that it is relatively complicated, each participant had to pass a short quiz about the procedure immediately before stating their minimum-

bet on ambiguous urn and 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.[15]

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 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.[16] 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.

6.3. Experimental results

Results from both experiments confirm the main findings in the survey data. Participants labeled more intuitive by our behavioral measure of thinking 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

---

willingness-to-accept values. Participants who failed the quiz re-took it until they passed before being allowed to proceed.

[15] While it is tempting to label as "ambiguity-loving" 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 pointing this out to us.

[16] In particular, they are told to consider *exactly* the same two urns. Note that in each choice indifference between the two urns is a valid option. It is explained that if a participant specifies that they are indifferent between the two urns then one of the two urns will be randomly chosen and that, in addition to whatever winnings are associated with extracting a ball from this randomly-chosen urn, he or she will earn a small fixed fee (€0.10). This ensures that stated urn preferences are strict. Finally, participants know that only one of the two questions can be chosen to count towards their earnings so whether the draw in the second question is carried out with or without replacement should not be an issue.

ambiguity-loving.[17] 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.[18] 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 thinking 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 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

---

[17] 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 mis-classify an individual as risk loving as it is to mis-classify an individual as risk averse. It is also not clear whether mistakes could explain the patterns in ambiguity preferences given our two different elicitation mechanisms. In particular, being classified as ambiguity loving requires consistent answers across two separate questions, reducing the likelihood that such classification is solely due to mistakes. Finally, the idea that intuitive thinkers are simply more prone to mistakes is not consistent with the evidence in the Iowa Card Task experiment in Section 7, where intuitive thinkers *perform better* than deliberative and partially deliberative thinkers.

[18] 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.

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.

7. 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 participate in an Iowa Gambling Task. In total, 168 students participated. Each participant was given an endowment of 10 euros and presented with four card decks on his or her computer screen.[19] Each participant selected cards, one at a time, from any of the four decks by clicking.[20] Participants knew nothing about the card decks, i.e. they operated in a completely 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.[21] All participants were actually paid their earnings from the card task. To classify participants in terms of decision mode, we use their behavioral decision mode indicator from Experiment 1 or 2.

[19] The Iowa Card Task experiment was programmed and conducted with the software z-Tree (Fischbacher 2007).
[20] The decks were pre-programmed to be identical to the decks used in the original Iowa Gambling Task (Bechara et al., 1994).
[21] The exact order of wins and losses in each deck was pre-randomized, so that everybody faced the exact same decks. The two bad decks were pre-programmed to pay -100 points every 10 draws, while the good decks paid +250 points every 10 draws. Participants started with 2000 points which were converted to euros at a rate of 200 points = 1 euro. The order in which the good decks and bad decks appeared on the computer screen was also randomized to avoid any ease-of-clicking confound. For example, each participant was faced with four card decks, but one participant might face the order: Good Deck, Bad Deck, Good Deck, Bad Deck; while another participant could have faced the order: Good Deck, Bad Deck, Bad Deck, Good Deck.

Figure 1 presents the average proportion of draws from good decks for 10-card decision blocks by decision mode. For example, intuitive thinkers drew, on average, about 56 percent of their first 10 cards from good decks (or 5.6 cards), while deliberative thinkers managed to draw only about 42 percent of their first 10 cards from good decks. 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: intuitive thinkers drew significantly more cards from good decks compared to all other participants. On average, controlling for demographics, intuitive thinkers drew about 7.4 percent more cards from good decks than partially deliberative thinkers who managed to draw about 53.7 percent of their cards from good decks.[22] There was no significant difference between the performance of deliberative thinkers and partially deliberative thinkers, as is also evident in Figure 1.

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.

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 that they 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

[22] This difference is statistically significant at the 1% level using simple OLS with standard errors clustered by session. Demographic controls include age, gender, family income and a measure of cognitive ability.

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 relatively to the mean rate at which stockholders were selling stocks, measured by γ. Parameter β measures this tendency but after the collapse relatively to the means 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) 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.

8. Conclusions

The paper documents substantial individual heterogeneity in the two attitudes that have been used to characterize choice under risk and uncertainty. Most individuals dislike risk as well as ambiguity, but the intensity varies with observable characteristics. 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 show that a common factor linking these attitudes is the predominant way in which people handle decisions: whether by intuitive thinking or through effortful reasoning.

We find that predominant thinking 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. Why is this so? We argue that one plausible interpretation 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 are a good measure of the power of intuitive thinking and suggest that intuition is particularly valuable when problems are analytically hard as those involving substantial ambiguity. This is consistent with our evidence from the Iowa card game and from market timing during the financial crisis showing that intuitive thinkers perform better when choices are made under substantial risk and ambiguity.

Though attitudes towards risk and ambiguity have as common root the individual thinking mode, we also find that they differ in the way they are related to important observable variables, such as age, gender and, most importantly, wealth. While aversion to risk is negatively related to wealth we find that aversion to ambiguity is positively correlated with wealth. 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. As pointed out by Bossaerts et. al (2006) a positive correlation between risk and ambiguity aversion can help explain the "value effect".

Furthermore, 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.[23] 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.

[23] 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).

References

Ahn, David, Syngjoo Choi, Douglas Gale and Shachar Kariv (1997), "Estimating Ambiguity Aversion in a Portfolio Choice Experiment", University of California Berkeley, mimeo.

Alvarez, Fernando, Luigi Guiso and Francesco Lippi (2011), "Durable Consumption and Asset Management with Transaction and Observation Costs", *American Economic Review* (forthcoming).

Barsky, Robert, B., Thomas F. Juster, Miles S. Kimball and Matthew D. Shapiro (1997), "Preference Parameters and Behavioral Heterogeneity: an Experimental Approach in the Health and Retirement Study", *Quarterly Journal of Economics* 102, 537-580.

Bechara, Antoine, Antonio Damasio, Hanna Damasio, and S. W. Anderson (1994), "Insensitivity to Future Consequences Following Damage to Human Prefrontal Cortex," *Cognition* 55, 7-15.

Bechara, Antoine, Hanna Damasio, Daniel Tranel and Antonio Damasio (1997), "Deciding Advantageously Before Knowing the Advantageous Strategy", *Science*, 275, 1293-1295.

Bechara, Antoine (2004), "The Role of Emotion in Decision-Making: Evidence from Neurological Patients with Orbitofrontal Damage", *Brain and Cognition* 55, 30-40.

Becker, G. M., M. H. DeGroot, and J. Marschak (1964), "Measuring Utility by a Single Response Sequential Method", *Behavioral Science* 9, 226–232.

Benjamin, Daniel, Sebastian M. Brown, and Jesse Shapiro (2006), "Who is "Behavioral"? Cognitive Ability and Anomalous Preferences", University of Chicago, mimeo.

Bewley, Truman (1998), "Knightian Uncertainty," in Donald Jacobs, Ehud Kalai and Morton Kamien eds., *Frontiers of Research in Economic Theory: the Nancy L. Schwartz Memorial Lectures*. New York: Cambridge University Press, 71-81.

Bombardini, Matilde and Francesco Trebbi,(2011), "Risk aversion and expected utility theory: A field experiment with large and small stakes", *Journal of the European Economic Association* (forthcoming).

Bossaerts, Peter, Paolo Ghirardato, Serena Guarneschelli, and William R. Zame (2006), "Ambiguity in Asset Markets: Theory and Experiment," *The Review of Financial Studies* (forthcoming).

Bouchard, Thomas J. Jr and Yoo-Mi Hur (1998), "Genetic and Environmental Influences on the Continuous Scales of the Myers Brigg Type Indicator: An Analysis Based on Twins Reared-Apart", *Journal of Personality* 66, 135-149.

Burks, Stephen, V., Carpenter, J., Götte, L., Aldo Rustichini, (2009), "Cognitive Skills Affect Economic Preferences, Social Awareness, and Job Attachment", Proceedings of the National Academy of Science (USA), 106, 7745-50.

Caballero, Ricardo J. (2009), "Commentary on "Global Imbalances and the Financial Crisis", Federal Reserve Bank of San Francisco Asia Economic Policy Conference October 2009.

Caballero, Ricardo J. and Alp Simsek_(2011), "Fire Sales in a Model of Complexity", MIT mimeo.

Chakravarty, Sujoy and Jaideep Roy (2006), "Risk , Ambiguity – Gains and Losses", Indian Institute of Management, Working Paper N. 2006-2-06.

Chakravarty, Sujoy and Jaideep Roy (2009), "Recursive Expected Utility and the Separation of Attitudes Towards Risk and Ambiguity: an experimental study," *Theory and Decision* 66, 199–228.

Chen, Z. and L. Epstein, (2002), "Ambiguity, Risk, and Asset Returns in Continuous Time," *Econometrica* 70, 1403-1443.

Choi, Syngjoo, Douglas Gale, Ray Fisman, and Shahar Kariv (2007), "Consistency and Heterogeneity of Individual Behavior under Uncertainty," *American Economic Review* 97, 1921-1938.

Cohen, Michèle, Jean-Marc Tallon and Jean-Christophe Vergnaud (2011), "An Experimental Investigation of Imprecision Attitude and its Relation with Risk Attitude and Impatience," *Theory and Decision* 71, 81-109.

Damasio, Antonio R., Daniel Tranel and Hanna Damasio (1990), "Individuals with Sociopathic Behavior Caused by Frontal Damage Fail to Respond Autonomically to Social Stimuli," *Behavioural Brain Research* 41, 81-94.

Damasio, Antonio R., Tranel, D. & Damasio, H. (1991), "Somatic Markers and the Guidance of Behaviour: Theory and Preliminary Testing", in H.S. Levin, H.M. Eisenberg and A.L. Benton eds. *Frontal Lobe Function and Dysfunction*. New York: Oxford University Press.

Damasio Antonio (1994). *Descartes' Error: Emotion, Reason and the Human Brain*. New York: G.P. Putnam' Sons.

Damasio Antonio R.(1996), "The Somatic Marker Hypothesis and the Possible Functions of the Prefrontal Cortex",

Dohmen, Thomas Armin Falk, David Huffman, Uwe Sunde, Jürgen Schupp, Gert G. Wagner (2011)," Individual Risk Attitudes: New Evidence from a Large, Representative, Experimentally-Validated Survey", *Journal of the European Economic Association* (forthcoming).

Dohmen,Thomas J., Armin Falk, David Huffman and Uwe Sunde (2010), "Are Risk Aversion and Impatience Related to Cognitive Ability?", *American Economic Review* 100, 1238–1260.

Donkers, Bas, Bertrand Melenberg and Arthur van Soest (2001), "Estimating Risk Attitudes Using Lotteries: A Large Sample Approach", *Journal of Risk and Uncertainty* 22, 165–95.

Dow, James, and Sérgio Ribeiro da Costa Werlang (1992), "Uncertainty Aversion, Risk Aversion and the Optimal Choice of Portfolio," *Econometrica* 60, 197-204.

Epstein, Larry G. and Martin Schneider (2010), "Ambiguity and Asset Markets," NBER Working Paper No. 16181.

Fischbacher, Urs (2007), "z-Tree: Zurich Toolbox for Ready-made Economic Experiments", *Experimental Economics* 10, 171-178.

Frederick, Shane (2005), "Cognitive Reflection and Decision-Making," *Journal of Economic Perspectives* 19, 24-42.

von Gaudecker, Hans-Martin, Arthur van Soest and Erik Wengstrom (2011), "Heterogeneity in Risky Choice Behavior in a Broad Population", *American Economic Review* 101, 664-94.

Ghirardato, Paolo, Fabio Maccheroni, and Massimo Marinacci (2004), "Differentiating Ambiguity and Ambiguity Attitude", *Journal of Economic Theory* 118, 133-173.

Gilboa, Itzhak, and David Schmeidler (1989), "Maxmin Expected Utility with a Non-Unique Prior", *Journal of Mathematical Economics* 18, 141-153.

Gilovich, Thomas, Dale Grifz and Daniel Kahneman (2002), *Heuristics and Biases: The Psychology of Intuitive Thought*. New York: Cambridge University Press.

Gollier, Christian (2006), "Does Ambiguity Aversion Reinforce Risk Aversion? Applications to Portfolio Choices and Asset Prices", University of Toulouse, mimeo.

Gollier, Christian, and Bernard Salanié (2006), "Individual Decisions under Risk, Risk Sharing and Asset Prices with Regret", University of Tolouse, mimeo.

Guiso, Luigi and Monica Paiella (2008), "Risk Aversion, Wealth and Background Risk," *Journal of the European Economic Association* 6, 1109-1150.

Guiso, Luigi, Paola Sapienza and Luigi Zingales (2008), "Trusting the Stock Market", Journal of Finance 63, 2557 – 2600.

Guiso, Luigi and Tullio Jappelli(2009), "Financial Literacy and Portfolio Diversification", CSEF Working Paper N. 212.

Halevy, Yoram (2007), "Ellsberg Revisited: An Experimental Study", *Econometrica* 75(2), 503-536.

Holt, Charles and Susan K. Laury, (2002), "Risk Aversion and Incentive Effects", *American Economic Review* 92, 1644-1655.

Hsu, Ming, Maghana Bhatt, Ralph Adolphs, Daniel Tranel and Colin F. Camerer (2005), “Neural Systems Responding to Degrees of Uncertainty in Human Decision-Making”, *Science* 310, 1680-1683.

Kahneman, Daniel (2003), “Maps of Bounded Rationality: Psychology for Behavioral Economics”, *American Economic Review* 93, 449-75.

Klein, Gary (1998). *Sources of Power: How People Make Decisions*. Cambridge, MA: MIT Press.

Klein, Gary (2003). *Intuition at Work: Why Developing your Gut Instincts Will Make You Better at What You Do*. New York: Doubleday.

Klibanoff, P., M. Marinacci and S. Mukerji (2005), “A Smooth Model of Decision Making under Ambiguity”, *Econometrica* 73, 1849-1892.

Mukerji, S., K. Sheppard and J.M. Tallon (2005), “Smooth Ambiguity Aversion and Equity Premium”, Paper presented at the RUD conference, Heidelberg.

Pacini, Rosemary and Seymour Epstein (1999), “The Relation of Rational and Experiential Information Processing Styles to Personality, Basic Beliefs and the Ratio-Bias Phenomenon”, *Journal of Personality and Social Psychology* 76, 972-987.

Rubinstein, Ariel (2007), “Instinctive and Cognitive Reasoning: A Study of Response Times”, *The Economic Journal* 117, 1243–1259.

Slovic, Paul, Melissa Finucane, Ellen Peters and Donald G. Mac Gregor (2002), “The Affect Heuristic”, in Thomas Gilovich, Dale Grifzn, and Daniel Kahneman, eds., *Heuristics and Biases: The Psychology of Intuitive Thought*. New York: Cambridge University Press, 421-40.

Stanovich, Keith E. and West, Richard F. (2000),“Individual Differences in Reasoning: Implications for the Rationality Debate?” *Behavioral and Brain Sciences* 23, 645-65.

Table 1. Sample statistics

The table reports sample statistics for the variables used in the estimation based on the UCS survey. The sample size 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 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 in the experimental data

	Experiment 1	*Experiment 2*	*Iowa Card Task*
Behavioral thinking 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 thinking 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
Number of observations	534	772	168

Table 6. Behavioral thinking mode and risk aversion

Columns 1-2 present estimates using an ordered probit model using our measure of risk aversion in the first experiment as the dependent variable. This measure is increasing in risk aversion. Columns 3-4 present estimates from an ordered probit model using our measure of risk aversion from the second experiment as the dependent variable. This measure is increasing in risk aversion. "Intuitive" is a dummy that takes the value of one if the average time it took an individual to decide on which color to bet on in the risky urn and in the ambiguous urn as described in the text is in the bottom 25th percentile in the data. "Deliberative" is a dummy defined analogously but comprised of those whose decision times were above the 75th percentile in the data. The excluded category includes those whose decision times were between the 25th and the 75th percentile and can therefore be thought of as 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. "Experimental design controls" include dummies for the order in which the two versions of each risk and ambiguity elicitation methods were presented to subjects (in experiment 2 they were presented in the same order). The income measure is the participant's family's total annual net income from all sources, in thousands of euros. Robust standard errors, clustered at the session level in parentheses.

	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 thinking 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" is a dummy that takes the value of one if the average time it took an individual to decide on which color to bet on in the risky urn and in the ambiguous urn as described in the text is in the bottom 25th percentile in the data. "Deliberative" is a dummy defined analogously but comprised of those whose decision times were above the 75th percentile in the data. The excluded category includes those whose decision times were between the 25th and the 75th percentile and can therefore be thought of as 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 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 each column is the proportion of cards in each 10-card block an individual drew from a "good deck," i.e., one with a positive expected return. The independent variables include dummies for being Intuitive or Deliberative thinker. The measure we use is the behavioral decision time measure from each participant's associated survey (Experiments 1 and 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
Intuitive	0.08*	0.05	0.06	0.05	0.10**	0.08*	0.05	0.11***	0.12**	0.03
	(0.04)	(0.07)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)
Deliberative	-0.00	-0.01	0.03	-0.05	-0.02	0.02	0.03	-0.05	0.04	0.06*
	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
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)	(0.01)	(0.01)	(0.01)	(0.00)
Male	0.00	0.08**	-0.03	-0.04	-0.02	-0.01	0.01	0.02	-0.07	-0.04
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
Math score	0.01	0.02**	-0.01	0.00	-0.01	0.00	0.01	-0.00	-0.01	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(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)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.06)	(0.05)	(0.03)	(0.05)
45 ≤Inc<70	-0.09	-0.02	0.06	-0.03	0.01	0.04	0.02	0.05	0.08*	0.05
	(0.06)	(0.05)	(0.04)	(0.04)	(0.03)	(0.04)	(0.08)	(0.06)	(0.04)	(0.04)
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)	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)
Inc ≥ 120	-0.12	0.03	0.01	-0.01	-0.04	-0.08**	-0.02	-0.11	-0.09**	0.01
	(0.12)	(0.06)	(0.08)	(0.06)	(0.06)	(0.03)	(0.12)	(0.10)	(0.04)	(0.15)
Constant	0.44***	0.30**	0.51**	0.51***	0.62**	0.59***	0.56***	0.59***	0.68**	0.56***
	(0.13)	(0.12)	(0.19)	(0.11)	(0.24)	(0.17)	(0.12)	(0.18)	(0.24)	(0.16)
Observations	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

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. *** significant at 1%; *** significant at 5%.

	(1)	(2)	(3)	(4)	(5)	(6)
Before *intuitive	0.014**	0.017**	0.017**	0.017**	0.027**	0.026**
	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
(1-*Before*) *intuitive	0.002	0.004	0.004	0.004	0.012	0.011
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
Before	0.057**	0.018	0.021	0.025	0.022	0.032
	(0.002)	(0.035)	(0.035)	(0.036)	(0.042)	(0.040)
(1-*Before*)	0.039**	0.002	-0.014	-0.005	-0.003	0.014
	(0.003)	(0.035)	(0.036)	(0.037)	(0.042)	(0.040)
Male		-0.010**	-0.009**	-0.010**	-0.014**	-0.013**
		(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Age		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	0.003	0.001	0.001	0.001
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Before *education			-0.002**			
			(0.000)			
(1-*Before*) * education			-0.002**			
			(0.000)			
Before *financial literacy				-0.002		
				(0.002)		
(1-*Before*) *financial literacy				0.001		
				(0.002)		
Before * financial ability					0.002	
					(0.003)	
(1-*Before*) * financial ability					0.005	
					(0.003)	
Before * financial information						-0.002
						(0.001)
(1-*Before*) * financial information						-0.002
						(0.002)
R-squared	0.05	0.05	0.05	0.05	0.06	0.06
Observations	21315	20405	20405	20405	14875	14875

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

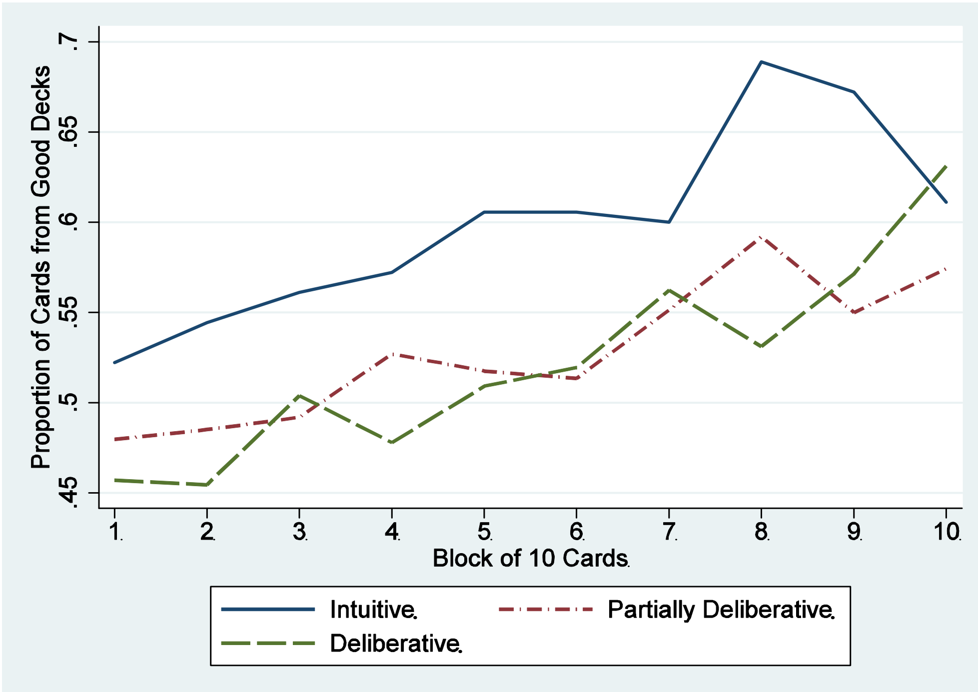
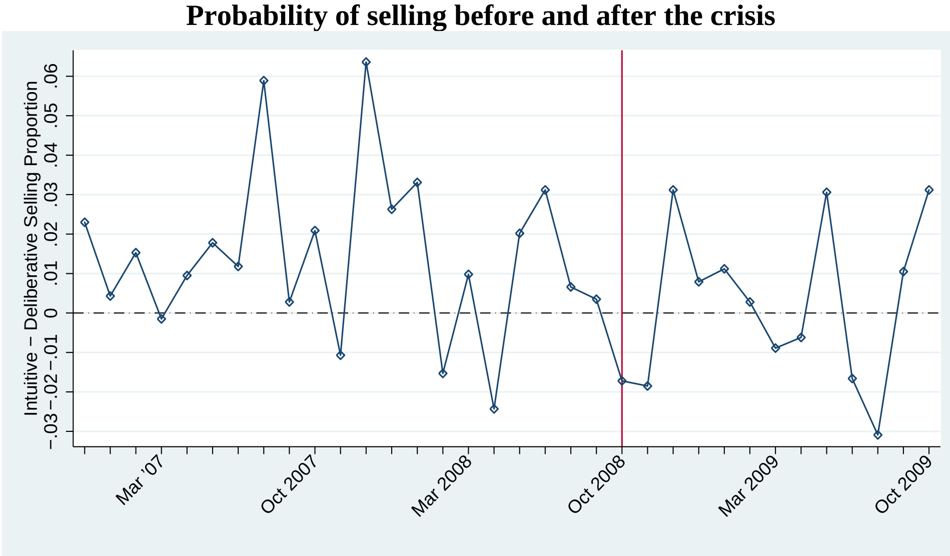


Figure 2
Probability of selling before and after the crisis



Not for publication

Appendix

A.1. The survey data

The survey data used draw on a sample of Italian retail investors of the Unicredit Group. The Unicredit Clients' Survey (UCS) was conducted between June and September 2007 and elicited detailed financial and demographic information on a sample of 1686 individuals with a checking account in one of the banks of the Unicredit Group. The eligible population of customers excludes customers under 20 and over 80, and customers with assets of less than 10,000 Euros with Unicredit. The sampled population size is around 1.3 million customers. The survey was aimed at acquiring information on the behavior and expectations of Unicredit Group customers and focused on multi-banking, attitude towards saving and investing, financial literacy and propensity for risk, pensions and need for insurance. The sample is stratified according to three criteria: geographical area, city size, financial wealth, and it explicitly over-samples rich clients. In particular, only clients with at least €10,000 of financial wealth at Unicredit at the end of 2006 are included in the sample.

An important feature of the survey is that the sample selection is based on Unicredit individual retail investors. The survey, however, contains also detailed information on the spouse, if present. Financial variables are elicited for both respondents and households. In the paper, demographic variables refer to the household head (even if different from the respondent), and economic variables (real and financial assets) to the household, not to the individual investor. The survey contains detailed information on ownership of real and financial assets, and amounts invested. For real assets, UCS reports separate data on primary residence, investment real estate, land, business wealth, and debt (distinguished between mortgage and other debt). Real asset amounts are elicited without use of bracketing.

The sampling scheme is similar to that of the Bank of Italy Survey of Household Income and Wealth (SHIW). The population is stratified along two criteria: geographical area of residence (North-East, North-West, Central and Southern Italy) and wealth held with Unicredit as of June 30 2006. The sample size is 1,686 customers, of whom 1,580 are from Unicredit Retail Bank, and 106 from Unicredit Private Bank (the upper tier customer bank). The survey was administered between May 1 and September 30 of 2007 by a leading Italian polling agency, which also conducts the SHIW for the Bank of Italy. Most interviewers had substantial experience of administering the SHIW, which is likely to increase the quality of the data. The UCS was piloted in the first quarter of 2007, and the Computer Assisted Personal Interview methodology was employed for all interviews. To overcome some of the problems arising from non-responses, the sample was balanced ex-post with respect to the true distribution of assets, area of residence, city size, gender, age and education of the eligible population.

The questionnaire has 9 sections. Sections A and B refer, respectively, to respondent and household demographic and occupation variables. Section C focuses on saving, investment and financial risk. Section D asks detailed questions about financial wealth and portfolio allocation, and Section E enquires about consumer debt and mortgages. By design, Sections

A, B, D and E allow a perfect matching with the SHIW questionnaire. Questions on real estate and entrepreneurial activities are included in Section F. Section G contains questions on subjective expectations, and section H focuses on insurance and private pension funds. The last two sections ask about income and expectations and need for insurance and pension products. As shown in Table A1, compared with the Italian population, as surveyed by the 2006 Bank of Italy SHIW, Unicredit Group customers are older, more educated, less likely to work in the manufacturing sector, and more likely to live in the North.

Table A1: UCS – SHIW comparison

	UCS	*SHIW* *Highest income earner*	*SHIW* *Bank account holder*
Gender			
Male	0.69	0.69	0.71
Female	0.31	0.31	0.29
Age			
up to 30	0.04	0.06	0.06
31 to 40	0.18	0.19	0.20
41 to 50	0.22	0.22	0.22
51 to 65	0.36	0.24	0.24
over 65	0.20	0.29	0.27
Education			
elementary school	0.10	0.27	0.22
middle school	0.29	0.36	0.37
high school	0.41	0.27	0.30
university degree	0.20	0.10	0.10
Sector of activity			
Agriculture	0.03	0.03	0.03
Industry	0.13	0.21	0.23
Public Administration	0.19	0.15	0.17
other sector	0.30	0.19	0.20
not employed	0.35	0.40	0.37
Household size			
1 member	0.21	0.25	0.23
2 members	0.29	0.28	0.29
3 members	0.26	0.21	0.22
4 members	0.20	0.18	0.19
5 or more members	0.04	0.07	0.06
Geographical area			
Northern Italy	0.73	0.48	0.52
Central Italy	0.14	0.20	0.21
South and Islands	0.13	0.32	0.27

Note: The table compares sample means of selected demographic variables in the UCS and 2006 SHIW. Means are computed using sample weights.

A2. Experimental design

A.2.1. Experiment 1

Participants in the experiment were recruited from among students attending one of two universities Rome, Italy. The first—LUISS Guido Carli—is a small private university, while the second, La Sapienza, is the largest public university in Rome with an enrollment of over 100,000 students. Thus, the student population from which we recruit is potentially quite heterogeneous. Invitations to take part in our experiment were sent out via e-mailto a large list of potential experimental participants at both universities. The experiment itself was conducted completely on-line to preserve anonymity and reduce experimenter demand effect. Ten percent of participants were randomly chosen by the computer to be paid their potential earnings from the experiment.

The experiment consisted of several sections, one of which was remunerated, in the following order: (i) 20 questions from the Rational Experiential Inventory (Pacini and Epstein, 1999); (ii) a non-remunerated section on attitudes towards risk, social risk and ambiguity; iii) a remunerated section eliciting risk and ambiguity preferences (detailed below); iv) the final 20 questions from the REI; v) a section collecting participants' demographic characteristics.

When participants reached the remunerated risk and ambiguity section, before seeing any of the constituent questions, they were told that this section—and only this section—would count toward their potential experimental earnings. Specifically, they were informed that one question in the section had already been chosen randomly by the computer to determine their potential experimental earnings so that their decisions could not in any way influence the question chosen. They were told, furthermore, that 10 percent of participants who completed the experiment would be chosen randomly by the computer to be actually paid their potential earnings from the experiment. Potential earnings from the remunerated section of the experiment theoretically ranged from €1 to €38.50 depending on participants' choices and the resolution of uncertainty, so that both potential and actual stakes were reasonably large compared to participants' opportunity costs of participating—i.e., about 20 minutes of their time in total.

In the remunerated section, risk aversion was measured using a procedure due to Holt and Laury (2002) involving two binary lotteries: lottery A and lottery B. Lottery A features a high maximum payoff (38.50 euros) but a low minimum payoff (0.10 euros), while lottery B features a lower maximum payoff but a higher minimum payoff (28.50 euros, and 16.00 euros, respectively). The high payoff in both lotteries occurs with (common) probability, p, while the low payoff occurs with probability ($1-p$). To obtain a measure of risk aversion, each participant makes a sequence of 10 choices between lotteries A and B where p is increased from 0.1 to 1 in steps of 0.1. The value of p at which a participant switches from the less risky lottery B to the riskier lottery A is our measure of risk aversion: more risk averse agents should switch later in the sequence.

To measure ambiguity aversion we used a two-phase procedure following Halevy (2007). In the first phase of this procedure, two urns are described to participants: one (risky) urn contains 5 red balls and 5 white balls, while the other (ambiguous) urn contains 10 red and white balls. Participants are informed that the computer will choose one ball at random from each of the two urns, and asked sequentially to guess which color ball will be drawn from each of the two urns. Each correct guess pays €20, while incorrect guesses pay €0. In the second phase of the procedure participants state the minimum amount of money they would accept to give up the right to the earnings from each of the two bets, separately, and are given incentives to report these values truthfully.[24] We use the difference in participants' valuations for the two urns as an indicator of ambiguity aversion: those who value the ambiguous urn strictly less are labeled ambiguity averse.

Each participant completed two slightly different versions of both the risk preferences and the ambiguity preferences elicitation mechanisms. The only difference between the versions relates to un-chosen options. In one version participants were told they would know outcomes of un-chosen options, while in another version participants were told they would only learn outcomes directly relevant to their earnings.[25] These two versions were conducted because in some models of decision-making under uncertainty this distinction is important, (see, e.g., Loomes and Sugden, 1986), and existing experiments vary in which version is used.[26] There were no significant differences in our measures between versions.[27] Therefore, to reduce the possible impact of participants' mistakes on our risk and ambiguity aversion measures we incorporate responses from both versions of the risk and ambiguity elicitation mechanisms: for our risk aversion measure, we average across the two versions for each respondent; with respect to ambiguity aversion, we label individuals as ambiguity averse only if they are classified this way by *both* versions of the ambiguity preferences elicitation mechanism.

To address concerns about order effects, we asked the questions in the remunerated section in four different orders: one of the two versions of our risk preferences elicitation procedure always came first, followed by two ambiguity preferences elicitation mechanisms—one of each version—followed by, finally, the remaining version of our risk preferences elicitation procedure. Ideally, we would have liked to have implemented all possible orders of the questions comprising our risk and ambiguity preferences elicitations mechanisms in order to

---

[24] For each of the two urn-guesses, separately, the procedure is as follows: the computer draws a number between 0 and 20 which can be thought of as a "price." If this price is higher than the participant's stated minimum willingness-to-accept, the participant receives a payment equal (in euros) to the price but gives up his or her right to the earnings from the urn-guess. Otherwise the participant retains the right to the earnings from his or her urn-guess. It is well-known that this mechanism provides incentives for participants to truthfully state their values for each of the bets irrespective of risk preferences. Since the main concern with this mechanism is that it is relatively complicated, each participant had to pass a short quiz about the procedure immediately before stating their minimum-willingness-to-accept values.

[25] For example, in our risk-preferences elicitation mechanism described above, the difference was whether subjects would find out the outcome of lottery A if they chose lottery B, and vice versa.

[26] For example, often to placate incredulous participants, experiments are designed to resolve uncertainty using a physical and familiar mechanism, (e.g., flipping a coin). In such a design participants will automatically know the outcomes of all lotteries depending on the coin flip, both chosen and un-chosen. In principle this could be avoided by flipping a separate coin for each outcome depending on uncertainty, independently. This is what we try to mimic here. However, for logistical reasons this is typically not done in experiments using physical randomizing devices.

[27] Neither Wilcoxon signed-rank tests of equality of distributions, nor simple t-tests for differences in means indicated any statistically significant differences.

fully address concerns of order effects. While this was not feasible due to the large number of possible question orders, the four orders we implemented should go a long way toward ameliorating order concerns.

The experiment was conducted in four separate sessions, each session being characterized by the range of dates over which it was conducted, by the population of participants invited, and by variation in design elements such as question order. Session 1 was conducted from November 30 to December 4, 2009. The second session was conducted the following week: from December 7 to December 11. Session 3 occurred about a month later, after the holidays, from January 13 to January 19. The final session was conducted a couple of weeks later, from January 30 to Feb 1, 2010. The first two sessions were conducted in English and only English-speaking LUISS students were invited to participate. The latter two sessions were conducted in Italian and both LUISS and La Sapienza students were invited to participate.

A.2.2. Experiment 2

Our second experiment was conducted on-line, in several sessions, from May to October 2010. Students of La Sapienza University in Rome, Italy were invited to participate from a pre-existing list of potential participants. In total 772 students participated. Ten percent of participants were randomly chosen by the computer to be paid their potential earnings from the experiment.

The design of the experiment was identical to that of Experiment 1, with the exception of the risk and ambiguity aversion measures in the remunerated section. To measure risk aversion, we again used a Holt and Laury procedure. However, this time, participants were simply asked to specify the minimum value of p, the probability of the high-paying outcome, for which they would switch from preferring the low variance outcome (20 euros vs. 16 euros) to the higher variance outcome (38.50 euros vs. 1 euro). This is common implementation of the Holt and Laury procedure which has the advantage of being simple to implement.

To measure ambiguity aversion, instead of the more complicated Halevy procedure, we used a more direct method. This method consisted of two questions. In the first question, two urns were described to participants exactly as in Experiment 1: one non-ambiguous (*Urn 1*, containing 5 red balls and 5 white balls) and one ambiguous (*Urn 2*, containing: 10 red or white balls). It was then explained that one ball would be drawn from one of the two urns and if that ball is red the participant will win €20 and €0 otherwise. Participants had to decide which urn they wanted the ball drawn from. Their options were: Urn 1, Urn 2 or "no preference." It was made known to the participants that if they chose "no preference" then the computer would select between the two urns randomly, with equal probability, and €0.10 would be added to the earnings from the resulting earnings. This feature ensures that urn preferences are strict. In the second question, participants were asked to consider *exactly* the same two urns and the same lottery, except with the winning ball being white. They faced the same choice set as before. They stated whether they preferred the ball to be extracted from Urn 1, Urn 2, or that they had no preference. Choosing the non-ambiguous urn both times implies the decision maker is ambiguity averse, since there is no single belief about the proportion of red and white balls in the ambiguous urn which would make it *strictly* preferable in both draws. Using the same reasoning, choosing the *ambiguous* urn both times implies the decision maker prefers ambiguity.

A.2.2. Questions used for our main thinking mode measure in the experiments

In each experiment, we used participants' average response time to two questions used in our ambiguity preferences elicitations procedures to construct our three-category behavioral thinking mode measure. Because we elicited ambiguity preferences in different ways in the two experiments, the precise questions used varied by experiment.

In Experiment 1, the first question we used asked participants to predict which color ball would be drawn from an (ambiguous Ellsberg) urn containing 10 red and white balls in unknown proportions. The second question asked participants to predict the color ball that would be drawn from an urn containing five red and five white balls. Each of these two questions paid participants €20 for a correct prediction while incorrect guesses paid zero. We used the average response time to both of these two questions to construct our main thinking mode measure for Experiment 1 participants.

In Experiment 2 our ambiguity preferences elicitation procedure was simpler and involved exactly two questions: i) a choice between either a risky or ambiguous urn from which the draw of a red ball paid €20; ii) a choice between either a risky or ambiguous urn from which the draw of a white ball paid €20. We used the average response time to both of these two questions to construct our main thinking mode measure for Experiment 2 participants.

A.2.3. The Iowa Card Task Experiment

We invited a random subset of the pool of students who participated in Experiment 1 or Experiment 2 to come to participate in a laboratory experiment conducted at the Einaudi Institute for Economics and Finance in Rome, Italy. In total, 168 students participated in our Iowa Card Task Experiment.

Participants were seated at individual computer workstations and separated by opaque dividers. Each participant was endowed with 2000 points, and it was explained that points were converted into euro at the rate of 200:1. Each participant was then instructed that they would be making a series of draws from (computerized) card decks and that they must keep drawing cards as long as this was an option. They were instructed they should try to make as much money as possible. After these instructions, four card decks appeared on each participant's computer screen, in a single row. Each card deck appeared identical. Clicking on a deck turned a card over, revealing a win and a loss, typically implying a net gain in points but sometimes a net loss.

The decks were pre-programmed so that two were "good" decks which had a positive return of 250 points every 10 draws; two were "bad" decks pre-programmed to yield a negative return of 100 points every 10 draws. The exact sequence of gains and losses for each deck was pre-programmed to be identical to the original Iowa Card Task experiment, so that each participant faced the exact same card decks. The order in which the card decks appeared on-screen was, however, randomized. This eliminates the possibility that, for instance, it was just easier to click on the left-most card deck which just happened to be a "good" deck so that variation in effort would explain a pattern where good decks were selected more frequently.

After a participant had made 100 draws, he or she was informed that the experiment was over and to sit quietly while other participants finished. When all participants had finished, each participant was paid the money he or she had earned from the card task. Because losses were possible on two of the decks, some participants made significantly less than their endowment. No participant, however, ended up earning zero or a negative amount.

Table A2. Time to complete first REI section

The dependent variable is the number of seconds a participant took to complete the first half of the REI, which was administered early in the experiment and before any risk- or ambiguity-related questions were asked. "Intuitive" is a dummy that takes the value of one if the average time it took an individual to decide on which color to bet on from the risky urn and from the ambiguous urn in the urn-valuation task was in the bottom 25th percentile in the data. "Deliberative" is a dummy defined analogously but encompassing those whose decision times were in the 75th percentile or above. The excluded category contains those whose decision times were between the 25th and the 75th percentile, who can be thought of as 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. "Experimental Design Controls" include dummies for the order in which the two versions of each risk and ambiguity elicitation methods were presented to subjects. 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 methods were presented to subjects (in experiment 2 they were presented in the same order).Robust standard errors, clustered at the session level in parentheses.

	Experiment 1		*Experiment 2*	
	(1)	(2)	(3)	(4)
Intuitive	-48.235**	-50.882**	-36.056	-47.419
	(13.259)	(12.884)	(26.346)	(36.512)
Deliberative	88.489***	81.828**	68.336**	44.856***
	(13.761)	(20.684)	(13.468)	(0.793)
Age		1.661		-0.066
		(1.376)		(1.866)
Male		-3.383		-12.209
		(7.786)		(15.469)
Math score		-4.085***		1.679
		(0.507)		(14.221)
30 ≤ Inc< 45		-2.027		-40.828*
		(12.745)		(13.416)
45 ≤ Inc<70		-3.586		-23.463
		(6.620)		(39.632)
70 ≤ Inc< 120		4.567		0.079
		(9.797)		(6.821)
Income ≥ 120		-12.300		-2.859
		(10.425)		(34.134)
Constant	180.048***	173.666**	251.768***	263.550**
	(8.479)	(43.335)	(8.461)	(80.565)
R-squared	0.212	0.226	0.014	0.015
Experimental Design Controls	Yes	Yes	n.a	n.a.
Observations	534	486	772	692