Cognitive abilities and risk-taking: Errors, not preferences[1]

Luis Amador

LoyolaBehLab & Department of Economics, Universidad Loyola

Pablo Brañas-Garza

LoyolaBehLab & Department of Economics, Universidad Loyola

Antonio M. Espín (corresponding author)

Department of Social Anthropology, Universidad de Granada

LoyolaBehLab, Universidad Loyola

Teresa García

Department of Quantitative Methods, Universidad de Granada

LoyolaBehLab, Universidad Loyola

Ana Hernández

LoyolaBehLab & Department of Economics, Universidad Loyola

[1] We thank the Associate Editor and two anonymous referees for their comments and suggestions. We are grateful to Pedro Caldentey for coordinating the experiment. We also thank Behave4's team (https://behave4.com/) for allowing us to use their platform. This project was funded by Excelencia Junta de Andalucía (P12-SEJ-1436, PY18-FR-0007) and the Spanish Ministry of Science (PGC2018-093506-B-I00).

Abstract

There is an intense debate whether risk-taking behavior is partially driven by cognitive abilities. The critical issue is whether choices arising from subjects with lower cognitive abilities are more likely driven by errors or lack of understanding than pure preferences for risk. The latter implies that the often-argued link between risk preferences and cognitive abilities (a common finding is that abilities relate negatively to risk aversion and positively to loss aversion) might be a spurious correlation. This experiment reports evidence from a sample of 556 participants who made choices in two risk-related tasks and completed three cognitive tasks, all with real monetary incentives: number-additions (including incentive-compatible expected number of correct additions), the Cognitive Reflection Test (to measure analytical/reflective thinking) and the Remote Associates Test (for convergent thinking). Results are unambiguous: none of our cognition measures plays any systematic role on risky decision making. Using structural equation modeling and factor analysis, we show that cognitive abilities are negatively associated with noisy, inconsistent choices and this effect may make higher ability individuals *appear* to be less risk averse and more loss averse. Yet we show that errors are more likely to appear when the two payoffs in a given decision exhibit similar probability. Therefore, our results suggest that failing to account for noisy decision making might have led to erroneously inferring a correlation between cognitive abilities and risk preferences in previous studies.

Keywords: decision making under uncertainty, cognitive abilities, online experiment, risk and loss aversion, factor analysis.

JEL Class.: D81, C91.

Introduction

Typically, experimental economists use individuals' risk-taking behavior (RTB) in lottery tasks to infer their preferences for risk. For instance, in the Holt and Laury (2002) mechanism, subjects have to choose between lottery A and B in 10 decisions (both lotteries with two possible outcomes and probabilities), while in Eckel and Grossman (2002) they have to choose among six gambles, all with a 0.5 probability of winning a higher prize. Generally speaking, Multiple Price List (MPL) experimental devices may involve a lot of probability computation. It is often observed that about 15%–20% of the participants make inconsistent choices which do not satisfy rational utility maximization; a percentage that can increase dramatically in non-student samples (see Charness et al. 2013). In a recent study, Charness et al. (2018) showed that the complexity of MPL devices yield noisy estimations and this may influence results to a large extent, for example, on the existence of gender differences in risk preferences.

The truth is that lotteries or computations involving probabilities are not easy tasks. Therefore, individuals' RTB in lottery games may stem from a combination of risk preferences and an error/noise term which is highly influenced by cognitive abilities (Cabs).

Assuming that RTB requires an ability to compute probabilities, it follows that *choices by subjects with lower Cabs might be partially the result of mistakes* or lack of understanding (randomness) rather than pure taste for specific prospects (risk preferences). However, if individuals are able to differentiate risky from non-risky prospects regardless of their innate capacity to evaluate probabilities, that is, even those endowed with low abilities can do it—then *their choices reflect pure preferences for risk.*

This question is not new and has been explored using administrative, survey (incentivized and hypothetical) and experimental data (typically from the lab) on RTB. In the next section, we summarize the main findings for each of these three strands of the literature. There is indeed converging evidence showing that individuals with higher Cabs are less risk averse and more loss averse (e.g., Dohmen et al. 2018, Chapman et al. 2018, Lilleholt 2019). However, as the literature review shows, previous studies suggest that these results might be affected by errors or inconsistent choices, as well as by the measurement instrument and the Cabs measures used.

Therefore, the critical issue is to unravel whether there is a true link between risk preferences and Cabs (i.e., not due to noise or errors) and whether this link depends on the risk-taking task and Cabs measures used. To address this question, we ran an experiment with two important features:

i) We measured RTB using incentive-compatible standard tasks in both the gain (Holt & Laury 2002) and mixed (including both gains and losses; Gächter et al. 2007) domain to elicit risk and loss aversion, respectively. We also tested for "noisy", inconsistent decision making in the two tasks. We define inconsistencies as those choices which do not satisfy rational utility maximization.

ii) Given that there is an ample spectrum of Cabs, we asked our subjects to complete three different tasks: summations under time pressure (to measure mathematical abilities; we also elicited the expected number of correct summations to measure over/under-confidence), CRT (to measure the disposition to rely on analytical thinking vs. intuition, see Brañas-Garza et al. 2019) and the Remote Associates Test (RAT; to measure convergent thinking, see Shen et al. 2018).

All the tasks were presented to the participants in random order. We used a representative sample of first-year, undergraduate Spanish students enrolled in Business Economics comprising 556 participants who made their decisions online.

Although we found no systematic significant relationship between Cabs and RTB in our sample, the observed trends are in line with previous findings that higher Cabs are associated with less risk aversion and more loss aversion. Moreover, we find that higher Cabs (especially analytical and convergent thinking) are significantly negatively related to noisy, inconsistent decision making.

In addition, we also observed that being inconsistent is associated with more risk-averse and less loss-averse choices, which implies that in these tasks risk aversion is overestimated and loss aversion is underestimated due to decision makers' errors. Along these lines, Andersson et al. (2016, 2020) argued that a relatively high number of decisions in the risk-averse domain is responsible for the overestimation of risk aversion due to errors because random decision making leads subjects to choose each option with equal probability. That is, individuals' true preferences are closer to risk neutrality than their choices reveal when there are (too) many decisions in the risk-averse domain. Applied to our results, this argument entails that our subjects' true preferences are less risk averse but more loss averse compared to what we observe. In other words, it seems that our risk aversion task (Holt and Laury 2002) has too many decisions in the risk-averse domain while our loss aversion task (Gächter et al. 2007) has too few decisions in the loss-averse domain.

In our sample, inconsistent individuals tended to choose left-hand side options more often in both tasks compared to consistent individuals. Left-hand choices imply risk-averse and non-loss-averse choices in the risk and loss aversion tasks, respectively. However, the sole fact that inconsistent individuals choose the left-hand option more often *cannot* explain Andersson et al.'s (2016, 2020) results because they found the opposite in one of their tasks. Thus, we discard this explanation.

Instead, both ours and Andersson et al.'s (2016, 2020) findings can be explained by the number of decisions in which probability calculation is difficult. We infer from the data that inconsistent individuals tend to choose according to expected payoff maximization when the realization probability of the smaller payoff is high (about 70% or higher) but start choosing randomly when the realization probability of both payoffs is similar. This indicates that difficulty/complexity increases as realization probabilities of the two payoffs get closer. Note that Andersson et al. are necessarily silent on the potential effect of changing probabilities because both payoffs in their tasks are always realized with 50% probability. Once inconsistent individuals start choosing randomly, they tend to continue doing so even though the probabilities of the two payoffs start diverging again, now in favor of the larger payoff, as happened in our risk aversion task (Holt and Laury 2002). The latter might be due either to path dependence or to the fact that computations are harder when the larger payoff is associated to a high realization probability. Future research should explore these possibilities in detail.

Given that in the risk aversion task the expected values of both options are closer the more similar the payoffs' probabilities are, it might be the case that difficulty is related to decisions in which expected payoffs are similar rather than decisions in which payoffs' probabilities are similar. The risk aversion task does not allow us to disentangle this. Yet, our results from the loss aversion task, where the payoff probabilities are always 50%, but the expected payoffs vary along the task, speak against such an alternative interpretation. If expected-payoff similarity were associated to random decision making, we should observe more random choices in the 5th decision than in the rest of decisions because it is in the 5th decision where the expected payoffs of both options are identical. However, we observe that decision 5 is precisely the only one in which we can reject random decision making among inconsistent individuals (although we attribute this to chance, this result allows us to conclude against the alternative explanation).

Therefore, we do not find that inconsistent individuals simply choose randomly, as suggested by Andersson et al. (2016, 2020), but that they generally do so when probability computations are hard, that is, when both payoffs have a similar realization probability. Both in our loss aversion task (Gächter et al. 2007) and in the risk aversion tasks of Andersson et al. (2016, 2020), all decisions have a 50% probability for both payoffs. Thus, inconsistent decision making is directly associated with randomness in these tasks and errors therefore tend to be associated with a number of safe choices closer to the central value. In the loss aversion task, the central value would be three safe choices out of six, which is exactly what we find for inconsistent individuals on average; for consistent individuals, the average is 3.53. This means that errors lead to an underestimation of loss aversion. In contrast, according to this account, computations become notoriously difficult in the Holt and Laury (2002) risk aversion task only after some point, precisely when consistent individuals start choosing the risky option more often. This explains why inconsistencies are associated with more safe choices in this task (6.08 and 5.44 for inconsistent and consistent individuals, respectively), which ultimately means that risk aversion is overestimated due to errors. Therefore, this explanation can account for our results in both the risk aversion and the loss aversion task, as well as the results of Andersson et al. (2016, 2020).

Using structural equation modeling and factor analysis to reduce measurement error (Jagelka 2020, Cunha et al. 2010; see Guillen et al. 2019 for a thorough discussion on the topic and alternative methods), we test whether the link between Cabs and RTB is mediated by inconsistent decision making. Our results indicate that such a mediation in fact exists, so that failing to account for computational errors by low Cabs individuals makes them *appear* to be more risk averse and less loss averse than high Cabs individuals in the (standard) tasks used. This, however, might dramatically change with different task parameterizations or in different samples.

It is also important to note that despite the number of individuals labeled as inconsistent due to “irrational” choices, there is also a potential and unknown proportion of consistent individuals who appear consistent by chance. Thus, the effects we observe can be considered as a lower bound of the true effects.

We find that the indirect effects of Cabs on RTB *through* inconsistent decision making are rather small, but this might be partially explained by the particular features of our dataset. Although small, the mediation is statistically significant, and this provides a powerful explanation as to why lower Cabs can be spuriously associated to more risk aversion and less loss aversion. Therefore, the strength of the relationship between Cabs and risk preferences, at the very least, might have been overestimated in previous studies.

These findings suggest that the experimental task used to measure RTB in the lab strongly influences the link between Cabs and risk taking. Our results cannot be easily extended to real-world risky decision making, however, since real-world choices are typically ambiguous regarding probabilities and/or payoffs. Future research should use tasks and real decisions with varying levels of ambiguity to test whether low Cabs individuals are bad at assessing risks also in those scenarios.

The rest of the paper is structured as follows. In the next section, we review the literature on the link between RTB and Cabs. The third section focuses on the methodology used, while the results are shown in the fourth section. The final section concludes.

Literature review

Administrative data

Christelis et al. (2010), Van Rooj et al. (2011), Grinblatt et al. (2011), Frisell et al. (2012), Cole et al. (2014), Beauchamp et al. (2017) and Angrisani and Casanova (2018) have studied the role of Cabs in RTB in different contexts of life: stock market participation, alcohol consumption and smoking, saving, portfolio selection and violent crime. Such studies do not measure RTB in purpose-designed tasks, but simply observe behaviors or choices that serve as indirect observations of RTB. In this regard, Dohmen et al. noted that:

> while risk-taking behavior has been found to be correlated with various facets of cognition, the sign and magnitude of the correlation seems to vary across contexts and studies. With a closer look at this variation, however, a pattern emerges. Cognitive ability tends to be positively correlated with avoidance of harmful risky situations and to be negatively correlated with risk aversion in advantageous situations. (2018: 120)

This might be indicating that high cognitive ability is associated with risk neutrality. According to these same authors (2018: 120), "evidence for this emerges both from studies of behavior in risky situations, often conducted by psychologists and psychiatrists, and also from studies focused on economic decision-making" as, for example, stock market participation.

That said, since these studies use proxies that indirectly infer risk taking from observed behavior in different facets of life, it is difficult to draw firm conclusions about RTB. For instance, time is an important underlying factor beyond risk (i.e., volatility) in many of these decisions, thus time preferences may also determine savings, drug use and violent crime, among others (Åkerlund et al. 2016, Bickel et al. 1999, Meier and Sprenger 2012). Moreover, the Cabs measures differ greatly from one study to another. For example, Christelis et al. (2010) employed math, verbal and recall tests and found similar results for each of the three measures; Angrisani and Casanova (2018) tested separately for numeracy and "cognition" (episodic memory and fluid intelligence) and also found similar relationships for the two types of measures, while Grinblatt et al. (2011) combined psychological tests assessing mathematical, verbal and logical skills into one composite score.

Survey data

Chapman et al. (2018) used incentivized experimental tasks (similar to MPL with dynamic optimization) to infer risk preferences in a survey conducted with a representative US sample. Their Cabs measure is given by the number of correct answers to nine items combining fluid intelligence, spatial ability and cognitive reflection. Booth and Katic (2013) used hypothetical lottery investment and a self-assessment questionnaire about risk attitudes (i.e., general and financial risk taking) in Australian birth-cohort data. However, their measure of cognitive abilities is just a proxy (academic performance ranking used for university entrance). Falk et al. (2018) developed the Global Preference Survey (GPS), an experimentally validated survey dataset on risk and time preference, positive and negative reciprocity, altruism and trust of 80,000 people in 76 countries. They elicited RTB through a series of related quantitative questions (hypothetical lottery choice sequence using the staircase method) as well as one qualitative question (self-assessment: willingness to take risks in general). The GPS also elicited a self-reported proxy for Cabs by asking people to assess themselves by the statement "I am good at math" on an 11-point Likert scale.

Chapman et al. (2018) showed that the choices of participants with higher Cabs are more loss averse and less risk averse. Falk et al. (2018) confirmed that risk-averse choices are more likely for individuals with lower Cabs. Yet, Booth and Katic (2013) did not find a statistically significant correlation between Cabs and RTB.

Again, however, the RTB as well as Cabs measures vary greatly from one study to another. In contrast to the above administrative data papers, these studies tend to combine their Cabs measures into a single variable rather than analyzing them separately.

Experimental data

The experimental study of the link between RTB and Cabs in the lab is fairly extensive.[2] Lab experiments typically involve controlled environments and self-selected samples of university students. Cabs are measured through different devices, such as grades, test scores, Raven's matrices, the Cognitive Reflection Test (CRT) and graduate examination records, among others.

These studies can be classified into three groups. First, several studies find that higher Cabs are associated with more risk taking, which is consistent with previous studies

[2] See for instance, Brañas-Garza et al. (2008), Oechssler et al. (2009), Cokely and Kelley (2009), Burks et al. (2009), Campitelli and Labollita (2010), Sousa (2010), Dohmen et al. (2010), Brañas-Garza and Rustichini (2011), Beauchamp et al. (2012), Mather et al. (2012), Tymula et al. (2012), Rustichini et al. (2012, 2016), Benjamin et al. (2013), Sutter et al. (2013), Taylor (2013, 2016), Booth et al. (2014), Cueva et al. (2015), Andersson et al. (2016), Park (2016), and Pachur et al. (2017).

using administrative and survey data (see, for instance, Cokely and Kelley 2009, Burks et al. 2009, Dohmen et al. 2010, Campitelli and Labollita 2010, Brañas-Garza and Rustichini 2011,[3] Rustichini et al. 2012, 2016, Benjamin et al. 2013, Taylor 2013, Booth et al. 2014, Cueva et al. 2015 and Park 2016[4]). According to Dohmen et al. (2018), however, a closer look at the existing results suggests that the sign of this relationship may change depending on whether lotteries involve both gains and losses or only gains. In particular, their literature review indicates that high Cabs individuals may be less risk averse (in the gains domain) but *more* loss averse.

Second, null results are found in Brañas-Garza et al. (2008), Sousa (2010), Tymula et al. (2012), Mather et al. (2012), Sutter et al. (2013), Taylor (2013,[5] 2016[6]) and Pachuret al. (2017).

Finally, while the above experimental evidence of a negative relation between Cabs and risk aversion seems compelling, much evidence has also shown that estimated risk preferences based on MPL are highly sensitive to the presentation of the task and to changes in the choice set. For instance, Beauchamp et al. (2012) tested whether choices over risky prospects and the resulting preference parameter estimates are affected by framing effects that are implicitly introduced by the experimenter. Their experimental results indicate that RTB is sensitive to scale effects but insensitive to information about expected value.[7]

Along these lines, Andersson et al. (2016) argued that the direction of the bias generated by behavioral noise depends on the choice set of the risk elicitation task (see also Andersson et al. 2020). They argue that although different studies suggest a

[3] These authors show that higher reasoning ability is associated with a higher willingness to take risks among males.

[4] Park shows that this result holds for a high probability of gain or a low probability of loss. When subjects face a low probability of gain or a high probability of loss the correlation reverses.

[5] Taylor estimates that cognitive ability is inversely related to risk aversion when choices are hypothetical but is unrelated when the choices are real.

[6] In this study, the author finds that the inverse relationship between risk aversion and Cabs is not robust and that high-ability subjects may misrepresent their preferences when facing hypothetical choices.

[7] They present subjects with several MPL and find that inferred risk preferences vary systematically with the type of list used. The lists differ depending on whether there are many decisions in the risk-averse or in the risk-loving domain.

negative correlation between risk aversion and Cabs, Cabs might be related to random decision making rather than to risk preferences. In particular, they show that noise causes underestimation of risk aversion in a risk-elicitation task containing many decisions in the risk-loving domain but causes overestimation in a task containing many options in the risk-averse domain. They find that such errors are correlated with Cabs in a large sample of subjects drawn from the general Danish population. To demonstrate that the danger of false inference is real for standard risk-elicitation tasks, they chose two risk-elicitation tasks such that one produces a positive correlation and the other a negative correlation of risk aversion and Cabs. Taken together, these results indicate that an observed correlation between RTB and Cabs is task-contingent and hence spurious. In fact, it is a relatively common finding that low Cabs individuals are more likely to make inconsistent choices in risk-taking tasks (Burks et al. 2009, Chapman et al. 2018, Dohmen et al. 2018).

Recently, Jagelka (2020), using a random preference model to isolate the role of irrational, inconsistent RTB from true risk preferences and factor analysis to reduce Cabs measurement error, arrived at similar conclusions. His analysis shows that a single factor of Cabs obtained from a set of eight (mostly self-reported) measures correlates negatively with inconsistent decision making in MPL tasks but is uncorrelated with underlying true risk preferences.

Therefore, the results in this branch of the literature are somewhat more mixed and seem to indicate that the relationship between Cabs and RTB is highly sensitive to the task used and that noise or errors may play an important role. Whether different Cabs measures yield different results has also often been overlooked, since much of the evidence is based on measures combining different Cabs. A recent meta-analysis, which did not account for inconsistent decision making and excluded studies using self-reported risk-taking measures and proxy (indirect) measures of Cabs, found a weak but significant negative relationship between Cabs and risk-averse choices in the gain domain but no relationship when losses are possible (Lilleholt 2019). However, further meta-regressions fail to find clear systematic moderators of this relationship (either task type, Cabs measures used, gender or age).

Experimental design and methods

a. Participants and recruitment

This paper uses a nationally-by-regions representative sample of $n = 556$ (the sample represents a population of 11,780 students; 52.5% females) comprising first-year, Spanish students enrolled in Business Economics (BusEc hereafter). We computed the participation or weight of every university in the national-by-regions representative population using the BusEc enrollment in September 2017 by universities provided by the Spanish Ministry of Education. This participation rate was the basis for computing the number of participants corresponding to each university. Institutions with few students were not included. Instead, the resulting shares were assigned to the largest universities of the same region.[8]

In order to find students from every region of Spain, we first contacted university professors by email to ask them to collaborate. We only contacted the professors in charge of courses taught in year one (freshmen) according to the official webpage. We asked them whether they were in fact the lecturer(s) in charge of the course and then we requested the person in charge to help with the recruitment.[9] All the lecturers were asked to announce the recruitment in class 48 hours before the experimental online platform was open. Apart from other practical information, a specific login/password was provided for each institution in the announcement.[10]

Self-selected participants logged in at home on Behave4 Diagnosis (a webpage specifically designed to run economic experiments online[11]) and completed the tasks. The participants were given one hour and informed that after 30 min of inactivity the system would automatically switch off. Once the number of required participants for a given university was achieved, no more students for this institution were allowed to participate. An important issue here is that, in the absence of a proper lab, we have

[8] The website https://sites.google.com/site/pablobranasgarza/projects/across-spain provides all the relevant information: weight calculations, maps and sample size by university and region.

[9] The two emails we sent are available on the website in both Spanish and English (see footnote 8).

[10] Our system does not preclude the possibility of students sharing the code with friends that do not match our sampling criteria. A questionnaire helps us to control for this potential issue.

[11] https://diagnosis.behave4.com/.

little control over subjects' behavior across the experiment. Moreover, we cannot ensure that they are making choices alone. Nevertheless, online economic experiments are being increasingly used, and recent evidence suggests that the results obtained are valid and comparable to those obtained in physical lab settings (Anderhub et al. 2001, Horton et al. 2011 and Arechar et al. 2018).

One out of every 10 participants was randomly selected for real payment (i.e., each participant had a 10% chance of getting paid for real). At the end of the experiment, a random mechanism determined whether the participant was one of the winners or not. If selected, participants were asked for their email in order to contact them. Payments were made by bank transfer. One decision (from the entire set of games and tasks) was randomly selected for each winning subject to compute his/her payment. This has been proven as a valid cost-saving payment method in economic experiments (Charness et al. 2016). The 56 participants who were selected to be paid earned on average €41.37. The payments ranged from €0 (12 individuals) to €120 (two individuals). The average length of the experiment was 50 min. There was no show-up fee, and therefore no payment, for non-selected participants.

This study was approved by the Ethics Committee of Middlesex University Business School. All participants signed an informed consent prior to participating.

b. Experimental tasks

Students faced a set of incentivized experimental economics tasks including measures of time preferences, risk aversion, loss aversion and distributive preferences. They also played seven incentivized one-shot canonical games on social behavior (Ultimatum, Dictator, Trust, Public Goods Game, Third Party Punishment, Stag Hunt and Beauty Contest). All participants performed all the tasks in a randomly generated order with no feedback. All tasks implemented real monetary incentives. For this research we used the following tasks:

a) Cabs. The Cabs-related tasks and measures are as follows:

- Number of correct 4-digit summations in 60 seconds (similar to the piece rate condition in Niederle and Vesterlund 2007): $sums_i$. This variable measures math proficiency in a stressful environment. Participants received €3 for each correct answer.

- Expected number of correct summations in the above task: *expect* $sums_i$. Participants received €60 if they made the correct guess and €0 otherwise.
- $Overconfidence_i$ = *expect* $sums_i$ - $sums_i$ (this way of measuring overconfidence is labeled as "overestimation" in Moore and Healy 2008; see also Guillen et al. 2019).
- 7-item CRT (Capraro et al. 2017; adapted from Frederick 2005 and Toplak et al. 2014). This test measures the disposition to override an intuitive/automatic answer to a problem, which is indeed incorrect. We obtain two measures: (i) Number of analytical or reflective responses in the test ($reflective_i$), that is, number of correct answers; (ii) number of intuitive, incorrect responses ($intuitive_i$). Participants received €50 if they gave the correct answer from a randomly chosen item and €0 otherwise.
- 13-item RAT (adapted from Mednick 1962). This task measures participants' convergent thinking or the ability to find a single solution from apparently unconnected information, often referred to as convergent creativity. More specifically, participants were shown 13 groups of three words related to another, single word and had to find the correct word for each item (e.g., for "square/cardboard/open" the correct answer is "box"). The measure of convergent thinking is determined by the number of correct answers ($convergent_i$). Participants received €60 if they gave the correct answer in a randomly selected item and €0 otherwise.

b) RTB. The basic measures regarding RTB are (see Appendix 2 for instructions):

- Number of risk-averse choices in a standard 10-item risk aversion task (Holt and Laury 2002): *risk* $aversion_i$.. Earnings: lottery A: p*€40, (1-p)*€32; lottery B: p*€77, (1-p)*€2; with p increasing from 0.1 to 1 in 0.1 increments. Note that this task contains 6 decisions in the risk-averse domain and 4 decisions in the risk-loving domain (see Andersson et al. 2016 for a discussion on the effect of these relative numbers on RTB).
- Number of loss-averse choices in a standard 6-item loss aversion task (Gächter et al. 2007, Mrkva et al. 2019): *loss* $aversion_i$. Initial endowment: €35. Potential losses/gains if accepting to play the lottery: 1st choice: 1/2*(-€10) + 1/2*(+€30); 2nd choice: 1/2*(-€15) + 1/2*(+€30); …6th choice: 1/2*(-€35) + 1/2*(+€30), that is, potential losses increase in €5 increments from €10

to €35 across decisions. Note that this task contains four decisions in the loss-averse domain and one decision in the "loss-loving" domain (the 5th choice does not correspond to any of these domains specifically since identical gains and losses are equally probable).

c) Measures of noisy, inconsistent decision making: Finally, we define binary variables that capture whether the individual made inconsistent ("irrational") choices in the RTB tasks (e.g., multiple switching between options A and B or choosing the strictly dominated option A in the last decision of the risk aversion task).[12] The variables are as follows:

- $Rinconsistent_i$ takes the value of 1 if the participant's choices in the risk aversion task were inconsistent.
- $Linconsistent_i$ takes the value of 1 if the participant's choices in the loss aversion task were inconsistent.

The analysis of inconsistent choices is extended in the results (section b) to account for different types of inconsistency.

Results

a. Preliminary analysis

Table 1 displays the descriptive statistics for all the basic dependent and explanatory variables used. As can be seen, the sample is reduced in three observations for *expect sums* and hence for *overconfidence* due to the exclusion of outliers (using the mean ± 3 SD rule).

---

[12] Note that our method to classify choices as inconsistent assumes that there is no preference shock during the task. That is, if the individual suffers a preference shock (for instance, arising from new important life information), she will change her utility function during the task. In such case, multiple switching could still be preserving rational utility maximization and would therefore not be "inconsistent". Although we cannot get rid of the potential existence of preference shocks, we consider them to be very unlikely.

Table 2 shows zero-order Pearson correlations between all the variables used. Even though our variables are not necessarily continuous or normally distributed, we employ Pearson parametric correlations because they allow for sampling weights.[13]

Table 1. Descriptive statistics (computed using sampling weights)

Variable	Obs	Mean	SD	Min	Max
Dependent variables					
Rinconsistent	556	0.18	0.38	0	1
Linconsistent	556	0.14	0.35	0	1
risk aversion	556	5.55	1.88	0	10
loss aversion	556	3.45	1.41	0	6
Explanatory variables					
sums	556	8.85	3.58	0	21
expect sums	553	6.90	2.98	1	29
overconfidence	553	-1.98	2.90	-12	27
reflective	556	2.89	1.90	0	7
intuitive	556	2.59	1.67	0	6
convergent	556	4.78	2.29	0	11
Control variables					
female	556	0.51	0.50	0	1
income	556	4.71	2.24	0	9
age	556	19.22	2.63	17	45

Note: Income information is only defined for 507 individuals, the rest is missing. To avoid losing observations in the analyses with controls, we imputed the missing values to the estimates of an OLS with income as the dependent variable and gender, age, and region as explanatory variables.

Regarding the relationships between our dependent variables, we observe that the number of risk-averse and loss-averse choices, that is, *risk aversion* and *loss aversion*, are positively albeit weakly correlated ($p = 0.03$), as expected. Also, a larger number of risk-averse choices is positively associated with being inconsistent in the risk aversion task (*Rinconsistent*; $p < 0.01$) and negatively, but marginally, associated with being inconsistent in the loss aversion task (*Linconsistent*; $p = 0.09$). On the other hand, a larger number of loss-averse choices is negatively associated with

[13] The use of a parametric rather than non-parametric approach, such as the Spearman correlation, is less problematic when the number of observations is large, as in our case, because both approaches tend to yield qualitatively similar results; Spearman does not allow sampling weights.

Linconsistent ($p < 0.01$). Finally, *Rinconsistent* and *Linconsistent* are positively related ($p < 0.01$). These results are important because they reflect the fact that being inconsistent is linked to a larger number of risk-averse choices and a smaller number of loss-averse choices.

The observed positive relationship between *risk aversion* and *Rinconsistent* is in line with the argument of Andersson et al. (2016) where the existence of a relatively large number of decisions in the risk-averse domain in a risk-taking task explains why decision errors tend to be associated to more risk-averse choices. In our task, indeed, there are six [four] decisions in the risk-averse [risk-loving] domain. Applied to our results on loss aversion, this means that there are too few decisions in the loss-averse domain in our task: the task has only one decision in the "loss-loving" domain and four decisions in the loss-averse domain, yet this seems insufficient to eliminate the underestimation of loss aversion (i.e., the negative relationship between *Linconsistent* and *loss aversion*).

For the explanatory variables, Table 2 shows that math proficiency (*sums*) is strongly positively correlated with individuals' expectations (*expect sums*) but negatively with *overconfidence* (both $p < 0.01$). As expected, *sums* are positively correlated with both *reflective* and, to a lesser extent, *convergent*, and negatively correlated with *intuitive* (all $p < 0.01$). Similar relationships are observed for *expect sums* (all $p < 0.01$). *Overconfidence* is negatively [positively] related to *reflective* [*intuitive*], although both relationships are marginal (both about $p = 0.09$). Finally, *reflective* [*intuitive*] is positively [negatively] related to *convergent* (stronger for *reflective*; both $p < 0.01$). These relationships follow expectations according to the previous literature (Bosch-Domènech et al. 2014; Frederick 2005; Corgnet et al. 2016). In sum, the array of Cabs measures used in this study are all correlated in the expected direction.

These findings suggest that these Cabs measures may have a common underlying factor, although they also capture different aspects of Cabs. For this reason, we perform a factor analysis to obtain a single factor capturing a general measure of Cabs, which reduces measurement error concerns (Cunha et al. 2010, Jagelka 2020). We also apply the same method to the risk and loss aversion measures to reduce measurement error. The analysis of the individual effect of each Cabs measure on our dependent variables is presented in the Appendix and only summarized here.

Table 2. Zero-order Pearson correlations for all the variables used

	risk aversion	*loss aversion*	*Rinconsistent*	*Linconsistent*	*sums*	*expect sums*	*overconfidence*	*reflective*	*convergent*
loss aversion	0.09**								
	(0.03)								
Rinconsistent	0.13***	-0.00							
	(0.00)	(0.95)							
Linconsistent	-0.07*	-0.14***	0.16***						
	(0.09)	(0.00)	(0.00)						
sums	-0.04	-0.02	-0.00	0.00					
	(0.37)	(0.59)	(0.89)	(0.95)					
expect sums	-0.03	-0.04	-0.03	-0.05	0.62***				
	(0.49)	(0.30)	(0.47)	(0.29)	(0.00)				
overconfidence	0.01	-0.01	-0.02	-0.05	-0.59***	0.26***			
	(0.80)	(0.72)	(0.65)	(0.29)	(0.00)	(0.00)			
reflective	0.00	0.09**	-0.14***	-0.21***	0.22***	0.20***	-0.07*		
	(0.92)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.08)		
convergent	-0.07*	-0.05	-0.12***	-0.09**	0.14***	0.17***	-0.00	0.22***	
	(0.10)	(0.21)	(0.00)	(0.03)	(0.00)	(0.00)	(1.00)	(0.00)	
intuitive	0.00	-0.08*	0.06	0.12***	-0.20***	-0.18***	0.07*	-0.76***	-0.13***
	(0.96)	(0.07)	(0.15)	(0.00)	(0.00)	(0.00)	(0.10)	(0.00)	(0.00)

Note: *p*-values in parentheses. Correlations computed using sampling weights. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

While these relationships will be studied in more detail in the structural equation models of subsection (d) and in the Appendix, it can be seen from Table 2 that the only Cabs measure that correlates significantly with *risk aversion* is *convergent*, which displays a negative relationship, albeit marginal (p = 0.10). Regarding *loss aversion*, only *reflective* and *intuitive* yield significant correlations, showing a positive and negative relationship, respectively (p = 0.03 and 0.07, respectively). Although rather weak, these findings are somewhat in line with previous studies reporting that high Cabs individuals are less risk averse and more loss averse (e.g., Dohmen et al. 2018, Chapman et al. 2018, Lilleholt 2019).

b. Factor analysis – accounting for measurement error

One important concern when using different measures of Cabs is measurement error (Jagelka 2020, Guillen et al. 2019). Typically, any measurement instrument makes errors with some probability. This is especially likely in instruments based on human responses (Cunha et al. 2010). In particular, it is well known that measures of cognitive skills tend to be correlated, as in our case, and are therefore often seen as imperfect measurements of a common underlying factor of general cognitive (or mental) ability (Jensen 1998). A standard way of reducing measurement error and getting a single measure of Cabs is using factor analysis (Jensen 1998, Jagelka 2020).

Factor analysis allows us to obtain a robust measure of the unobserved latent characteristic "general Cabs" in which measurement error is substantially reduced compared to each Cabs individual measure separately. We apply factor analysis to a combination of 20 dummy variables, reflecting whether the participant gave the reflective response in each of the 7 CRT questions and the correct word in each of the 13 RAT questions, plus (standardized) *sums* and *expect sums* as continuous variables.[14]

[14] *Intuitive* and *overconfidence* are not included to avoid overspecification of the model and multicollinearity issues. We conduct the factor analysis using the three outliers detected in *expect sums* in order to keep all the 556 observations. If we instead exclude them, the results are very similar. Alternatively, one factor combining only the CRT and RAT questions also yields very similar results. These analyses are available upon request. In all cases, we use sampling weights to build the principal factor.

We label the resulting principal factor, which is standardized by construction, as *CAfactor* and the loadings of each variable can be found in Table A.1 (Appendix 1). Although all 22 variables load positively on *CAfactor*, the highest loadings are observed for question 9 of the RAT and questions 3 and 4 of the CRT, respectively, with loadings >0.45. The lowest loadings are observed for questions 7 and 13 of the RAT and for *expect sums*, with loadings <0.15. Therefore, we obtain a single measure of Cabs in which each Cabs-related variable has a different weight, calculated to minimize measurement error.

To consider potential measurement errors created by the elicitation tasks (MPL devices) on top of respondents' errors, we extend the previous factor analysis to our measures of risk and loss aversion. That is, we combine the 10 decisions in the risk aversion task into one single measure of risk aversion which, rather than merely adding-up the number of safe choices, gives a different weight to each choice. We label the resulting principal factor as *RAfactor* and the loadings can be found in Table A.2. In fact, although all the variables load positively on *RAfactor*, decisions 7 and 6, respectively, yield the highest loadings (≥0.70) whereas decisions 1 and 2, respectively, yield the lowest loadings (≤0.15). This was somewhat expected because a majority of individuals switch in decisions 6 and 7. Still, the differences between *RAfactor* and *risk aversion* are (qualitatively) small since they are strongly positively correlated (Pearson r = 0.98, $p < 0.01$). This procedure allows us to obtain a measure of risk preferences which is less dependent on the specific task parameterization. In other words, our initial definition of *risk aversion* does not account for measurement error, and this might be different in "important" choices (such as decisions 6 or 7) as compared to "unimportant" choices (decisions 1 and 2). However, *risk aversion* treats all decisions identically as it is given by the total number of safe choices. Factor analysis alleviates concerns about the existence of such potentially asymmetric measurement errors and therefore allows us to obtain a more robust measure of the latent trait (i.e., risk preferences). This is given by *RAfactor*.

We repeat the factor analysis for the six decisions of the loss aversion task and obtain *LAfactor*, which reflects loss aversion. Loadings can be found in Table A.3. Decisions 5 and 6, respectively, display the highest loadings (> 0.74), whereas decision 2 displays the lowest loading (0.02). Interestingly, decision 1 loads negatively on *LAfactor*, albeit weakly (-0.16), but *LAfactor* is still strongly correlated to *loss* *aversion* (Pearson r = 0.80, $p < 0.01$). These findings suggest that the first decision (in which the potential loss is €10 and the potential gain is €30 over an initial endowment of €35) performs slightly against the underlying latent factor of loss aversion, whereas the second decision (-€15 vs. +€30) is virtually orthogonal to it.

In sum, using factor analysis we create three variables: on *CAfactor* for cognitive abilities, *RAfactor* for risk aversion and *LAfactor* for loss aversion.

c. Inconsistent choices and their relationship with Cabs

Before analyzing in detail the relationship between Cabs and the RTB measures, we focus on inconsistent choices. First, we want to explore the difference between the choices of consistent and inconsistent individuals. It is important to emphasize that the definition of inconsistency is just a lower bound since individuals making consistent choices by chance are also labeled as consistent, and the number of these individuals is impossible to be assessed.

Regarding the risk aversion task, Figure 1 displays the fraction of safe choices in each decision for both consistent and inconsistent individuals. Consistent individuals (blue line) show a very clear trend: they begin by choosing the safe option (98.4% for the first two decisions, 97% for the third decision) and then reduce their safe choices monotonically until decision 10, in which none of them choose the safe (dominated) option. Since random decision making implies that each option is chosen with a probability = 0.5, we test whether the fraction of safe choices is different from 0.5 in each decision using proportion tests (corrected for multiple hypothesis testing). For consistent individuals, we can reject random decision making in all decisions ($p < 0.01$) except decision 6 ($p = 1$), in which they seem to be indifferent between the two options.

The same analysis is performed for inconsistent individuals (orange line in Figure 1). For the first three decisions, the pattern of safe choices is similar to that of consistent individuals, although the line is slightly below (≥85% of the individuals choose the safe option). Hence it is rather clear that they do not choose randomly in these decisions (all proportions are higher than 0.5, $p < 0.01$). For decisions 4, 5, 7, 8 and 9, however, the proportion test cannot reject that they play randomly at the 5% significance level (although it is marginally significant in decision 4, $p = 0.08$; $p = 1$

in the rest). Decisions 6 and 10 are different: the proportion test rejects random decision making ($p < 0.02$). In decision 6 [10], inconsistent individuals are more likely to choose the safe [risky] option. A possible explanation for this behavior is the following. When probability computation is easy, as in decisions 1, 2 and 3 where the smaller payoff is realized with ≥70% probability in both options, inconsistent subjects calculate the expected payoff and select the option yielding the highest value (i.e., the safe option). However, when probability computation becomes harder after decision 4, in which the smaller payoff is realized with 60% probability in both options, inconsistent individuals start making random choices. Since the last decision involves no computation (the larger payoff is realized with 100% probability), the majority selects the choice with higher expected value although a fraction of them continue making random choices, probably due to inattention or simple path dependence. The case of decision 6 does not match this explanation, yet this is arguably due to chance because the erratic pattern of safe choices among inconsistent individuals is visible in decisions 4 to 9.

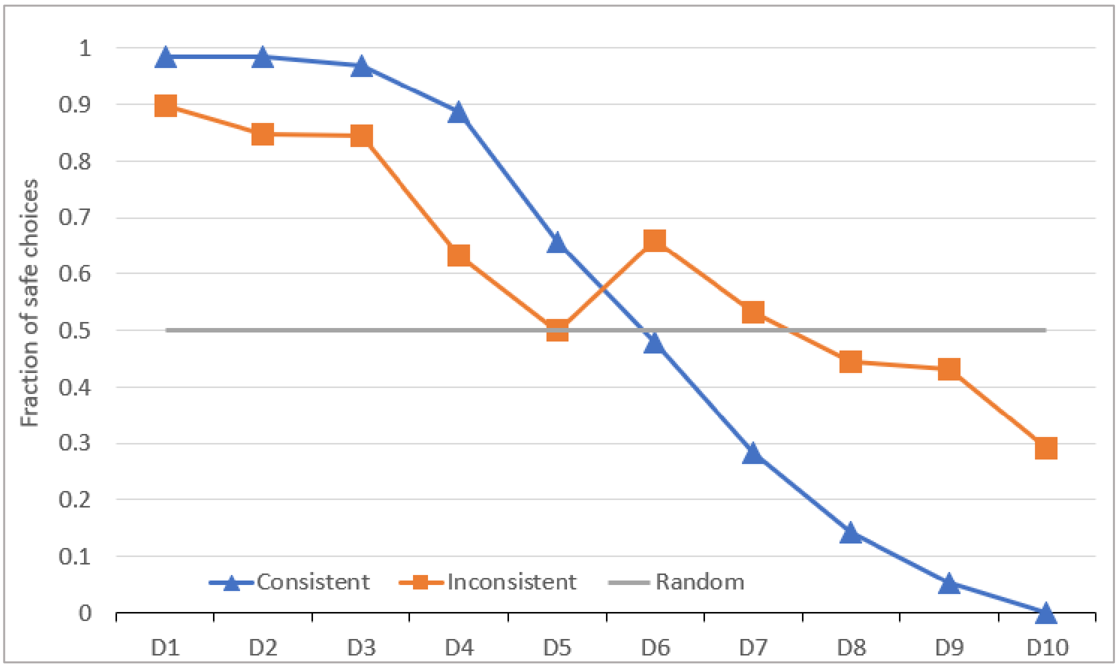

Figure 1. Risk aversion task: fraction of safe choices in each decision by consistent and inconsistent individuals

In short, inconsistent subjects start choosing according to expected payoff maximization because computation is simple. However, as computation becomes harder, they switch to random choices. Given that *risk aversion* is calculated as the sum of safe choices, the fact that inconsistent individuals choose randomly in those decisions in which the safe option attracts consistent individuals less means that the value of *risk aversion* increases (relatively) among the former.

It is important to emphasize that this problem is different in the loss aversion task, since the probabilities do not change across the task (50% probability in all scenarios), but the payoffs do change (see Bruner 2017 for a discussion on the role of changing probabilities vs. changing payoffs for decision errors). According to the above rationale, computations are more difficult when both payoffs have a similar probability of realization, which means that inconsistent individuals should choose randomly in all decisions in the loss aversion task.

Figure 2 reports a decision-by-decision analysis for the loss aversion task. The same protocol as above allows us to reject that consistent individuals (blue line) play randomly for all of the six decisions ($p < 0.01$). They start by choosing the safe option with 7.5% probability and this proportion increases monotonically until decision 6, in which 95.2% of them do so. However, inconsistent individuals (orange line) display a clearly erratic pattern already from decision 1 (39.2% choose the safe option). In fact, the results of the proportion tests indicate that we cannot reject that inconsistent individuals choose randomly in decisions 1, 2, 3, 4 and 6 ($p > 0.38$). The only exception is decision 5 ($p < 0.01$), yet this can be again attributed to chance because the pattern of choices of inconsistent individuals along the task does not follow any clear trend. Since, on average, consistent individuals choose the safe option in four out of the six decisions, inconsistent individuals' random choices (adding up to three safe choices on average) make them appear less loss averse than consistent individuals.

In sum, random choices arise when probability calculations are more difficult, and this seems to be associated to decisions in which both payoffs have a similar probability of realization. An alternative rationale might be that random choices are more likely when both options have a similar expected payoff. This could explain our findings on risk aversion, since payoff-probability similarity in the risk aversion task goes along with expected-payoff similarity (both increase from the extreme to the central decisions). However, for the loss aversion task, this account would entail that randomness should feature more likely in decision 5 than in the other decisions, because it is only in decision 5 where both options have an identical expected payoff (€35; since accepting the lottery entails 50% probability of losing €30 or winning €30, out of the initial €35). Our findings do not support this alternative explanation; if anything, decision 5 is associated to *less* randomness than the rest of decisions.

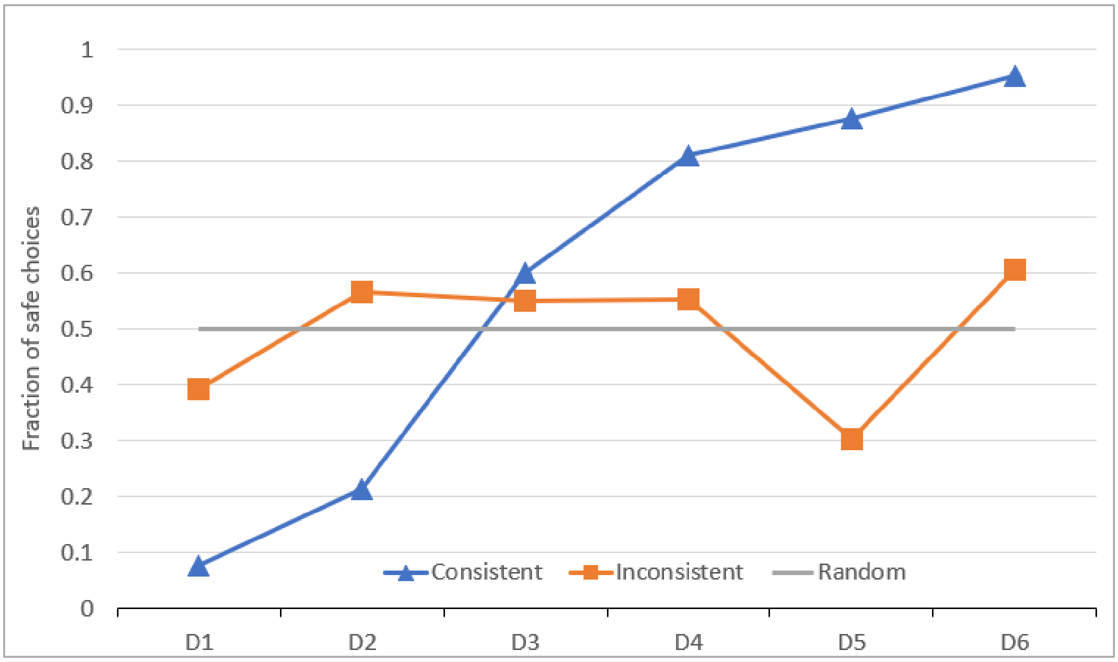

Figure 2. Loss aversion task: fraction of safe choices in each decision by consistent and inconsistent individuals

Next, we explore the impact of Cabs on inconsistent choices. For the sake of brevity, in the main text we focus on the Cabs measure obtained using factor analysis (i.e. *CAfactor*), whereas the analysis of the individual Cabs measures is relegated to the Appendix. As we will see in subsection (d), *CAfactor* is a negative predictor of both *Rinconsistent* and *Linconsistent*. Both with and without controls for age, gender and household income, a one standard deviation increase in *CAfactor* is associated with a reduction of 0.07 [0.08] in the likelihood of being inconsistent in the risk [loss] aversion task ($p < 0.01$, logit estimates). That is, higher Cabs individuals are less likely to make choices which do not satisfy rational utility maximization. This ultimately implies that restricting the sample to participants who make consistent MPL choices implies *selecting* those endowed with better cognitive abilities. This result is in line with previous studies (Andersson et al. 2016, 2020, Burks et al. 2009, Chapman et al. 2018, Dohmen et al. 2018, Jagelka 2020).

To further explore the nature of these findings, we conduct an additional analysis. For this analysis we first disentangle the two possible reasons why a participant can be labeled as inconsistent in the risk aversion task. A participant could have been coded as inconsistent in this task either:

i) for having switched back, that is, choosing the risky lottery B in one row/decision and then choosing the safe lottery A in the next one (usually referred to as "multiple switching") or

ii) for having chosen lottery A in the last row where it is strictly dominated by lottery B (since lottery A offers €40 and lottery B €77, both with 100% probability).

Whereas the first reason also applies to the loss aversion task, the second one does not. Thus, we define three new variables: number of switchbacks in the risk aversion task (*Rswitchbacks*; ranging from 0 to 4; average [SD] = 0.205 [0.529]), number of switchbacks in the loss aversion task (*Lswitchbacks*; ranking from 0 to 3; average [SD] = 0.157 [0.414]), and whether the participant chose the dominated option in the last decision of the risk aversion task (*choose_dominated*; dummy variable; proportion = 0.056). In this way, we are able to perform a more fine-grained analysis of multiple switching patterns, initially assuming noisier decision making for those making a larger number of switchbacks.

Most importantly, this procedure allows us to partially separate the inability to calculate probabilities or expected values (the first nine decisions in the risk aversion task and all six decisions in the loss aversion task require calculating probabilities) from the *inattention* associated to choosing the dominated option in the last decision of the risk aversion task (which does not require making calculations). The former is measured by *Rswitchbacks* and *Lswitchbacks*, whereas the latter is captured by *choose_dominated*. Note, however, that there are individuals who also made several switchbacks among those who chose the dominated option.

Table 3 shows the results of a series of regressions in which these three measures of inconsistency are modeled as a function of *CAfactor*. In the regressions without controls, we find that a one standard deviation increase in *CAfactor* is associated with a reduction of 0.11 [0.08] in the number of switchbacks in the risk aversion [loss aversion] task ($p < 0.01$). Adding controls barely affects the results.

Table 3. Impact of *CAfactor* on the number of switchbacks in the RTB tasks and on the choice of the dominated option in the risk aversion task

	Rswitchbacks		*Lswitchbacks*		*choose_dominated*	
	Without controls	With controls	Without controls	With controls	Without controls	With controls
CAfactor	-0.11***	-0.10***	-0.08***	-0.08***	-0.02	-0.02
	(0.00)	(0.00)	(0.00)	(0.00)	(0.23)	(0.28)
	0.20***	0.09	0.16***	0.43***	-2.97***	-4.96***
Constant	(0.00)	(0.69)	(0.00)	(0.00)	(0.00)	(0.00)
(pseudo) R-squared	0.03	0.05	0.03	0.04	0.02	0.03
F-test/	12.73***	3.81***	11.55***	4.53***	1.37	9.21*
Chi^2-test	(0.00)	(0.00)	(0.00)	(0.00)	(0.24)	(0.06)
N	556	556	556	556	556	556

Notes: OLS estimates for *Rswitchbacks* and *Lswitchbacks*; logit estimates (presented as marginal effects) for *choose_dominated*. We use robust standard errors in all regressions. P-values are shown in parentheses. Sampling weights are enabled in all regressions. *Rswitchbacks* ranges from 0 to 4; *Lswitchbacks* ranges from 0 to 3; *choose_dominated* is a dummy variable. Controls variables are gender, age and household income. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Even though the proportion of participants choosing the dominated option is small (31 participants or 5.6%), it is remarkable that *CAfactor* is not significantly related to *choose_dominated* ($p > 0.23$). Therefore, these results appear to indicate that better cognitive abilities only impact on inconsistent decision making by reducing the likelihood of making wrong probability or expected-payoff calculations but not by reducing the likelihood of being inattentive to the task.

To expand on these results, we combine the above variables and perform a multinomial regression analysis to test the effect of Cabs on the likelihood that a participant is classified into one of the following mutually exclusive groups. For the risk aversion task:

(i) consistent individuals (82%),

(ii) individuals making one switchback (12%),

(iii) individuals making more than one switchback (4%),

(iv) individuals choosing the dominated option in the last decision but not making any switchback (i.e., those choosing the safe lottery A in all 10 decisions; 2%).

Similarly, for the loss aversion task:

(i) consistent individuals (87%),

(ii) individuals making one switchback (11%),

(iii) individuals making more than one switchback (2%).

The results of the multinomial regressions for the risk aversion task are presented in Table 4.

Table 4. Impact of *CAfactor* on inconsistency in the risk aversion task. Multinomial regression

	Dominated			*1 switchback*			*More than 1 switchback*		
Base group:		Without controls	With controls		Without controls	With controls		Without controls	With controls
Consistent (base)	*CAfactor*	0.00 (0.76)	0.00 (0.99)	*CAfactor*	-0.05** (0.01)	-0.05** (0.02)	*CAfactor*	-0.03*** (0.02)	-0.02*** (0.00)
Dominated (base)				*CAfactor*	-0.05 (0.33)	-0.05 (0.43)	*CAfactor*	-0.03 (0.16)	-0.02 (0.32)
1 switchback (base)							*CAfactor*	-0.03 (0.32)	-0.02 (0.63)

Notes: Multinomial logit estimates (marginal effects). We use robust standard errors in all regressions. P-values are shown in parentheses. Sampling weights are enabled in all regressions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

We find that those individuals choosing the dominated option (without switchbacks) are not significantly different from consistent individuals in terms of Cabs, as measured by *CAfactor* ($p > 0.87$ with and without controls). However, higher Cabs individuals are significantly more likely to be classified in the consistent group than in the "one switchback" group and even more so than in the "more than one switchback" group ($p < 0.02$ with and without controls). Marginal effects indicate that an increase of one standard deviation in *CAfactor* is associated with about a 5% reduction in the probability of making one switchback and a 2–3% reduction in the probability of making more than one switchback in the risk aversion task. Therefore, again, these results suggest that (low) Cabs are related to the likelihood of making errors in calculations involving probabilities, not to inattention during the task. Moreover, it seems that the effect of Cabs increases monotonically along with the number of errors (i.e., switchbacks).

Table 5 shows the multinomial regressions for the loss aversion task. Higher Cabs individuals are significantly more likely to be classified in the consistent group than in the "one switchback" group ($p < 0.01$ with and without controls: marginal effect = 6–

7%); the difference with respect to the "more than one switchback" group is zero, however (p > 0.29 with and without controls). The latter result suggests that for the loss aversion task the effect of Cabs does not increase monotonically along with the number of errors (i.e., switchbacks). Ultimately, these findings indicate that for the main analyses the most appropriate measures of inconsistency are given by *Rinconsistent* and *Linconsistent*, which combine all those cases in which choices do not satisfy rational utility maximization into one category and can therefore be applied to any MPL task.

Table 5. Impact of *CAfactor* on inconsistency in the loss aversion task. Multinomial regression

	1 switchback			*More than 1 switchback*		
Base group:		Without controls	With controls		Without controls	With controls
Consistent (base)	*CAfactor*	-0.07*** (0.00)	-0.06*** (0.00)	*CAfactor*	-0.00 (0.29)	-0.00 (0.43)
Dominated (base)				*CAfactor*	-0.00 (0.31)	-0.00 (0.47)

Notes: Multinomial logit estimates (marginal effects). We use robust standard errors in all regressions. P-values are shown in parentheses. Sampling weights are enabled in all regressions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

As analyzed in the Appendix (see Tables A.5 to A.13 and the accompanying text in Appendix 1), when we consider each Cabs measure separately, we observe that *reflective* (and to a lesser extent *intuitive*, in the opposite direction) and *convergent* are the measures that can explain the above results, with no effect of *sums*, *expect sums* or *overconfidence*.

Taken together, these results suggest that cognition (especially reflective vs. intuitive thinking and convergent thinking) is associated with the process of making probability calculations rather than with paying attention to the task or not.

As we mentioned before, it is important to remark that our analysis of errors is necessarily affected by the fact that we use inconsistent choices as an "imperfect" proxy for irrational behavior. Indeed, among those making consistent choices there might be a fraction of them who did so by chance (even though they are unable to assess the options' risk correctly). These individuals are impossible to uncover, thus their number remains unknown. This implies that the effects we observe may represent a lower bound of the true effects.

d. The effect of Cabs on RTB mediated by inconsistent decision making

Finally, we explore the impact of Cabs on our RTB dependent variables using structural equation modeling (SEM). SEM allows us to study whether inconsistent decision making mediates the relationship between Cabs and RTB. We can say that inconsistent decision making explains (i.e., mediates) part of this relationship if the indirect effect of Cabs on RTB through *Rinconsistent*/*Linconsistent* is statistically significant, regardless of whether a total effect exists (Rucker et al., 2011). In particular, if inconsistent decision making explains why higher Cabs individuals may *appear* to be less risk averse and more loss averse, we expect the indirect effect of Cabs through *Rinconsistent* to be negative on *risk aversion* and the indirect effect through *Linconsistent* to be positive on *loss aversion*.

In addition, since decisions in the loss aversion task involve risk and we cannot assume linear utility for the relevant range of payoffs (i.e., between €0 and €65), we model loss aversion as being potentially affected by risk preferences. Note that our tasks do not allow us to estimate preference parameters for risk aversion and loss aversion simultaneously. Thus, we can only control for the potential effect of *risk aversion* on *loss aversion*.

The conceptual framework of the resulting SEM is presented in Figure 3. With this SEM we will be able to estimate the total, direct and indirect effects for the impact of Cabs on both *risk aversion* (mediated by *Rinconsistent*) and *loss aversion* (mediated by *Rinconsistent*, *risk aversion* and *Linconsistent*) simultaneously.

We first study the total, direct and indirect effects of *CAfactor* (a combination of CRT, RAT questions plus *sums* and *expect sums*, see Table A.1, Appendix 1) on *risk aversion* and *loss aversion* (Table 6). Then we replicate the SEM using *RAfactor* and *LAfactor* instead (Table 7).

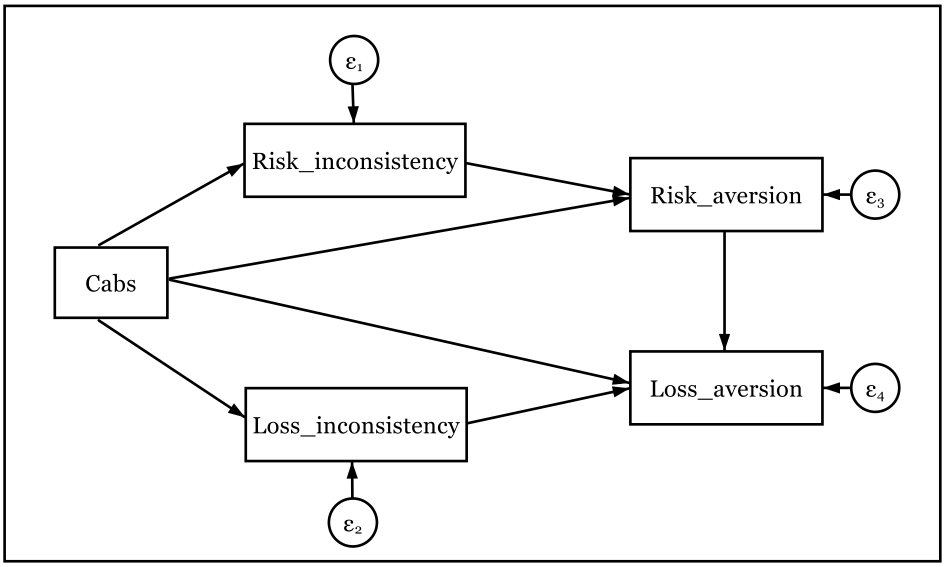

Figure 3. Conceptual framework of the structural equation model

Table 6 displays the effects estimated using SEM. We show estimates with and without control variables in adjacent columns. The top panel of the table refers to the equations explaining *risk aversion*, which include *CAfactor* and *Rinconsistent* as explanatory variables and *Rinconsistent* as an intermediate dependent variable (i.e., as a mediator). Apart from the indirect effect of *CAfactor* on *risk aversion* through *Rinconsistent*, which is our main focus, the direct/total effects of *CAfactor* on *Rinconsistent* and the direct/total effects of *Rinconsistent* on *risk aversion* are also reported. Since *Rinconsistent* is a dummy variable, we implement logit as the link function to the equation in which *Rinconsistent* is the dependent variable; OLS is used as the link function for the remaining equations. Therefore, we conduct a generalized SEM which allows different functional forms for each equation (the results are qualitatively similar if we apply OLS to all equations; not reported). Logit estimates are reported as marginal effects to be comparable with OLS estimates. The bottom panel shows the estimates for the equations in which *loss aversion* is the main dependent variable, with *CAfactor*, *Linconsistent*, *Rinconsistent* and *risk aversion* as explanatory variables, and *Linconsistent*, *Rinconsistent* and *risk aversion* as intermediate dependent variables (i.e., mediators). We use sampling weights in all cases.

Regarding inconsistent decision making, we can see that the direct effect of *CAfactor* on both *Rinconsistent* and *Linconsistent* is negative and significant ($p < 0.01$ with and without controls), which corroborates that individuals with higher Cabs are less likely to be inconsistent. A one standard deviation increase in *CAfactor* is associated with a 7% [8%] reduction in the probability of being inconsistent in the risk [loss] aversion task. In addition, the direct effect of *Rinconsistent* is positive and significant on *risk aversion* ($p = 0.02$ with and without controls), whereas the direct effect of *Linconsistent* is negative and significant on *loss aversion* ($p < 0.01$ with and without controls), in line with previous analyses. According to the effect sizes, being inconsistent in the risk [loss] aversion task is associated with about 0.6 more risk-averse [0.5 less loss-averse] choices. Although, as expected, the total effect of *CAfactor* is negative on *risk aversion* and positive on *loss aversion*, none of the estimates are significant ($p > 0.46$). The direct effects of *CAfactor* on *risk aversion* and *loss aversion* (i.e., after the effect through inconsistent decision making is eliminated) are again largely insignificant ($p > 0.74$).

Table 6. SEM: Impact of *CAfactor* on *risk/loss aversion* mediated by *Rinconsistent/Linconsistent*

	Direct effects		Indirect effects (via R/Linconsistent)		Indirect effects (via Risk aversion)		Total effects	
	Without controls	With controls	Without controls	With controls	Without controls	With controls	Without controls	With controls
Risk aversion as function of *CAfactor*								
CAfactor	-0.04	-0.03	-0.04*	-0.04*			-0.08	-0.07
	(0.75)	(0.79)	(0.07)	(0.07)			(0.47)	(0.53)
Rinconsistent	0.63**	0.62**					0.63**	0.62**
	(0.02)	(0.02)					(0.02)	(0.02)
Dep var: *Rinconsistent*								
CAfactor	-0.07***	-0.07***					-0.07***	-0.07***
	(0.00)	(0.00)					(0.00)	(0.00)
Loss aversion as function of *CAfactor*								
CAfactor	0.01	-0.01	0.04**	0.03**	-0.00	-0.00	0.05	0.02
	(0.86)	(0.91)	(0.01)	(0.02)	(0.22)	(0.23)	(0.56)	(0.81)
Linconsistent	-0.53***	-0.51***					-0.53***	-0.51***
	(0.00)	(0.00)					(0.00)	(0.00)
Rinconsistent					0.04	0.04	0.04	0.04
					(0.20)	(0.21)	(0.20)	(0.21)
Risk aversion	0.06	0.06					0.06	0.06
	(0.13)	(0.13)					(0.13)	(0.13)
Dep var: *Linconsistent*								
CAfactor	-0.08***	-0.08***					-0.08***	-0.08***
	(0.00)	(0.00)					(0.00)	(0.00)

Notes: Testing mediation effects using (generalized) structural equation modeling. The link functions are OLS, except for when *Rinconsistent* or *Linconsistent* are the dependent variables, in which we use logit. Marginal effects are reported and *p*-values are shown in parentheses. We use robust standard errors. Control variables are gender, age and household income. Sampling weights are enabled in all regressions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The indirect effects of *Rinconsistent* and *Linconsistent*, on the other hand, are significant for *risk aversion* (p = 0.07 with and without controls) and *loss aversion* (p = 0.01 without controls, p = 0.02 with controls), respectively. A one standard deviation increase in *CAfactor* is associated with a 0.04 reduction [increase] in the number of risk-averse [loss-averse] choices through inconsistent decision making (with controls the effect is reduced to 0.03 for *loss aversion*). Interestingly, the indirect effects on *loss aversion* through *risk aversion* are not significant (p > 0.20) and, in fact, removing the possibility of an effect of *risk aversion* on *loss aversion* from the model does not affect the results (not reported).

This analysis indicates that decision-making errors can partly explain why individuals with higher Cabs may appear to be less risk averse and more loss averse. Admittedly, the indirect effects are rather small; yet they are statistically significant, thus indicating mediation. We expect this mediation to be larger in experiments with design features leading to a significant relationship between Cabs and RTB. In addition, as mentioned earlier, the observed effects can be considered as a lower bound of the true effects because there is an unknown share of consistent individuals whose pattern of behavior resembles rational utility maximization by chance.

When we consider each Cabs measure separately (see Tables A.14 to A.19 and the accompanying text), we again observe that analytical (reflective) and convergent thinking are the measures that better explain the observed indirect effects, with no influence of *sums*, *expect sums* or *overconfidence*. However, the estimates are rather weak and change substantially across Cabs measures, thus suggesting that the factor analysis indeed provides for a good solution to reduce measurement error.

Table 7 replicates the SEM of Table 6 but using *RAfactor* and *LAfactor* instead of *risk aversion* and *loss aversion*, respectively. Here we can see that being inconsistent in the risk [loss] aversion task is associated with about a 0.5 [1.06] standard deviation increase [reduction] in *RAfactor* [*LAfactor*] (p < 0.01 with and without controls). The total and direct effects of *CAfactor* on *RAfactor* and *LAfactor* are again non-significant, although in the expected direction (p > 0.16). However, the indirect effect of *CAfactor* through inconsistent decision making is significantly negative on *RAfactor* (p = 0.02 with and without control) and significantly positive on *LAfactor* (p < 0.01 with and without controls). A one standard deviation increase in *CAfactor* is associated with a 0.04 [0.08] standard deviation decrease [increase] in *RAfactor*

[*LAfactor*] due to the effect of inconsistent decision making. Note that the sizes of the indirect effects are still small but more robust than in the previous analysis. In addition, the direct effect of *RAfactor* on *LAfactor* as well as the remaining potential mediations (i.e., the indirect effects on *LAfactor* through *RAfactor*) are not significant ($p > 0.72$).

Therefore, once measurement errors are reduced on both the dependent and the explanatory variable, the mediation is even stronger. This corroborates our hypothesis and suggests that factor analysis is indeed a good method to further exploit the information underlying RTB and Cabs (imperfect) measures (Cunha et al. 2010, Jagelka 2020).

Table 7. SEM: Impact of *CAfactor* on *RAfactor/LAfactor* mediated by *Rinconsistent/Linconsistent*

	Direct effects		Indirect effects (via R/Linconsistent)		Indirect effects (via RAfactor)		Total effects	
	Without controls	With controls	Without controls	With controls	Without controls	With controls	Without controls	With controls
RAfactor as function of *CAfactor*								
CAfactor	-0.01	-0.01	-0.04**	-0.04**			-0.05	-0.05
	(0.82)	(0.88)	(0.02)	(0.02)			(0.38)	(0.44)
Rinconsistent	0.50***	0.49***					0.50***	0.49***
	(0.00)	(0.00)					(0.00)	(0.00)
Dep var: *Rinconsistent*								
CAfactor	-0.07***	-0.07***					-0.07***	-0.07***
	(0.00)	(0.00)					(0.00)	(0.00)
LAfactor as function of *CAfactor*								
CAfactor	-0.01	-0.01	0.08***	0.08***	0.00	0.00	0.07	0.07
	(0.82)	(0.82)	(0.00)	(0.00)	(0.78)	(0.73)	(0.17)	(0.21)
Linconsistent	-1.06***	-1.06***					-1.06***	-1.06***
	(0.00)	(0.00)					(0.00)	(0.00)
Rinconsistent					-0.00	-0.00	-0.00	-0.00
					(0.78)	(0.72)	(0.78)	(0.78)
RAfactor	-0.01	-0.01					-0.01	-0.01
	(0.78)	(0.72)					(0.78)	(0.72)
Dep var: *Linconsistent*								
CAfactor	-0.07***	-0.07***					-0.07***	-0.07***
	(0.00)	(0.00)					(0.00)	(0.00)

Notes: Testing mediation effects using (generalized) structural equation modeling. The link functions are OLS, except for when *Rinconsistent* or *Linconsistent* are the dependent variables, in which we use logit. Marginal effects are reported and *p*-values are shown in parentheses. We use robust standard errors. Control variables are gender, age and household income. Sampling weights are enabled in all regressions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Conclusions

Using a large, nationally representative sample of business economics students from Spain, our study yields several important results.

In general, the study supports the hypothesis that risk preferences are not correlated to individuals' cognitive abilities, such as math proficiency, analytical (reflective) thinking or convergent thinking. Instead, we find that individuals with higher Cabs (in particular, those who rely more on reflection than intuition and those displaying better convergent thinking) are less likely to make inconsistent choices in the risk-related tasks.

Therefore, our results indicate that *preferences for risk in either the gain or the loss domain are not driven by cognitive abilities*. Taken together, our results support the notion that low Cabs are related to irrational decision making rather than to risk preferences. Moreover, from further analyses we are able to conclude that it is the process of computing probabilities—or expected values— rather than paying attention to the task that is associated with cognition: individuals with higher cognitive abilities make less mistakes, but are not more (or less) attentive to the task.

Using structural equation models and factor analysis to reduce measurement error, we show that being inconsistent is associated with more risk-averse choices and less loss-averse choices. And, precisely, it is the lack of consistency *that makes lower Cabs individuals appear to be more risk averse and less loss averse*. Our results suggest that failing to properly account for irrational choices might lead to a spurious negative [positive] relationship between Cabs and risk [loss] aversion (in contrast to the suggestion of Chapman et al. 2018, however). In this regard, we observe that inconsistent individuals tend to choose according to expected value maximization when computations are easy, and this seems to be associated with decisions in which the smaller payoff is realized with high probability (about ≥70%). As the realization probabilities of the larger and smaller payoffs get closer, computations appear to become more complex and inconsistent individuals start choosing randomly. Due to the tasks typically used, this account entails that risk aversion may have been overestimated and loss aversion may have been underestimated in previous studies. However, this is not because inconsistent individuals just choose randomly in all scenarios but particularly when the probabilities of the two options are similar.

The above findings suggest that the relationship between Cabs and risk taking is highly dependent on the task used, that is, on whether probabilities or payoffs change across decisions (see Bruner 2017). Ultimately, this means that the current results cannot be easily extended to real-world risky decision making, except to those (rare) cases when there is no ambiguity about probabilities and payoffs. Future research should explore the link between Cabs and risk taking using tasks and real decisions with varying levels of ambiguity in order to test whether low Cabs individuals are bad at assessing risks also when probabilities and/or payoffs are unknown.

An important contribution of this paper is related to selection. If subjects who fail to pass the consistency requirement are dropped from the sample and these are the subjects with lower cognitive abilities, then the *restricted sample selects participants who have higher cognitive abilities*.

Still there is a more intricate problem related to the potential number of individuals whose choices are wrongly labeled as consistent. This may be the case, for instance, of subjects who never switch back or make consistent choices by chance although they do not understand the decisions. Detecting these individuals does not seem to be an easy endeavor. A possible solution might be to ask subjects about the procedure they follow to make the choices or to use a larger number of MPL tasks (e.g., Andersson et al. 2016, 2020, Jagelka 2020).

All in all, the effects and magnitudes seem to be highly sensitive to the task itself and the statistical analysis of inconsistent choices. This might explain why previous results are mixed and somewhat weak (Andersson et al. 2016, Dohmen et al. 2018, Lilleholt 2019).

References

Åkerlund, D., Golsteyn, B.H., Grönqvist, H. and Lindahl, L. (2016). Time discounting and criminal behavior. *Proceedings of the National Academy of Sciences, 113*(22), 6160–6165.

Anderhub, V., Müller, R. and Schmidt, C. (2001). Design and evaluation of an economic experiment via the Internet. *Journal of Economic Behavior & Organization 46*(2), 227–247.

Andersson, O., Holm, H. J., Tyran, J. R. and Wengström, E. (2016). Risk Aversion relates to cognitive ability: Preferences or noise? *Journal of the European Economic Association, 14*(5), 1129–1154.

Andersson, O., Holm, H. J., Tyran, J. R., & Wengström, E. (2020). Robust inference in risk elicitation tasks. *Journal of Risk and Uncertainty*, 1-15.

Angrisani M. and Casanova, M. (2011). Understanding heterogeneity in household portfolios: The role of cognitive ability and preference parameters. *Mimeo* USC.

Angrisani M. and Casanova, M. (2018). Portfolio allocations of older Americans: The role of cognitive ability and preference parameters. *Mimeo* USC.

Arechar, A. A., Gächter, S. and Molleman, L. (2018). Conducting interactive experiments online. *Experimental Economics, 21*(1), 99–131.

Beauchamp, J. P., Benjamin, D. J. and Chabris, C. F. (2012). How malleable are risk preferences and loss aversion? *Mimeo* USC.

Beauchamp, J. P., Cesarini, D. and Johannesson, M. (2017). The psychometric and empirical properties of measures of risk preferences. *Journal of Risk and Uncertainty, 54*(3), 203–237.

Benjamin, D. J., Brown, S. A. and Shapiro, J. M. (2013). Who is behavioral? Cognitive ability and anomalous preferences. *Journal of the European Economic Association, 11*(6), 1231–1255.

Bickel, W. K., Odum, A. L. and Madden, G. J. (1999). Impulsivity and cigarette smoking: delay discounting in current, never, and ex-smokers. *Psychopharmacology, 146*(4), 447–454.

Booth, A. I. and Katic, P. (2013). Cognitive skills, gender and risk preferences. *Economic Record, 89*(284), 19–30.

Booth, A., Cardona-Sosa, L. and Nolen, P. (2014). Gender differences in risk aversion: Do single-sex environments affect their development? *Journal of Economic Behavior & Organization*, *99*, 126–54.

Bosch-Domènech, A., Brañas-Garza, P. and Espín, A. M. (2014). Can exposure to prenatal sex hormones (2D: 4D) predict cognitive reflection? *Psychoneuroendocrinology*, *43*, 1–10.

Brañas-Garza, P., Guillen, P., Lopez, R. (2008). Math skills and risk attitudes. *Economics Letters*, *99*(2), 332–36.

Brañas-Garza, P., and Rustichini A. (2011). Organizing effects of testosterone and economic behavior: Not just risk taking. *PLoS ONE*, *6*(12), e29842.

Brañas-Garza, P., Kujal, P. and Lenkei, B. (2019). Cognitive Reflection Test: Whom, how, when. *Journal of Behavioral and Experimental Economics, 89,* 101455.

Bruner, D. M. (2017). Does decision error decrease with risk aversion? *Experimental Economics, 20*(1), 259-273.

Burks, S. V., Carpenter, J. P., Goette, L. and Rustichini, A. (2009). Cognitive skills affect economic preferences, strategic behavior, and job attachment. *Proceedings of the National Academy of Sciences*, *106*(19), 7745–50.

Campitelli, G. and Labollita, M. (2010). Correlations of cognitive reflection with judgments and choices. *Judgment and Decision Making*, *5*(3), 182–91.

Capraro, V., Corgnet, B., Espín, A. M. and Hernán-González, R. (2017). Deliberation favours social efficiency by making people disregard their relative shares: evidence from USA and India. *Royal Society Open Science*, *4*(2): 160605.

Chapman, J., Snowberg, E., Wang, S. and Camerer. C. (2018). Loss attitudes in the U.S. population, Evidence from dynamically optimized sequential experimentation (DOSE). *NBER Working Paper 25072*.

Charness, G., Gneezy, U. and Imas, A. (2013). Experimental methods: Eliciting risk preferences. *Journal of Economic Behavior & Organization, 87,* 43–51.

Charness, G., Gneezy, U., and Halladay, B. (2016). Experimental methods: Pay one or pay all. *Journal of Economic Behavior & Organization*, *131*(Part A), 141–150.

Charness, G., Eckel, C., Gneezy, U., & Kajackaite, A. (2018). Complexity in risk elicitation may affect the conclusions: A demonstration using gender differences. *Journal of Risk and Uncertainty*, *56*(1), 1–17.

Christelis, D., Jappelli, T. and Padula, M. (2010). Cognitive abilities and portfolio choice. *European Economic Review*, *54*(1),18–38.

Cokely, E. T. and Kelley, C. M. (2009). Cognitive abilities and superior decision making under risk: A protocol analysis and process model evaluation. *Judgment and Decision Making*, *4*(1), 20–33.

Cole, S., Paulson, A. and Shastry, G. K. (2014). Smart money? The effect of education on financial outcomes. *The Review of Financial Studies, 27*(7), 2022–2051.

Corgnet, B., Espín, A. M. and Hernán-González, R. (2016). Creativity and cognitive skills among millennials: thinking too much and creating too little. *Frontiers in Psychology*, *7*, 1626.

Cueva, C., Iturbe-Ormaetxe, I., Mata-Pérez, E., Ponti, G., Sartarelli, M., Yu,H. and Zhukova, V. (2015). Cognitive (ir)reflection: New experimental evidence. *Journal of Behavioral & Experimental Economics*, *64*, 81–93.

Cunha, F., Heckman, J. J., and Schennach, S. M. (2010). Estimating the technology of cognitive and noncognitive skill formation. *Econometrica*, *78*(3), 883-931.

Dohmen, T., Falk, A., Huffman, D. and Sunde, U. (2010). Are risk aversion and impatience related to cognitive ability? *The American Economic Review, 100*(3), 1238–1260.

Dohmen, T., Falk, A., Huffman, D. and Sunde, U. (2018). On the relationship between cognitive ability and risk preference. *Journal of Economic Perspectives, 32*(2), 115–134.

Eckel, C. C. and Grossman, P. J. (2002). Sex differences and statistical stereotyping in attitudes toward financial risk. *Evolution and Human Behavior*, *23*(4), 281–295.

Falk, A., Becker, A., Dohmen, T., Enke, B., Huffman, D. and Sunde, U. (2018). Global evidence on economic preferences. *The Quarterly Journal of Economics, 133*(4), 1645–1692.

Frederick, S. (2005). Cognitive reflection and decision making. *Journal of Economic Perspectives*, *19*(4), 25–42.

Frisell, T., Pawitan, Y. and Långström, N. (2012). Is the association between general cognitive ability and violent crime caused by family-level confounders? *PLoS ONE, 7*(7), e41783.

Gächter, S., Johnson, E. J. and Herrmann, A. (2007). Individual-level loss aversion in riskless and risky choices. *IZA Discussion Paper 2961.*

Grinblatt, M., Keloharju, M. and Linnainmaa, J. (2011). IQ and stock market participation. *The Journal of Finance, 66*(6), 2121–64.

Gillen, B., Snowberg, E., and Yariv, L. (2019). Experimenting with measurement error: Techniques with applications to the Caltech cohort study. *Journal of Political Economy*, *127*(4), 1826-1863.

Holt, C. A. and Laury, S. K. (2002). Risk aversion and incentive effects. *The American Economic Review, 92*(5), 1644–1655.

Horton, J. J., Rand, D. G. and Zeckhauser, R. J. (2011). The online laboratory: Conducting experiments in a real labor market. *Experimental Economics, 14*(3), 399–425.

Jagelka, T. (2020). Are Economists' Preferences Psychologists' Personality Traits? A Structural Approach. *IZA Discussion Paper* 13303.

Jensen, A. R. (1998). *The g factor: The science of mental ability* (Vol. 648). Westport, CT: Praeger.

Lilleholt, L. (2019). Cognitive ability and risk aversion: A systematic review and meta-analysis. *Judgment and Decision Making, 14*(3), 234–279.

Mather, M., Mazar, N., Gorlick, M. A., Lighthall, N. R., Burgeno, J., Schoeke, A. and Ariely, D. (2012). Risk preferences and aging: the "certainty effect" in older adults´ decision making. *Psychology and Aging, 27*(4), 801–16.

Mednick, S. A. (1962). The associative basis of the creative process. *Psychological Review, 69*(3), 220–32.

Meier, S. and Sprenger, C. D. (2012). Time discounting predicts creditworthiness. *Psychological Science, 23*(1), 56–58.

Mrkva, K., Johnson, E. J., Gächter, S., & Herrmann, A. (2019). Moderating loss aversion: loss aversion has moderators, but reports of its death are greatly exaggerated. *Journal of Consumer Psychology, 30*(3), 407-28.

Moore, D. A., and Healy, P. J. (2008). The trouble with overconfidence. *Psychological Review, 115*(2): 502-517.

Niederle, M. and Vesterlund, L. (2007). Do women shy away from competition? Do men compete too much? *The Quarterly Journal of Economics, 122*(3), 1067–1101.

Oechssler, J., Roider, A. and Schmitz, P. W. (2009). Cognitive abilities and behavioral biases. *Journal of Economic Behavior and Organization, 72*(1), 147–52.

Pachur, T., Mata, R. and Hertwig, R. (2017). Who dares, who errs? disentangling cognitive and motivational roots of age differences in decisions under risk. *Psychological Science, 28*(4), 504–518.

Park, N. Y. (2016). Domain-specific risk preference and cognitive ability. *Economics Letters, 141*, 1–4.

Rucker, D. D., Preacher, K. J., Tormala, Z. L., & Petty, R. E. (2011). Mediation analysis in social psychology: Current practices and new recommendations. *Social and Personality Psychology Compass, 5*(6), 359-371.

Rustichini, A., DeYoung, C. G., Anderson, J. and Burks, S. V. (2016). Toward the integration of personality theory and decision theory in explaining economic behavior: An experimental investigation. *Journal of Behavioral and Experimental Economics, 64*, 122-37.

Shen, W., Hommel, B., Yuan, Y., Chang, L. and Zhang, W. (2018). Risk-taking and creativity: Convergent, but not divergent thinking is better in low-risk takers. *Creativity Research Journal, 30*(2), 224–231.

Sousa, S. (2010). Are smarter people really less risk averse? *CeDEx Discussion Paper Series 2010-17*.

Sutter, M., Kocher, M. G., Glätzle-Rützler, D. and Trautmann, S. T. (2013). Impatience and uncertainty: experimental decisions predict adolescents' field behavior. *The American Economic Review, 103*(1), 510–531.

Taylor, M. P. (2013). Bias and brains: Risk aversion and cognitive ability across real and hypothetical settings. *Journal of Risk and Uncertainty, 46*(3), 299–320.

Taylor, M. P. (2016). Are high-ability individuals really more tolerant of risk? a test of the relationship between risk aversion and cognitive ability. *Journal of Behavioral and Experimental Economics, 63*, 136–147.

Toplak, M. E., West, R. F. and Stanovich, K. E. (2014). Assessing miserly information processing: An expansion of the Cognitive Reflection Test. *Thinking and Reasoning, 20*(2), 147–168.

Tymula, A., Rosenberg-Belmaker, L. A., Roy, A. K., Ruderman, L., Manson, K., Glimcher, P. W. and Levy, I. (2012). Adolescents' risk-taking behavior is driven by tolerance to ambiguity. *Proceedings of the National Academy of Sciences, 109*(42), 17135–17140.

Van Rooij, M., Lusardi, A. and Alessie, R. (2011). Financial literacy and stock market participation. *Journal of Financial Economics, 101*(2), 449–472.

APPENDIX 1: Additional statistical analyses – testing for different Cabs measures

Table A.4 shows the results of a series of regressions in which the two dummy variables of inconsistency, *Rinconsistent* and *Linconsistent*, are modeled as a function of all the six Cabs gathered. We find that more *reflective* individuals are less likely to make inconsistent choices in both tasks (*Rinconsistent*, $p = 0.01$ without controls, $p = 0.02$ with controls; *Linconsistent*, $p < 0.01$ with and without controls; the opposite is observed for *intuitive*, but only significant for *Linconsistent*, $p = 0.04$ without controls, $p = 0.07$ with controls). The individuals displaying better *convergent* thinking are also less likely to make inconsistent choices in the risk aversion task ($p = 0.02$ without controls, $p = 0.01$ with controls; not significant for *Linconsistent*, $p = 0.12$ without controls, $p = 0.14$ with controls).

A robustness check is implemented in Table A.5 in which the main explanatory variables (i.e., *sums*, *expect sums*, *reflective* and *convergent*) are all included together (since *overconfidence* is determined by *sums* and *expect sums*, it is not included; in addition, we only enable *reflective* for the CRT since including *intuitive* as well would yield collinearity). From this analysis, we observe that both *reflective* and *convergent* remain significant or marginally significant in predicting inconsistent risk choices (*Rinconsistent*) when included together, which may mean that they operate independently to some extent. *Reflective* is still also significant in predicting inconsistent choices in the loss aversion task. Adding controls does not substantially change the results. In sum, our data show that subjects who score high in the CRT and the RAT are less likely to be inconsistent.

As shown in Table A.6, the number of switchbacks in both the risk aversion and the loss aversion tasks is predicted negatively by *reflective* ($p < 0.01$ with and without controls) and positively, albeit more weakly ($p = 0.08$ without controls, $p = 0.18$ with controls), by *intuitive*. *Convergent* also relates negatively to *Rswitchbacks* but not significantly so to *Lswitchbacks*. When all explanatory variables are included simultaneously in the regressions (Table A.7), both *reflective* and *convergent* remain significant on *Rswitchbacks*, but only reflective is significant on *Lswitchbacks*. The same regressions with *choose_dominated* as the dependent variable do not report any significant coefficient (all $p > 0.13$); see Tables A.8 and A.9).

Table A.10 shows the output of the multinomial regression for the risk aversion task. We find that individuals choosing the dominated option (without switchbacks) are not significantly different from consistent individuals in terms of any of the Cabs measures. However, more *reflective* individuals are significantly more likely to be classified in the consistent group than in the “one switchback” group and even more so than in the “more than one switchback” group (the relationship with *intuitive* is also monotonically increasing across the two latter groups, but it is of opposite sign and only significant for “more than one switchback”). This difference is significant for *convergent* with respect to “one switchback” but not with respect to “more than one switchback”. The effects of *sums*, *expect sums* and *overconfidence* are never significant. The results are similar when all explanatory variables are included simultaneously in the regression (Table A.11).

Table A.12 shows the output of the multinomial regression for the loss aversion task. We observe a similar pattern here: consistent individuals are significantly more *reflective* (and marginally less *intuitive*) than those making one switchback and even more so than those making more than one switchback, and they also display more *convergent* thinking than those making one switchback (not significant for “more than one switchback”). As before, *sums*, *expect sums* and *overconfidence* are never significant. Like in risk aversion, the results are qualitatively similar when all the explanatory variables are included simultaneously in the regression (Table A.13).

Tables A.14 to A.19 present the results of the SEM for *sums*, *expect sums*, *overconfidence*, *reflective*, *convergent* and *intuitive*, respectively.

In the top panel of the tables we can see that, as in previous analyses, both *reflective* ($p = 0.01$ with and without controls) and *convergent* ($p = 0.02$ with and without controls) yield a negative and significant direct effect on *Rinconsistent*. In particular, an increase of one correct answer in the CRT and RAT is associated, respectively, with a 3% and 2% reduction in the probability of being inconsistent in the risk aversion task. The estimates of the remaining Cabs measures on *Rinconsistent* are non-significant ($p > 0.28$). On the other hand, *Rinconsistent* yields a positive and significant direct effect on *risk aversion* in all models ($p < 0.02$), also confirming previous analyses. Inconsistent individuals report about 0.6 more risk-averse choices than consistent individuals.

In addition, the total effects on *risk aversion* are not significant for any of the Cabs measures (*convergent* is the measure for which the total [negative] effect is closer to significance, $p = 0.19$ with and without controls). This also applies to the direct effect of Cabs on *risk aversion* (i.e., after the effect through *Rinconsistent* is eliminated): all estimates are largely insignificant and *convergent* is the closest to significance ($p = 0.29$ without controls, $p = 0.28$ with controls).

Regarding indirect effects, we observe the expected negative sign in all cases (positive for *intuitive*), but it only reaches marginal significance for *reflective* ($p = 0.08$ with and without controls) and is close to significance for *convergent* ($p = 0.10$ without controls, $p = 0.11$ with controls). Each unit increase in *reflective* [*convergent*] is associated with a reduction of 0.02 [0.01] risk-averse choices due to the effect of *Rinconsistent*. The remaining indirect effects yield $p > 0.32$.

In the bottom panel of the tables, we can see for the direct effects of the Cabs measures on *Linconsistent* that only the negative direct effect of *reflective* ($p < 0.01$ with and without controls) and the positive direct effect of *intuitive* ($p = 0.04$ with and without controls) are significant. In particular, an increase of one correct [intuitive] answer in the CRT is associated with a 4% reduction [2% increase] in the probability of being inconsistent in the loss aversion task. *Convergent* also reports a negative direct effect on *Linconsistent*, but it is just close to significance ($p = 0.12$ with and without controls). The rest of Cabs measures are not significant ($p > 0.44$). This is coherent with previous analyses. On the other hand, confirming previous analyses as well, *Linconsistent* yields a negative and significant direct effect on *loss aversion* ($p < 0.01$ with and without controls). Inconsistent individuals report about 0.5–0.6 loss-averse choices less than consistent individuals according to the estimates.

The total effects on *loss aversion* are not significant for any of the Cabs measures except for *reflective*, which reports a marginally significant positive estimate ($p = 0.09$ with and without controls); for all the remaining measures, $p > 0.14$. Each unit increase in *reflective* is associated with an increase of 0.07 loss-averse choices (with controls, this is reduced to 0.05). This is similar to what we observed in the preliminary analysis. The direct effects of the Cabs measures on *loss aversion* (i.e., after the effect through *Linconsistent* is eliminated) are also non-significant ($p > 0.15$).

As expected, the indirect effect through *Linconsistent* is positive (it is virtually zero for *sums*, $p = 0.97$) in all cases (negative for *intuitive*), although it only reaches significance for *reflective* ($p = 0.02$ with and without controls) and marginal significance for *intuitive* ($p = 0.09$ with and without controls). A one-unit increase in *reflective* [*intuitive*] is associated with a 0.02 increase [0.01 reduction] in the number of loss-averse choices due to the effect of *Linconsistent*. For *convergent*, the indirect effect is just close to significance ($p = 0.14$ and $p = 0.13$ with and without controls, respectively). The remaining indirect effects yield $p > 0.45$.

Supplementary tables

Table A.1. Factor loadings - factor for Cabs

Variable (item)	Cabs Factor
CRT 1	0.3994
CRT 2	0.4368
CRT 3	0.4510
CRT 4	0.4581
CRT 5	0.4126
CRT 6	0.2940
CRT 7	0.2972
RAT 1	0.2509
RAT 2	0.3720
RAT 3	0.4321
RAT 4	0.3186
RAT 5	0.1944
RAT 6	0.2050
RAT 7	0.0648
RAT 8	0.3581
RAT 9	0.4612
RAT 10	0.2570
RAT 11	0.2391
RAT 12	0.2325
RAT 13	0.1404
sums (standardized)	0.2794
expect sums (standardized)	0.1461

Notes: Factor analysis with principal factor. For each of the CRT and RAT items, the variable takes the value of 1 if the response is correct, 0 otherwise. The CRT and RAT questionnaires can be found at https://sites.google.com/site/pablobranasgarza/projects/across-spain.

Table A.2. Factor loadings - factor for *risk aversion*

Variable (item)	Risk aversion Factor
risk 1	0.1508
risk 2	0.1548
risk 3	0.2000
risk 4	0.3117
risk 5	0.5661
risk 6	0.6999
risk 7	0.7369
risk 8	0.6627
risk 9	0.4686
risk 10	0.2907

Notes: Factor analysis with principal factor. For each item, the variable takes the value of 1 if the risk averse option is selected (left-hand option) and 0 if the risky option is selected (right-hand option).

Table A.3. Factor loadings - factor for *loss aversion*

Variable (item)	Loss aversion Factor
loss 1	-0.1642
loss 2	0.0239
loss 3	0.4679
loss 4	0.7452
loss 5	0.7458
loss 6	0.6084

Notes: Factor analysis with principal factor. For each item, the variable takes the value of 1 if the loss-averse option (reject playing the lottery) is selected and 0 if the non-loss-averse option is selected (accept playing the lottery).

Table A.4. Impact of Cabs on inconsistent decision making

	Rinconsistent		*Linconsistent*	
	Without controls	With controls	Without controls	With controls
sums	-0.00	0.00	0.00	0.00
	(0.88)	(0.76)	(0.97)	(0.86)
expect sums	-0.00	-0.00	-0.00	-0.00
	(0.49)	(0.75)	(0.45)	(0.50)
overconfidence	-0.00	-0.00	-0.01	-0.01
	(0.67)	(0.60)	(0.48)	(0.48)
reflective	-0.03**	-0.03**	-0.04***	-0.04***
	(0.01)	(0.02)	(0.00)	(0.00)
intuitive	0.01	0.01	0.02**	0.02*
	(0.29)	(0.40)	(0.04)	(0.07)
convergent	-0.02**	-0.02**	-0.01	-0.01
	(0.02)	(0.01)	(0.12)	(0.14)
N	556	556	556	556

Notes: Logit estimates (marginal effects). Each cell corresponds to a different regression. We use robust standard errors in all regressions. *P*-values are shown in parentheses. Regressions using *expect sums* or overconfidence also exclude the three outliers detected. Sampling weights are enabled in all regressions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.5. Regression analysis with all explanatory variables simultaneously. Impact of Cabs on inconsistent RTB

	Rinconsistent		*Linconsistent*	
	Without controls	With controls	Without controls	With controls
sums	0.00	0.00	0.00	0.01
	(0.46)	(0.47)	(0.31)	(0.25)
expect sums	-0.00	.0.00	-0.00	-0.00
	(0.87)	(0.96)	(0.63)	(0.61)
reflective	-0.03**	-0.02*	-0.04***	-0.04***
	(0.02)	(0.05)	(0.00)	(0.00)
convergent	-0.01*	-0.01**	-0.01	-0.01
	(0.06)	(0.03)	(0.36)	(0.46)
Pseudo-R^2	0.03	0.05	0.06	0.08
Chi^2-test	8.76*	15.49**	16.65***	27.20***
	(0.07)	(0.03)	(0.00)	(0.00)
N	553	553	553	553

Notes: Logit estimates (marginal effects). We use robust standard errors in all regressions. *P*-values are shown in parentheses. Regressions using *expect sums* exclude the three outliers detected. Sampling weights are enabled in all regressions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table A.6. Impact of Cabs on the number of switchbacks in the RTB tasks

	Rswitchbacks		*Lswitchbacks*	
	Without controls	With controls	Without controls	With controls
sums	-0.01	-0.00	-0.00	0.00
	(0.34)	(0.67)	(0.95)	(0.98)
expect sums	-0.01	-0.01	-0.01	-0.01
	(0.21)	(0.41)	(0.30)	(0.35)
overconfidence	-0.00	-0.00	-0.01	-0.01
	(0.89)	(0.80)	(0.43)	(0.43)
reflective	-0.05***	-0.04***	-0.04***	-0.04***
	(0.00)	(0.00)	(0.00)	(0.00)
intuitive	0.03*	0.02	0.03**	0.03*
	(0.08)	(0.18)	(0.04)	(0.06)
convergent	-0.03**	-0.03**	-0.01	-0.01
	(0.02)	(0.01)	(0.29)	(0.31)
N	556	556	556	556

Notes: OLS estimates. Each cell corresponds to a different regression. We use robust standard errors in all regressions. *P*-values are shown in parentheses. Regressions using *expect sums* or overconfidence also exclude the three outliers detected. Sampling weights are enabled in all regressions. *Rswitchbacks* ranges from 0 to 4; *Lswitchbacks* ranges from 0 to 3. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.7. Regression analysis with all explanatory variables simultaneously. Impact of Cabs on the number of switchbacks in the RTB tasks

	Rswitchbacks		*Lswitchbacks*	
	Without controls	With controls	Without controls	With controls
sums	0.00	0.00	0.01	0.01
	(0.74)	(0.67)	(0.32)	(0.35)
expect sums	-0.00	-0.00	-0.01	-0.01
	(0.70)	(0.78)	(0.38)	(0.36)
reflective	-0.04***	-0.03***	-0.04***	-0.04***
	(0.01)	(0.02)	(0.00)	(0.00)
convergent	-0.02*	-0.02*	-0.00	-0.00
	(0.09)	(0.06)	(0.76)	(0.84)
	0.42***	0.29	0.28***	0.58***
Constant	(0.00)	(0.26)	(0.00)	(0.00)
R-squared	0.04	0.05	0.05	0.06
	3.34**	2.27**	4.94***	3.60***
F-test	(0.01)	(0.03)	(0.00)	(0.00)
N	556	556	556	556

Notes: OLS estimates. We use robust standard errors in all regressions. *P*-values are shown in parentheses. Regressions using *expect sums* exclude the three outliers detected. Sampling weights are enabled in all regressions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table A.8. Impact of Cabs on the choice of the dominated option in the risk aversion task

	choose_dominated	
	Without controls	With controls
sums	-0.00	0.00
	(0.98)	(0.77)
expect sums	-0.00	-0.00
	(0.77)	(0.96)
overconfidence	-0.00	-0.00
	(0.77)	(0.71)
reflective	-0.01	-0.00
	(0.34)	(0.50)
intuitive	0.01	0.01
	(0.32)	(0.41)
convergent	-0.01	-0.01
	(0.20)	(0.14)
N	556	556

Notes: Logit estimates (marginal effects). Each cell corresponds to a different regression. We use robust standard errors in all regressions. *P*-values are shown in parentheses. Regressions using *expect sums* or overconfidence also exclude the three outliers detected. Sampling weights are enabled in all regressions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.9. Regression analysis with all explanatory variables simultaneously. Impact of Cabs on the choice of the dominated option in the risk aversion task

	choose_dominated	
	Without controls	With controls
sums	0.00	0.00
	(0.67)	(0.66)
expect sums	-0.00	-0.00
	(0.91)	(0.99)
reflective	-0.01	-0.00
	(0.39)	(0.63)
convergent	-0.01	-0.01
	(0.22)	(0.14)
Constant	-2.24***	-4.42**
	(0.00)	(0.02)
Pseudo-R^2	0.02	0.04
	1.81	9.57
Chi^2-test	(0.77)	(0.21)
N	553	553

Notes: Logit estimates (marginal effects). We use robust standard errors in all regressions. *P*-values are shown in parentheses. Regressions using *expect sums* exclude the three outliers detected. Sampling weights are enabled. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table A.10. Impact of Cabs on inconsistency in the risk aversion task. Multinomial regression

Base group:	*Dominated*			*1 switchback*			*More than 1 switchback*		
		Without controls	With controls		Without controls	With controls		Without controls	With controls
Consistent (base)	*sums*	0.00	0.00	*sums*	0.00	0.00	*sums*	-0.00	-0.00
	expect sums	0.00	0.00	*expect sums*	-0.00	-0.00	*expect sums*	-0.00	-0.00
	overconfidence	0.00	0.00	*overconfidence*	-0.01	-0.00	*overconfidence*	-0.00	-0.00
	reflective	0.00	0.00	*reflective*	-0.02**	-0.02*	*reflective*	-0.02***	-0.01**
	intuitive	-0.00	0.00	*intuitive*	0.01	0.00	*intuitive*	0.01**	0.01*
	convergent	0.00	-0.00	*convergent*	-0.02**	-0.02**	*convergent*	-0.00	-0.00
Dominated (base)				*sums*	0.00	0.00	*sums*	-0.00	-0.00
				expect sums	-0.00	-0.00	*expect sums*	-0.01	-0.00
				overconfidence	-0.01	-0.01	*overconfidence*	-0.00	-0.00
				reflective	-0.02	-0.02	*reflective*	-0.02**	-0.01
				intuitive	0.01	0.00	*intuitive*	0.01	0.01
				convergent	-0.02	-0.02	*convergent*	-0.00	-0.00
1 switchback (base)							*sums*	-0.00	-0.00
							expect sums	-0.00	-0.00
							overconfidence	-0.00	-0.00
							reflective	-0.02	-0.01
							intuitive	0.01	0.01
							convergent	-0.00	-0.00

Notes: Multinomial logit estimates (marginal effects). We use robust standard errors and sampling weights in all regressions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table A.11. Regression analysis with all explanatory variables simultaneously. Impact of Cabs on inconsistency in the risk aversion task. Multinomial regression

Base group:	*Dominated*			*1 switchback*			*More than 1 switchback*		
		Without controls	With controls		Without controls	With controls		Without controls	With controls
Consistent (base)	*sums*	0.00	0.00	*sums*	0.00	0.00	*sums*	0.00	0.00
	expect sums	0.00	0.00	*expect sums*	-0.01	-0.01	*expect sums*	-0.00	-0.00
	reflective	0.00	0.00	*reflective*	-0.02*	-0.01	*reflective*	-0.02**	-0.01*
	convergent	-0.00	-0.00	*convergent*	-0.01*	-0.01*	*convergent*	-0.00	-0.00
Dominated (base)				*sums*	0.01	0.01	*sums*	0.00	0.00
				expect sums	-0.01	-0.01	*expect sums*	-0.00	-0.00
				reflective	-0.02	-0.01	*reflective*	-0.02*	-0.01
				convergent	-0.01	-0.01	*convergent*	-0.00	-0.00
1 switchback (base)							*sums*	0.00	0.00
							expect sums	-0.00	-0.00
							reflective	-0.02	-0.01
							convergent	-0.00	-0.00

Notes: Multinomial logit estimates (marginal effects). We use robust standard errors and sampling weights in all regressions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table A.12. Impact of Cabs on inconsistency in the loss aversion task. Multinomial regression

Base group:	*1 switchback*			*More than 1 switchback*		
		Without controls	With controls		Without controls	With controls
Consistent (base)	*sums*	0.00	0.00	*sums*	0.00	0.00
	expect sums	-0.00	-0.00	*expect sums*	-0.00	-0.00
	overconfidence	-0.00	-0.00	*overconfidence*	-0.00	-0.00
	reflective	-0.03***	-0.03***	*reflective*	-0.01***	-0.01***
	intuitive	0.02*	0.02*	*intuitive*	0.00	0.00
	convergent	-0.02*	-0.01*	*convergent*	0.00	0.00
1 switchback (base)				*sums*	-0.00	0.00
				expect sums	-0.00	-0.00
				overconfidence	-0.00	-0.00
				reflective	-0.01	-0.01
				intuitive	0.00	0.00
				convergent	0.00	0.00

Notes: Multinomial logit estimates (marginal effects). We use robust standard errors and sampling weights in all regressions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table A.13. Regression analysis with all explanatory variables simultaneously. Impact of Cabs on inconsistency in the loss aversion task. Multinomial regression

Base group:	*1 switchback*			*More than 1 switchback*		
		Without controls	With controls		Without controls	With controls
Consistent (base)	*sums*	0.01	0.01	*sums*	0.00	0.00
	expect sums	-0.00	-0.00	*expect sums*	-0.00	-0.00
	reflective	-0.03***	-0.03***	*reflective*	-0.01***	-0.01***
	convergent	-0.01	-0.01	*convergent*	0.00	0.00
1 switchback (base)				*sums*	0.00	0.00
				expect sums	-0.00	-0.00
				reflective	-0.01	-0.01
				convergent	0.00*	0.00*

Notes: Multinomial logit estimates (marginal effects). We use robust standard errors and sampling weights in all regressions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table A.14. SEM: Impact of *sums* on *risk /loss aversion* mediated by *Rinconsistent/Linconsistent*

	Direct effects		Indirect effects (via R/Linconsistent)		Indirect effects (via Risk aversion)		Total effects	
	Without controls	With controls	Without controls	With controls	Without controls	With controls	Without controls	With controls
Risk aversion as function of *sums*								
Sums	-0.02	-0.02	-0.00	-0.00			-0.02	-0.02
	(0.41)	(0.46)	(0.88)	(0.88)			(0.41)	(0.41)
Rinconsistent	0.64**	0.63**					0.64**	0.63**
	(0.01)	(0.01)					(0.01)	(0.01)
Dep var: *Rinconsistent*								
Sums	-0.00	-0.00					-0.00	-0.00
	(0.88)	(0.88)					(0.88)	(0.88)
Loss aversion as function of *sums*								
Sums	-0.01	-0.01	-0.00	-0.00	0.00	0.00	-0.01	-0.01
	(0.63)	(0.42)	(0.97)	(0.97)	(0.53)	(0.55)	(0.57)	(0.57)
Linconsistent	-0.56***	-0.51***					-0.56***	0.51***
	(0.00)	(0.00)					(0.00)	(0.00)
Rinconsistent					0.04	0.04	0.04	0.04
					(0.20)	(0.20)	(0.20)	(0.20)
Risk aversion	0.06	0.06					0.06	0.06
	(0.13)	(0.13)					(0.13)	(0.13)
Dep var: *Linconsistent*								
Sums	0.00	0.00					0.00	0.00
	(0.97)	(0.97)					(0.97)	(0.97)

Notes: Testing mediation effects using structural equation modeling. Marginal effects are reported and *p*-values are shown in parentheses. We use robust standard errors. Control variables are gender, age and household income. Sampling weights are enabled in all regressions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.15. SEM: Impact of *expect sums* on *risk/loss aversion* mediated by *Rinconsistent/Linconsistent*

	Direct effects		Indirect effects (via R/Linconsistent)		Indirect effects (via Risk aversion)		Total effects	
	Without controls	With controls	Without controls	With controls	Without controls	With controls	Without controls	With controls
Risk aversion as function of *expect sums*								
Expect sums	-0.02	-0.01	-0.00	-0.00			-0.02	-0.01
	(0.64)	(0.66)	(0.49)	(0.49)			(0.59)	(0.59)
Rinconsistent	0.66**	0.65**					0.66**	0.65**
	(0.01)	(0.01)					(0.01)	(0.01)
Dep var: *Rinconsistent*								
Expect sums	-0.00	-0.00					-0.00	-0.00
	(0.49)	(0.49)					(0.49)	(0.49)
Loss aversion as function of *expect sums*								
Expect sums	-0.02	-0.03	0.00	0.00	0.00	-0.00	-0.02	-0.03
	(0.26)	(0.15)	(0.46)	(0.47)	(0.48)	(0.49)	(0.32)	(0.32)
Linconsistent	-0.54***	-0.52***					-0.54***	-0.52***
	(0.00)	(0.00)					(0.00)	(0.00)
Rinconsistent					0.04	0.04	0.04	0.04
					(0.21)	(0.21)	(0.21)	(0.21)
Risk aversion	0.06	0.06					0.06	0.06
	(0.15)	(0.14)					(0.15)	(0.14)
Dep var: *Linconsistent*								
Expect sums	-0.00	-0.00					-0.00	-0.00
	(0.45)	(0.45)					(0.45)	(0.45)

Notes: Testing mediation effects using structural equation modeling. Marginal effects are reported and *p*-values are shown in parentheses. We use robust standard errors. Control variables are gender, age and household income. Sampling weights are enabled in all regressions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.16. SEM: Impact of *overconfidence* on *risk/loss aversion* mediated by *Rinconsistent/Linconsistent*

	Direct effects		Indirect effects (via R/Linconsistent)		Indirect effects (via Risk aversion)		Total effects	
	Without controls	With controls	Without controls	With controls	Without controls	With controls	Without controls	With controls
Risk aversion as function of *overconfidence*								
Overconfidence	0.01	0.01	-0.00	-0.00			0.01	0.01
	(0.83)	(0.85)	(0.67)	(0.67)			(0.86)	(0.86)
Rinconsistent	0.66**	0.66**					0.66**	0.66**
	(0.01)	(0.01)					(0.01)	(0.01)
Dep var: *Rinconsistent*								
Overconfidence	-0.00	-0.00					-0.00	-0.00
	(0.67)	(0.67)					(0.67)	(0.67)
Loss aversion as function of *overconfidence*								
overconfidence	-0.01	-0.01	0.00	0.00	-0.00	-0.00	-0.01	-0.01
	(0.66)	(0.71)	(0.48)	(0.48)	(0.94)	(0.93)	(0.77)	(0.77)
Linconsistent	-0.54***	-0.51***					-0.54***	-0.51***
	(0.00)	(0.00)					(0.00)	(0.00)
Rinconsistent					0.04	0.04	0.04	0.04
					(0.20)	(0.20)	(0.20)	(0.20)
Risk aversion	0.06	0.06					0.06	0.06
	(0.14)	(0.13)					(0.14)	(0.13)
Dep var: *Linconsistent*								
overconfidence	-0.00	-0.00					-0.00	-0.00
	(0.48)	(0.48)					(0.48)	(0.48)

Notes: Testing mediation effects using structural equation modeling. Marginal effects are reported and *p*-values are shown in parentheses. We use robust standard errors. Control variables are gender, age and household income. Sampling weights are enabled in all regressions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.17. SEM: Impact of *reflective* on *risk/loss aversion* mediated by *Rinconsistent/Linconsistent*

	Direct effects		Indirect effects (via R/Linconsistent)		Indirect effects (via Risk aversion)		Total effects	
	Without controls	With controls	Without controls	With controls	Without controls	With controls	Without controls	With controls
Risk aversion as function of *reflective*								
Reflective	0.02	0.03	-0.02*	-0.02*			0.00	0.01
	(0.63)	(0.51)	(0.08)	(0.08)			(0.93)	(0.93)
Rinconsistent	0.66**	0.65**					0.66**	0.65**
	(0.01)	(0.01)					(0.01)	(0.01)
Dep var: *Rinconsistent* *reflective*	-0.03**	-0.03**					-0.03**	-0.03**
	(0.01)	(0.01)					(0.01)	(0.01)
Loss aversion as function of *reflective*								
Reflective	0.05	0.03	0.02**	0.02**	-0.00	-0.00	0.07*	0.05*
	(0.21)	(0.42)	(0.02)	(0.02)	(0.31)	(0.33)	(0.09)	(0.09)
Linconsistent	-0.48***	-0.47***					-0.48***	-0.47***
	(0.00)	(0.00)					(0.00)	(0.00)
Rinconsistent					0.04	0.04	0.04	0.04
					(0.19)	(0.19)	(0.19)	(0.20)
Risk aversion	0.06	0.06					0.06	0.06
	(0.14)	(0.12)					(0.14)	(0.12)
Dep var: *Linconsistent* *reflective*	-0.04***	-0.04***					-0.04***	-0.04***
	(0.00)	(0.00)					(0.00)	(0.00)

Notes: Testing mediation effects using structural equation modeling. Marginal effects are reported and *p*-values are shown in parentheses. We use robust standard errors. Control variables are gender, age and household income. Sampling weights are enabled in all regressions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.18. SEM: Impact of *convergent* on *risk/loss aversion* mediated by *Rinconsistent/Linconsistent*

	Direct effects		Indirect effects (via R/Linconsistent)		Indirect effects (via Risk aversion)		Total effects	
	Without controls	With controls	Without controls	With controls	Without controls	With controls	Without controls	With controls
Risk aversion as function of *convergent*								
Convergent	-0.05	-0.05	-0.01	-0.01			-0.06	-0.06
	(0.29)	(0.28)	(0.10)	(0.11)			(0.19)	(0.19)
Rinconsistent	0.61**	0.59**					0.61**	0.59**
	(0.02)	(0.02)					(0.02)	(0.02)
Dep var: *Rinconsistent*								
Convergent	-0.02**	-0.02**					-0.02**	-0.02**
	(0.02)	(0.02)					(0.02)	(0.02)
Loss aversion as function of *convergent*								
Convergent	-0.04	-0.03	0.01	0.01	0.00	0.00	-0.03	-0.03
	(0.22)	(0.25)	(0.13)	(0.14)	(0.22)	(0.22)	(0.28)	(0.28)
Linconsistent	-0.56***	-0.53***					-0.56***	-0.53***
	(0.00)	(0.00)					(0.00)	(0.00)
Rinconsistent					0.03	0.03	0.03	0.03
					(0.23)	(0.23)	(0.23)	(0.23)
Risk aversion	0.06	0.06					0.06	0.06
	(0.16)	(0.15)					(0.16)	(0.15)
Dep var: *Linconsistent*								
Convergent	-0.01	-0.01					-0.01	-0.01
	(0.12)	(0.12)					(0.12)	(0.12)

Notes: Testing mediation effects using structural equation modeling. Marginal effects are reported and p-values are shown in parentheses. We use robust standard errors. Control variables are gender, age and household income. Sampling weights are enabled in all regressions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.19. SEM: Impact of *intuitive* on *risk/loss aversion* mediated by *Rinconsistent/Linconsistent*

	Direct effects		Indirect effects (via R/Linconsistent)		Indirect effects (via Risk aversion)		Total effects	
	Without controls	With controls	Without controls	With controls	Without controls	With controls	Without controls	With controls
Risk aversion as function of *intuitive*								
Intuitive	-0.01	-0.01	0.01	0.01			0.00	0.00
	(0.91)	(0.83)	(0.33)	(0.33)			(0.96)	(0.96)
Rinconsistent	0.64**	0.63**					0.64**	0.63**
	(0.01)	(0.01)					(0.01)	(0.01)
Dep var: *Rinconsistent*								
Intuitive	0.01	0.01					0.01	0.01
	(0.29)	(0.28)					(0.29)	(0.28)
Loss aversion as function of *intuitive*								
intuitive	-0.05	-0.04	-0.01*	-0.01*	-0.00	-0.00	-0.06	-0.05
	(0.23)	(0.35)	(0.09)	(0.09)	(0.56)	(0.60)	(0.15)	(0.15)
Linconsistent	-0.50***	-0.48***					-0.50***	-0.48***
	(0.00)	(0.00)					(0.00)	(0.00)
Rinconsistent					0.04	0.04	0.04	0.04
					(0.19)	(0.19)	(0.19)	(0.19)
Risk aversion	0.06	0.06					0.06	0.06
	(0.13)	(0.12)					(0.13)	(0.12)
Dep var: *Linconsistent*								
intuitive	0.02**	0.02**					0.02**	0.02**
	(0.04)	(0.04)					(0.04)	(0.04)

Notes: Testing mediation effects using structural equation modeling. Marginal effects are reported and *p*-values are shown in parentheses. We use robust standard errors. Control variables are gender, age and household income. Sampling weights are enabled in all regressions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

APPENDIX 2: Instructions for risk and loss aversion tasks

Risk aversion (screen 1 and 2)

Instructions

In this task you will have to make a series of **10 decisions** over different amounts of money associated with different probabilities. In each decision, you will have to choose between **two lotteries** attaching a particular probability to two possible monetary gains (prizes). Choosing a lottery means playing it.

The decisions are completely independent to each other and **there are no correct or incorrect answers**. You must choose the option you really prefer in each case, regardless of what you chose or will choose in the remaining decisions. If this task is selected for real payment **you will only get paid for one randomly-selected decision from the 10**. Thus, please think carefully about your decisions because what you choose will determine your payment (if you are selected for payment). The payment will result from **playing the lottery you chose** (with its corresponding prizes and probabilities) in the decision that finally counts for real payment.

Please click Continue to start the task.

Continue

Please select the lottery you prefer in each decision:

Example: at decision 1, you have to choose between playing lottery A, in which you earn **40.00** € with 10% probability or **32.00** € with 90% probability, and playing lottery B, in which you earn **77.00** € with 10% probability or **2.00** € with 90% probability. A probability of 100% indicates that the prize is for sure.

Lottery A	Lottery B
40.00 € with 10% probability **32.00** € with 90% probability	**77.00** € with 10% probability **2.00** € with 90% probability
40.00 € with 20% probability **32.00** € with 80% probability	**77.00** € with 20% probability **2.00** € with 80% probability
40.00 € with 30% probability **32.00** € with 70% probability	**77.00** € with 30% probability **2.00** € with 70% probability
40.00 € with 40% probability **32.00** € with 60% probability	**77.00** € with 40% probability **2.00** € with 60% probability
40.00 € with 50% probability **32.00** € with 50% probability	**77.00** € with 50% probability **2.00** € with 50% probability
40.00 € with 60% probability **32.00** € with 40% probability	**77.00** € with 60% probability **2.00** € with 40% probability
40.00 € with 70% probability **32.00** € with 30% probability	**77.00** € with 70% probability **2.00** € with 30% probability
40.00 € with 80% probability **32.00** € with 20% probability	**77.00** € with 80% probability **2.00** € with 20% probability
40.00 € with 90% probability **32.00** € with 10% probability	**77.00** € with 90% probability **2.00** € with 10% probability
40.00 € with 100% probability **32.00** € with 0% probability	**77.00** € with 100% probability **2.00** € with 0% probability

Continue

Loss aversion (screen 1 and 2)

Instructions

To start this task, you receive **35 €, which are directly for you**. In this task, you will have to make a series of **6 decisions** about positive (gains) or negative amounts of money (losses). In each decision you will have to choose whether you **accept or reject** to play a lottery. This lottery is based on a (virtual) coin toss and you can **lose money** if it is tails or **earn money** if it is heads. To accept a lottery means playing it, while to reject a lottery entails not losing or earning anything.

The decisions are completely independent to each other and **there are no correct or incorrect answers**. You must choose the option you really prefer in each case, regardless of what you chose or will choose in the remaining decisions. If this task is selected for real payment, in addition to the initial 35 €, you will only get paid according to one randomly-selected decision from the 6. Thus, please think carefully about your decisions because what you choose will determine your payment (if you are selected for payment). The payment corresponding to the decision that determines the real payment will result from **playing the lottery** in case you have **accepted** it, or will be **zero**, in case you have **rejected** it. The initial 35 € will be used to cover eventual losses.

Please click Continue to start the task.

Continue

In each decision, choose if you accept or reject to play the lottery. If you reject it, you will not win or lose anything.

You lose **10.00** € if it is TAILS and you win **30.00** € if it is HEADS	○ Accept	○ Reject
You lose **15.00** € if it is TAILS and you win **30.00** € if it is HEADS	○ Accept	○ Reject
You lose **20.00** € if it is TAILS and you win **30.00** € if it is HEADS	○ Accept	○ Reject
You lose **25.00** € if it is TAILS and you win **30.00** € if it is HEADS	○ Accept	○ Reject
You lose **30.00** € if it is TAILS and you win **30.00** € if it is HEADS	○ Accept	○ Reject
You lose **35.00** € if it is TAILS and you win **30.00** € if it is HEADS	○ Accept	○ Reject

Continue