Risk aversion relates to cognitive ability: preferences or noise?

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Recent experimental studies suggest that risk aversion is negatively related to cognitive ability. In this paper we report evidence that this relation might be spurious. We recruit a large subject pool drawn from the general Danish population for our experiment. By presenting subjects with choice tasks that vary the bias induced by random choices, we are able to generate both negative and positive correlations between risk aversion and cognitive ability. Our results suggest that cognitive ability is more related to random decision making than to risk preferences.

Keywords: Risk preference, cognitive ability, experiment, noise
JEL-codes: C81; C91; D12; D81

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I. Introduction

Preferences cannot be observed directly and economists therefore usually infer preferences from choices. A potential problem with this so-called revealed preference approach is that people make mistakes. Errors in decision making are essentially unproblematic for inference if they do not bias choices one way or another. But depending on the preference-elicitation task at hand, random errors may bias choices in a particular way, which then implies that preference estimates will be biased. An additional potential complication results from heterogeneity. We all make mistakes sometimes, but in accomplishing any given task some people are more prone to error than others. The danger of confounding bounded rationality (errors) with preferences in general, and then detecting spurious correlations between estimated preference and explanatory variables in particular, therefore looms large.

This paper illustrates the problem of inferring risk preferences from observed noisy choices. In particular, we revisit and take a fresh look at the relation between cognitive ability and risk preferences, and argue that this relation is inherently hard to identify since cognitive ability is related to noisy decision making.

We build on an extensive literature on eliciting risk preferences in general, and complement a recent and relatively sparse literature relating risk preferences to measures of cognitive ability. Prior research shows that people differ in their propensities to make mistakes when choosing between risky prospects (e.g. Harless and Camerer 1994; Hey and Orme 1994), and that error propensities vary with observable characteristics (Dave et al. 2010; von Gaudecker, van Soest and Wengström 2011). We argue that the recent stream of literature that relates cognitive ability and choice behavior under risk (e.g. Burks et al. 2009; Dohmen et al. 2010; Benjamin, Brown and Shapiro 2013) do not account for this heterogeneous propensity to make mistakes, which may lead to biased inference about preferences for risk from observed choices.

Specifically, we first show by way of a simple example that errors in decision making can bias estimates of risk preferences in standard elicitation tasks to over- or underestimate risk aversion, depending on the construction of the risk elicitation task. To demonstrate that the danger of false inference is real for standard risk elicitation tasks, we conduct two risk elicitation tasks on a large sample drawn from the general Danish population. In line with our bias conjecture, one produces a positive correlation and the other a negative correlation between risk aversion and cognitive ability.

The basic intuition for our result is simple. We use a typical multiple-price list (MPL) in which individuals face a series of decisions between two lotteries, where one is more risky than the other.[1] To illustrate what happens if we introduce the possibility to make mistakes, consider two individuals Ann and Beth with identical risk preferences, but Ann makes no errors when choosing between lotteries while Beth randomly makes mistakes. Consider a particular risk elicitation task (MPL1) in which Ann switches relatively "high up" in the table, i.e. makes fewer safe than risky choices. Now, error-prone Beth with the same risk preference as Ann makes a mistake at every decision with a small probability. Because there are more opportunities for Beth to err towards the safe than towards the risky option, Beth is likely to make more safe choices than error-free Ann. Hence, when estimating preferences using this elicitation task, errors cause risk aversion to be *overestimated.* Now, consider a different risk elicitation task (MPL2) in which error-free Ann switches "low down" in the table. Error-prone Beth with the same risk preferences now has more opportunities to err towards the

[1] The MPL elicitation format was popularized by Holt and Laury (2002), but the use of choice-lists to elicit risk preferences has a long tradition. For early examples, see Miller, Meyer and Lanzetta (1969) and Binswanger (1980).

risky than towards the safe option. As a consequence, errors cause an *underestimation* of risk aversion in this task. In summary, errors can cause bias in estimation of risk aversion from observed choices, and the direction of the bias depends on the specifics of the risk elicitation task.

Let us now suppose we can accurately measure the cognitive ability of subjects, and that cognitive ability is entirely unrelated to risk aversion, but negatively related to the propensity to make errors. In the example above, suppose Ann has higher cognitive ability than Beth. We would then find a *negative* correlation of cognitive ability and risk aversion in risk elicitation task MPL1. Similarly we would find a *positive* correlation of cognitive ability and risk aversion in risk elicitation task MPL2. To demonstrate that the relation is spurious, we use both tasks on a given set of subjects, and then find a negative correlation between cognitive ability and risk aversion in MPL1, but a positive correlation in MPL2.

The fact that people make mistakes and that some are more likely to do so than others does not mean that any attempt at measuring risk preferences (and relating these preferences to cognitive ability and other background variables that are linked to noisy decision making) is futile. But our results highlight the need to use balanced experimental elicitation designs (e.g. several price lists with varying switch points for given risk preferences).

The rest of the paper is organized as follows. Section II provides a literature review and Section III presents a simple example showing how the design of the elicitation task may lead to biased estimates of the relation between risk aversion and cognitive ability. Section IV outlines the experimental design and procedures. Section V reports results, and Section VI provides concluding remarks.

II. Related literature

Studies on how risk avoidance relates to cognitive ability differ in many respects (e.g., in how risk avoidance is measured).[2] We focus on studies using the MPL format because this is a widely used method for eliciting risk preferences, and because the bulk of the papers claiming a relation between cognitive ability and risk aversion use this measure. Employing the MPL format, Dohmen et al. (2010) find a negative correlation between cognitive ability and risk avoidance in a representative sample of the German population, Benjamin, Brown and Shapiro (2013) find it in a sample of Chilean high school graduates, and Burks et al. (2009) find it in a sample of trainee truckers.

While the experimental evidence above for a negative relation between cognitive ability and risk aversion seems compelling, evidence is also accumulating showing that estimated risk preferences based on MPL are sensitive to the presentation of the task and to changes in the choice set. Previous studies have used treatments with skewed tables in order to address the concern that subjects are biased towards choosing a switch point in the middle of the table (see Harrison et al. 2005, Andersen et al. 2006, Harrison, Lau and Rutström 2007, Harrison, List and Towe 2008, Beauchamp et al. 2012). Our reading of the existing literature is that the evidence, overall, is consistent with subjects employing such a heuristic of choosing a switch point in the middle of the table.[3]

2 To emphasize the distinction between observed behavior and inferred underlying risk preferences, we use risk avoidance or risk taking when we refer to behavior and risk aversion or risk loving when we refer to preferences. In Online Appendix E we list studies of various kinds reporting results on the relationship between risk avoidance and cognitive ability.

3 The results of Harrison et al. (2005) are consistent with a bias towards choosing a switch point in the middle of the table. Harrison, Lau and Rutström (2007) also find (borderline) significant evidence that skewing the MPLs can both increase and decrease the estimated risk aversion. Using a similar design, Andersen et al. (2006) report somewhat mixed support; in the case where skewing the table has a significant effect, the direction is consistent with a bias towards the middle of the table. Harrison, List and Towe (2007) present structural estimations on an experimental data set that includes the same type of treatments, but they find that the manipulation intended to decrease risk aversion in fact increased risk

However, the main pattern is also consistent with choice simply being noisy which implies that MPLs with many decisions on the risk averse domain lead to increased risk aversion estimates and conversely that many decisions in the risk loving domain reduce risk aversion estimates.

The prevalence of behavioral noise has been documented in many previous studies and is not confined to the MPL format (see for example Mosteller and Nogee 1951, Camerer 1989 and Starmer and Sugden 1989 for some early evidence). We report evidence that lower cognitive ability is significantly correlated with subjects having multiple switch points, which suggests that it is noisy decision making rather than a heuristic of choosing a switch point in the middle of the table that drives our results.

Our argument implies that the negative relation between risk aversion and cognitive ability found in some of the recent studies (Dohmen et al. 2010, Benjamin, Brown and Shapiro 2013, and Burks et al. 2009) might be spurious. The reason is that these studies systematically used MPL with more choices in the risk averse domain in which noise, according to our argument, causes overestimation of risk aversion. The bias in the previous literature is likely driven by a wish to obtain precise estimates for the majority of subjects that are risk averse. Unfortunately, the choice sets of the MPLs used in these studies make those with low cognitive ability look as if they were more risk averse than they are.

Our argument may also reconcile the sometimes diverging results reported in the previous literature. In Figure 1, we have summarized the reported relationships between cognitive ability and risk avoidance and how it relates to

aversion. However, it should be noted that the latter two studies used rather limited samples sizes of around 100 subjects spread across nine different treatments. More recently, Beauchamp et al. (2012) report risk aversion estimates from an experiment with a larger sample size (n = 550) and they again report that the effects of their choice-set manipulations are consistent with subjects being biased towards switching in the middle of the table.

the characteristics of the choice set. For each previous study, the figure displays how biased towards risk aversion the elicitation task is according to our argument (along the vertical axis) and what relationship between cognitive ability and risk avoidance they report (along the horizontal axis). The risk-aversion bias displayed on the vertical axis is measured by the percentage of alternatives where it is *possible* to make a choice indicating risk aversion. The bias will depend on the subject's underlying risk preferences and for a risk-neutral subject there will be a bias towards risk aversion if the percentage of possible choices indicating risk aversion is above 50 percent. We have included studies reporting results (from subject groups of at least 50) on the correlation between cognitive ability and risk avoidance and where the latter is measured in an incentivized task with a restricted choice set (typically a MPL). Since many studies report results from more than one non-identical list we report results from the separate lists.

Figure 1 shows that the significant negative correlations lie in the upper left area, which indicates that they stem from lists where noise would overestimate risk aversion. We also observe some significant positive correlations and these come from studies in the lower right area, and these studies are biased in the opposite direction or are balanced for a risk-neutral subject. Admittedly, the studies differ in various respects (with respect to cognitive measure, incentives, subject pool etc.), and comparisons between them should therefore be done with care. To emphasize the most informative comparisons, we connected results from the same studies that use different lists and where the results change qualitatively. We can then make some "within study" comparisons. For example, the study of Burks et al. (2009) includes several MPLs. In three of these (B1, B2, B3), noise causes overestimation of risk aversion and in these lists the authors observe a negative relationship between risk avoidance and cognitive ability. In a fourth list (B4), noise creates the opposite bias and in that list, they indeed obtain a highly significant positive relation between cognitive ability and risk avoidance.[4] Clearly, the slopes of the lines do not appear be random, but mainly downward sloping from the left to the right when the bias are substantially altered. When the bias is not altered much, the correlation results are mainly qualitatively the same, which means that no lines are drawn between these observations.

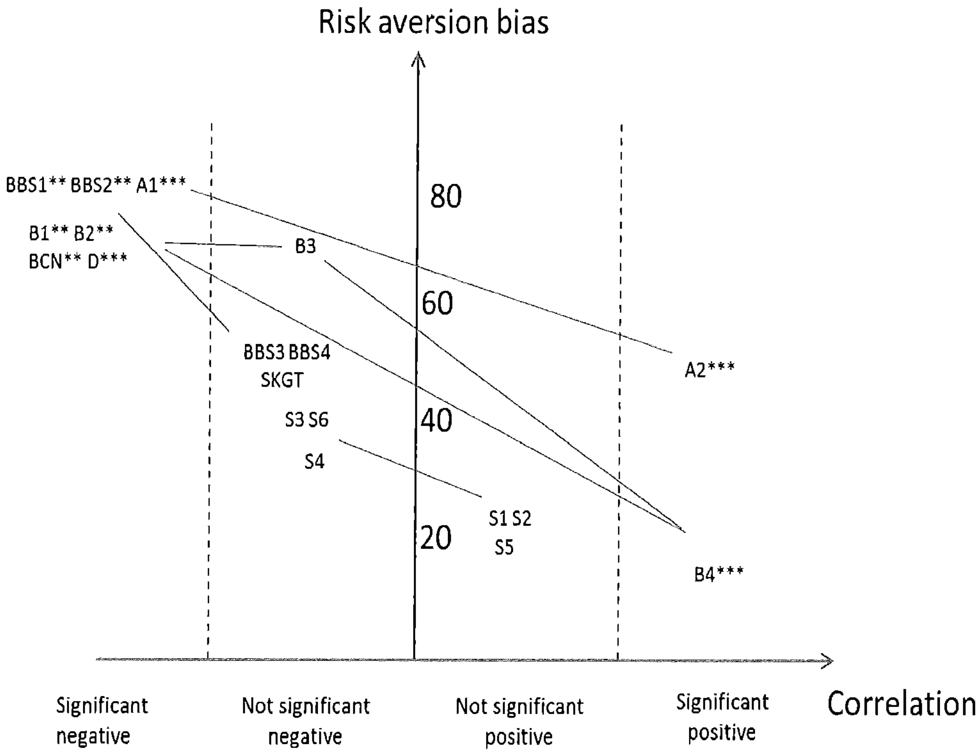

Figure 1: Relationship between bias in multiple price lists and the correlation between cognitive ability and risk avoidance reported in the literature.

Notes: (A1, A2) = Andersson et al. 2014 (this paper), (B1-4) = Burks et al. 2009, (D) = Dohmen et al. 2010, (BBS1-4) = Benjamin et al. 2013, (BCN) = Booth et al. 2014, (S1-6) = Sousa 2010, (SKGT) = Sutter et al. 2013. Correlation between risk avoidance and cognitive ability (CA) is measured by the CA parameter in regressions including controls or if no regression result is reported, measured by the correlation coefficient. **- significant at p = 0.05, ***- significant at p = 0.01.The observations in this figure are based on Table E1 in the online appendix.

4 However, this particular list involves outcomes in the negative domain, so the finding that subjects with low cognitive ability take more risk in this task may also have other causes. For example, individuals with low cognitive ability may distinguish more sharply between decisions on the positive and the negative domain (i.e. their behavior may comply more with the reflection effect).

Further support for our argument that noise is heterogeneous and linked to cognitive ability is provided by Dave et al. (2010). They find that higher math scores are related to less noisy behavior in the MPL but are unrelated to risk preferences.

While we test our argument that noisy decision making may bias estimates of risk preferences in a particular experimental setting designed to estimate risk preferences, it bears a message (and warning) that has relevance beyond the MPL elicitation format. In fact, other experimental elicitation methods that employ discrete or restricted choice, like the risk task proposed in Eckel and Grossman (2002), may also be prone to the same type of problems, and we believe that testing the robustness of results from such elicitation methods would be worthwhile.

III. Experimental design

Two risk elicitation tasks

The core features of our experimental design are two price lists, MPL1 and MPL2, displayed in Table 1. In each row, the decision maker chooses between two lotteries, called Left and Right. Each lottery has two outcomes (Heads and Tails) that are equally likely. For example, decision 1 in MPL1 offers a choice between a relatively safe lottery with a 50:50 chance of winning 30 or 50 Danish crowns (DKK), and a more risky lottery with a 50:50 chance of winning 5 or 60 DKK. As we move down the lists, the expected value of the Right lottery increases while it stays constant on the Left. A rational decision maker starts by choosing Left and at some point switches to Right (and then never switches back).[5] The switch point of a risk-neutral decision maker is printed in bold face and is located relatively "high up" (above the middle row) in MPL1 but relatively "low down" (below the middle row) in MPL2.

Table 1. Multiple Price List 1 and 2 (MPL1 and MPL2)

	MPL 1				**MPL 2**			
	Left		Right		Left		Right	
	Heads	Tails	Heads	Tails	Heads	Tails	Heads	Tails
Decision 1	30	50	5	60	25	45	5	40
Decision 2	30	50	5	70	25	45	5	50
Decision 3	**30**	**50**	**5**	**80**	25	45	5	55
Decision 4	30	50	5	90	25	45	5	60
Decision 5	30	50	5	100	25	45	5	65
Decision 6	30	50	5	110	**25**	**45**	**5**	**70**
Decision 7	30	50	5	120	25	45	5	75
Decision 8	30	50	5	140	25	45	5	95
Decision 9	30	50	5	170	25	45	5	135
Decision 10	30	50	5	220	25	45	5	215

Notes: Bold face indicates decision at which a risk-neutral subject would switch from Left to Right. Payoffs are in DKK.

Using the terminology introduced above, the risk-aversion bias is higher in MPL1 since the percentage of alternatives where it is possible to make a choice indicating risk aversion is higher in MPL1 than in MPL2. If we assume that decision makers are risk neutral, introducing random decision errors will generate higher estimates of risk aversion in MPL1 while errors tend to cancel out and will have no effect in MPL2. If we on the other hand assume a moderate degree of risk

[5] We assume monotonic preferences. Strongly risk-loving decision makers choose Right already at Decision 1.

aversion (the typical finding in the experimental literature), decision errors will cause overestimation of risk aversion in MPL1 but underestimation in MPL2. Consequently, if cognitive ability is unrelated to risk preferences but correlated with error propensities, we will observe a negative relation between cognitive ability and measures of risk aversion in MPL1 but a positive relation in MPL2.

This result is obtained for broad class of error structures. One straightforward error model is the constant error model, which is also called the tremble model (Harless and Camerer 1994). In this model, decision makers make a mistake with a fixed probability $e > 0$ (and then pick between Left or Right at random), and choose the lottery that maximizes expected utility with $1-e$. This type of decision error is introduced when the decision maker systematically evaluates differences in expected utility between lotteries. Error-prone decision makers will switch back and forth in an inconsistent manner (see McFadden 2001). Another way to think about the errors is that it is the realization of a distribution over the set of risk preferences before making the decisions (see Gul and Pesendorfer 2006). For instance one such model could entail switching at a random row with probability e and switch at their preferred row with probability $1-e$. Under this latter way of modeling noise, error-prone individuals are consistent in the sense that they do not switch back and forth between the two lotteries. However, the switch points of the error-prone decision makers are stochastic and hence susceptible to the same spurious correlation between cognitive ability and risk aversion as in the tremble model.

The upshot of this discussion is that, for plausible levels of risk aversion, *we expect a negative relation between risk aversion and cognitive ability in MPL1 and positive relation between risk aversion and cognitive ability in MPL2.*

Experimental procedures and measures

Our study uses a "virtual lab" approach based on the iLEE (internet Laboratory of Experimental Economics) platform developed at the University of Copenhagen. It follows the standards (e.g. no deception, payment according to choices) and procedures (e.g. with respect to instructions) that routinely guide conventional laboratory experiments, but subjects make choices remotely, over the internet. The platform has been used to run several waves of experiments and we use data from the first two waves (iLEE1 and iLEE2), fielded in May, 2008 and June, 2009.[6] In May, 2008, a random sample of the adult Danish population (aged 18–80) was invited by Statistics Denmark (the Danish National Bureau of Statistics) to participate in our experiment.[7] The invitations, sent by standard mail, invited recipients to participate in a scientific experiment in which money could be earned (earnings were paid out via electronic bank transfer). The letter pointed out that choices are fully anonymous between both subjects and with the researchers from iLEE. Anonymity was achieved by letting participants log into the iLEE webpage using a personal identification code whose key was only known to Statistics Denmark. The collaboration with Statistics Denmark enables us to match the experimental data with official register data.

In the first experiment, iLEE1, subjects participated in several modules, including two versions of the public good game, the first risk elicitation task (MPL1), tests of cognitive ability and personality and answered standard survey questions. We give a more detailed description of the relevant parts in the next section. About one year after iLEE1, subjects who completed the experiment were re-

6 See http://www.econ.ku.dk/cee/ilee/ for a detailed description of the iLEE platform. The platform has been used for studies on a broad range of topics; see Thöni, Tyran and Wengström (2012) for an example.

7 Random samples of the Danish population have previously been used for preference elicitation experiments by for example Harrison, Lau and Rutström (2007) and Andersen et al. (2008).

The MPLs used here keep the probability of outcomes fixed (at 50%) and vary prices (as in e.g. Binswanger 1980 or Tanaka, Camerer and Nguyen 2010). Others have used fixed payoffs and vary probabilities (e.g. Holt and Laury 2002). In our analysis we do not aim to distinguish between risk avoidance stemming from concavity of the utility function and rank-dependent probability weighting (Quiggin 1982; Fehr-Duda and Epper 2012; Bruhin et al. 2010). One advantage of 50-50 gambles is that they are easy to understand. This is especially important since in our study our participants are drawn from the general population, including subjects with low education. For example, Dave et al. (2010) find that people with a low level of numeracy tend to have difficulties in understanding MPL formats with varying probabilities.

Measures of attitude to risk, cognitive ability and personality

Our measure of risk attitudes is the number of safe choices (Left) a subject makes in MPL1 and MPL2. To filter out subjects that paid no or minimal attention to our task, we drop subjects who always chose the Left lottery or always the Right lottery. However, our results are robust to the set of subjects included in the analysis. In particular, the results are robust to keeping subjects who always make the same choice in the sample, to restricting the sample even further by dropping subjects that spend very little time on the task, or to dropping all except those with a unique interior switch point (see Online Appendix C).

Our main measure of cognitive ability is a module of a standard intelligence test called "IST 2000 R". The module we use is a variation of Raven's Progressive Matrices (Raven 1938). It provides a measure of fluid intelligence and does not depend much on verbal skills or other kind of knowledge taught during formal education. The test consists of 20 tasks in which a matrix of symbols has to be completed by picking the symbol that fits best from a selection presented to invited to participate in iLEE2 which included the MPL2 risk elicitation task among other modules. Average total earnings from all tasks was DKK 276 (or EUR 37) in iLEE1 and DKK 207 (or EUR 28) in iLEE2.

Using internet experiments is ideal for our purposes, allowing us to elicit preferences and collect a broad range of correlates on a large and heterogeneous sample of subjects. Apart from sample selection effects, using the internet does not seem to affect risk preference estimates compared to standard laboratory procedures (von Gaudecker, van Soest and Wengström 2012).

In total, our sample consists of 2,289 participants completing iLEE1 and 1,374 completing iLEE2. We have a response rate of around 11 percent for iLEE1, and around 60 percent of the completers of iLEE1 chose to participate also in iLEE2.[8] In our analysis we check for selection into the experiment and attrition between the two experiments, but we do not find any indication that these factors are affecting our results. We thoroughly discuss these issues in Section IV.

Upon beginning iLEE1, subjects were informed that they would make a series of choices between two lotteries, as shown in Table 1 (MPL1).[9] The instructions explained that each lottery had two outcomes that occurred with equal probabilities (Heads and Tails), that one decision would be randomly selected, and the chosen lottery for that row was played out and paid.

The design of the risk elicitation task in iLEE2 was identical to that of iLEE1 except that payoffs were now as shown in Table 1 (MPL2).

[8] The Center Panel at the University of Tilburg is a similar internet-based panel that also uses a probability-based recruitment scheme (random draws from phone numbers in Dutch households). According to Hoogendorn and Daalmans (2009), their overall total sample rate (essentially the share of people who effectively participate as a share of recruited people) is 11.5 percent, which is similar to our participation rate in iLEE1. The authors document similar selectivity for age and income as in our sample. von Gaudecker, van Soest and Wengström (2012) investigate the issue of selection effects using the Center Panel and conclude that self-selection appears to have a minor impact on estimated risk preferences.

[9] See Online Appendix B for screenshots. The experiments also contained tasks to elicit preferences for loss aversion. However, these loss aversion tasks were constructed not to reveal any information about the subject's degree of constant relative risk aversion. They are hence not useful for our purposes and we restrict attention to the risk task here.

subjects (see Online Appendix B for a screenshot). Subjects had 10 minutes to work on the tasks. The *cognitive ability* (IST) score used in the analysis below is simply the number of tasks a subject managed to solve correctly. Figure A1 in the Online Appendix displays the distribution of the cognitive ability scores in our sample.

Experiment 1 also includes the *Cognitive Reflection Test (CRT)* proposed by Frederick (2005). The test is designed to capture the ability or disposition to reflect on a question and to resist reporting the first response that springs to mind. In Online Appendix C, we redo all analyses reported below using the subjects' *CRT* score, instead of the *IST* score. The conclusions emerging from using this alternative measure of cognitive ability are essentially the same (see Online Appendix C for details).

All subjects also completed a Big Five personality test (administered after iLEE1), the most prominent measurement system for personality traits (see Almlund et al. 2011 for a review). The test organizes personality traits into five factors: Openness to experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (also called by its obverse, Emotional stability). We used the Danish NEO-PI-R Short Version which consists of five 12-item scales measuring each domain, with 60 items in total.[10] It takes most participants 10 to 15 minutes to complete.

Table 2 shows summary statistics of the key variables used in the empirical analysis for both experiments. In addition to the variables from the experiments; we also use a set of background variables from the official registers hosted by Statistics Denmark. We use a gender dummy, age dummies, educational dummies and income dummies. See the notes below Table 2 for more details.

[10] The personality and cognitive ability tests are validated instruments developed by Dansk psykologisk forlag, www.dpf.dk. We are grateful for permission to use the tests for our research.

Table 2. Summary statistics of key variables

	MPL1				MPL2			
	Mean	s.d.	Min	Max	Mean	s.d.	Min	Max
# safe choices	4.36	1.94	1	9	5.53	1.79	1	9
Cognitive ability	8.77	3.19	0	19	8.98	3.20	0	19
Cognitive reflection	1.52	1.11	0	3	1.51	1.11	0	3
Female	0.48	0.50	0	1	0.47	0.50	0	1
Age 18—29	0.17	0.38	0	1	0.17	0.38	0	1
Age 30–39	0.18	0.38	0	1	0.13	0.34	0	1
Age 40–49	0.25	0.43	0	1	0.24	0.43	0	1
Age 50–64	0.29	0.45	0	1	0.31	0.46	0	1
Age 65+	0.11	0.31	0	1	0.14	0.35	0	1
Education 0	0.07	0.25	0	1	0.07	0.26	0	1
Education 1	0.22	0.42	0	1	0.24	0.43	0	1
Education 2	0.36	0.48	0	1	0.36	0.48	0	1
Education 3	0.22	0.41	0	1	0.21	0.41	0	1
Education 4	0.13	0.34	0	1	0.12	0.33	0	1
Income 1st quartile	0.25	0.43	0	1	0.27	0.44	0	1
Income 2nd quartile	0.25	0.43	0	1	0.25	0.43	0	1
Income 3rd quartile	0.25	0.43	0	1	0.24	0.43	0	1
Income 4th quartile	0.25	0.43	0	1	0.24	0.43	0	1
Big5a	32.05	5.61	5	46	32.11	5.65	5	46
Big5c	32.80	5.58	12	47	33.26	5.47	15	47
Big5e	30.49	6.36	6	48	30.61	6.22	6	47
Big5n	19.34	7.00	2	44	19.15	7.12	1	46
Big5o	27.00	6.08	8	47	27.01	6.21	8	46
Observations		1724				1125		

Notes: In line with our main risk measure we have excluded subjects who never switched. Education 0 refers to subjects with maximum 9 years of schooling, Education 1 maximum 12 years of schooling, Education 2 less than 15 years of schooling, Education 3 maximum 16 years of schooling and Education 4 more than 16 years of schooling. Income 1st quartile refers to subjects in the first quartile of the gross income distribution of the sample (yearly income less than 207,730 DKK) , Income 2nd quartile the second quartile (yearly income between 207,730 DKK and 322,205 DKK), Income 3rd quartile the third quartile of the distribution (yearly income between 322,205 DKK and 420,779 DKK) and Income 4th quartile the fourth quartile of income distribution (yearly income above 420,779 DKK). Big5a to Big5o refer to the scores of the Big five personality dimensions.

IV. Results

Section A shows that our experimental variation produces opposed correlations between risk preferences and cognitive ability. Section B presents a more detailed analysis of rational behavior and how it relates to cognitive ability.

A. Spurious relation between cognitive ability and risk aversion

We provide evidence in support of our claim by providing simple correlations (without adding any controls), and then by linear regression with an extensive set of controls.

Figure 2 visualizes our main result. We find a negative relation between risk aversion and cognitive ability in MPL1 (left panel) and a positive relation in MPL2 (right panel). Both the negative and the positive correlation are highly significant (MPL1: $\rho = -0.079$, p-value = 0.001; MPL2: $\rho = 0.094$, p-value = 0.002, Spearman's rank correlation coefficients). The same pattern is found if we restrict attention to the subset of subjects that participated in both experiments.[11]

Figure 3 reproduces the same pattern found in Figure 2 by using the cognitive reflection measure (CRT) instead of the cognitive ability measure. In fact, our conclusions do not depend on which measure is used and we therefore concentrate on one measure (the cognitive ability) in the remainder of the main text and show the results for the other measure (the CRT) in Online Appendix C.

Taken together, Figure 2 and 3 suggest that higher cognitive ability is associated with more risky decisions in MPL1, but less risky decisions in MPL2. Since the measure of cognitive ability and the set of people on which it is measured are held constant, the correlation must be spurious.

[11] MPL1: $\rho = -0.120$, p-value < 0.001; MPL2: $\rho = 0.068$, p-value = 0.042, Spearman's rank correlation coefficients. The number of observations is 893 (including only subjects who participated in both experiments and switched at least once in each experiment).

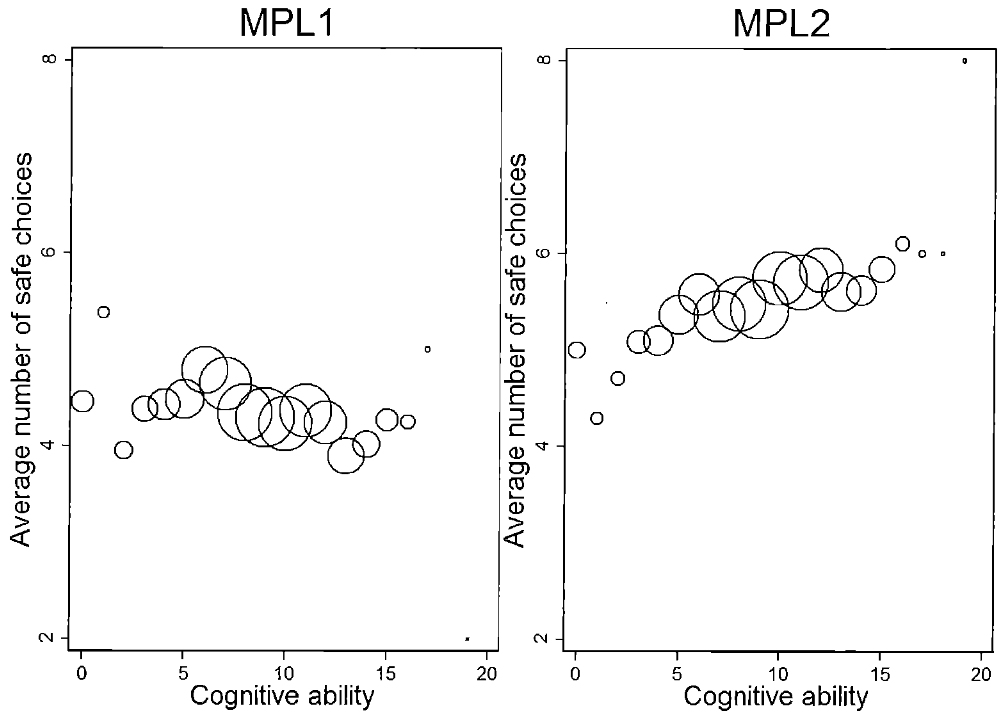

Figure 2: Opposite relation of risk aversion and cognitive ability in MPL1 and MPL2

Notes: Figure shows average number of safe choices in MPL1 (left) and MPL2 (right) by cognitive ability. The center of each bubble indicates the average number of safe choices and the size of the bubble the number of observations for each cognitive ability score. N = 1,724 in the left panel and 1,125 in the right panel.

This finding of a spurious correlation is consistent with cognitive ability being correlated with random decision making, rather than with underlying preferences towards risk. In order to more closely investigate the relation between cognitive ability and risky choices, we next present the results from regressions that control for socioeconomic and psychometric variables.

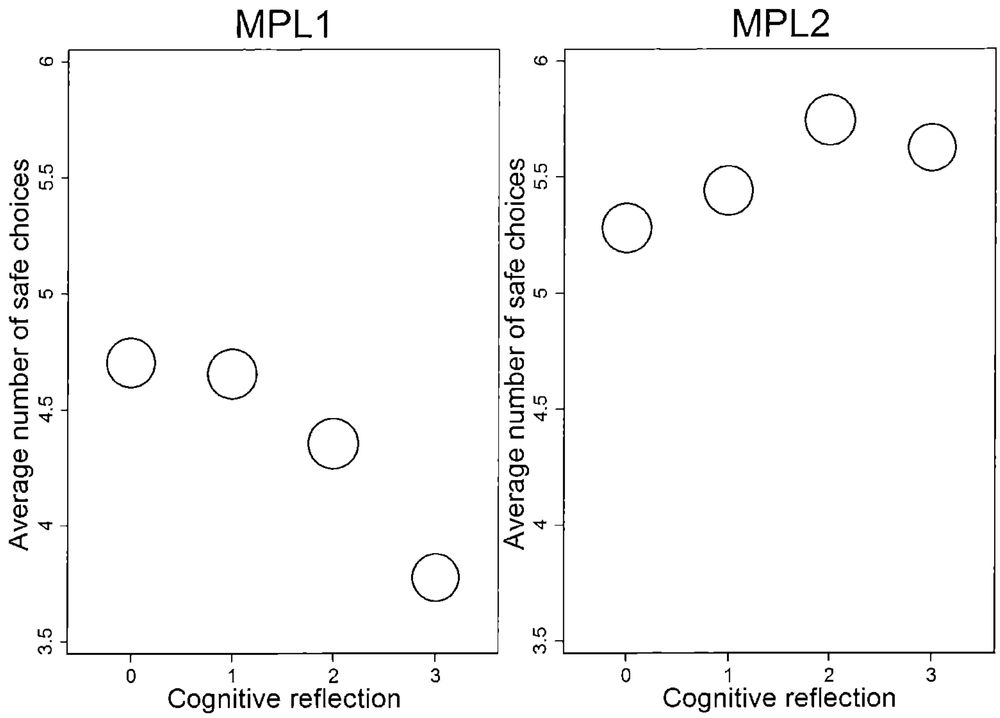

Figure 3: Opposite relation of risk aversion and cognitive reflection in MPL1 and MPL2.

Notes: Figure shows average number of safe choices in MPL1 (left) and MPL2 (right) by cognitive reflection. The center of each bubble indicates the average number of safe choices and the size of the bubble the number of observations for each cognitive ability score. N = 1,724 in the left panel and 1,125 in the right panel.

Table 3 reports OLS regressions of the number of safe choices in MPL1 and MPL2.[12] In line with our arguments, the first row shows that there is a highly significant negative relation between cognitive ability and the number of safe choices in MPL1 (model 1 without controls, model 2 with socio-demographic controls, model 3 with socio-demographic controls and Big Five personality scores). We see that the opposite results hold for MPL2 (model 4 without controls, model 5 with socio-demographic controls, model 6 with socio-

[12] Since the number of safe choices is an ordered categorical variable, we also ran ordered probit estimations with essentially identical results (see Online Appendix C). In Table 3 we also present results from interval regressions.

demographic controls and Big Five personality scores). That is, there is an estimated positive correlation between cognitive ability and the number of safe choices. To illustrate the strength of the estimated effects, we note that an increase in cognitive ability by one standard deviation results in a 7 percent of a standard deviation change in the number of safe choices in MPL1 (around 0.13 less safe choices), and a 8 to 11 percent of a standard deviation change in the number of safe choices in MPL2 (between 0.13 and 0.20 more safe choices). The opposite effects in the two experiments clearly support our hypothesis that cognitive ability is correlated to mistakes rather than to risk preferences. We also note that our finding seems to have relevance beyond the particular case of cognitive ability and risk preferences. The coefficient estimates of other variables that are likely to be correlated with noise such as education also show opposite signs in the two MPLs.

The second experiment containing MPL2 was executed around one year after the first experiment with MPL1. Given the time between the two experiments it seems unlikely that the ordering of the screens affected the results. Another possible concern is that attrition gives raise to selection effects. Our results could only be driven by attrition if the people selecting out of the experiment display the opposite relationship between cognitive ability and risk taking in the two MPLs. While this seems unlikely a priori, we correct for selection into the second experiment using the Heckman two-step selection procedure. Despite such correction, the relationship between risk taking and cognitive ability observed in MPL2 remains significant. If anything, the observed relationship between cognitive ability and risk taking becomes stronger after correcting for selection effects. The details are described in Online Appendix C. In the appendix, we also apply population weights to our observations in order for our sample to better reflect the general population (in terms of observable characteristics). Again, our results are robust to using weights in the regressions.

Table 3. Correlates of risk preferences. Dependent variable: safe choices

	MPL1			MPL2		
VARIABLES	(1)	(2)	(3)	(1)	(2)	(3)
Cognitive ability	−0.043***	−0.040**	−0.040**	0.064***	0.044**	0.043**
	[0.015]	[0.016]	[0.016]	[0.017]	[0.018]	[0.018]
Female		0.339***	0.194*		−0.138	−0.160
		[0.098]	[0.105]		[0.111]	[0.119]
Age 30-39		−0.074	−0.084		−0.020	−0.017
		[0.176]	[0.176]		[0.203]	[0.203]
Age 40-49		0.218	0.212		0.066	0.029
		[0.171]	[0.172]		[0.195]	[0.196]
Age 50-64		0.040	0.004		−0.178	−0.242
		[0.168]	[0.172]		[0.187]	[0.191]
Age 65+		−0.145	−0.156		−0.385*	−0.435**
		[0.198]	[0.202]		[0.215]	[0.219]
Education 1		−0.141	−0.137		0.710***	0.686***
		[0.207]	[0.207]		[0.226]	[0.226]
Education 2		−0.113	−0.113		0.813***	0.804***
		[0.198]	[0.197]		[0.221]	[0.221]
Education 3		−0.028	−0.08		0.955***	0.882***
		[0.210]	[0.211]		[0.235]	[0.237]
Education 4		−0.474**	−0.477**		0.973***	0.865***
		[0.234]	[0.236]		[0.265]	[0.268]
Income 2nd quartile		0.106	0.128		−0.339**	−0.297*
		[0.142]	[0.143]		[0.165]	[0.166]
Income 3rd quartile		0.035	0.069		−0.262	−0.214
		[0.151]	[0.152]		[0.175]	[0.177]
Income 4th quartile		−0.202	−0.110		−0.500***	−0.414**
		[0.166]	[0.168]		[0.189]	[0.193]
Control for Big5	No	No	Yes	No	No	Yes
Constant	4.735***	4.670***	3.183***	4.955***	4.781***	4.311***
	[0.137]	[0.268]	[0.609]	[0.158]	[0.294]	[0.678]
Observations	1,724	1,724	1,724	1,125	1,125	1,125
R-squared	0.005	0.030	0.042	0.013	0.037	0.044

Notes: OLS regressions. Education 1 refers to subjects with maximum 12 years of schooling, Education 2 less than 15 years of schooling, Education 3 maximum 16 years of schooling and Education 4 more than 16 years of schooling. Subjects with less than 9 years of schooling constitute the left out category. Income 2nd quartile refers to subjects in the second quartile of the gross income distribution of the sample (yearly income between 207,730 DKK and 322,205 DKK), Income 3rd quartile the third quartile of the distribution (yearly income between 322,205 DKK and 420,779 DKK) and Income 4th quartile the fourth quartile of income distribution (yearly income above 420,779 DKK). Subjects in the first income quartile are the left out category. Control for Big5 refers to the scores of the Big five personality dimensions (coefficients are reported in Appendix C). Standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Another way to measure risk aversion that has been used in the literature (see e.g. Dohmen et al. 2010) is to study where a subject switches from the Left to the Right lottery in the respective MPL. Assuming subjects to be expected utility maximizers with a constant relative risk aversion (CRRA) utility function, the row at which a subject switches then implicitly defines an interval for the subject's CRRA coefficient.

Table 4 presents results from interval regressions using these CRRA intervals for MPL1 and MPL2. The table clearly shows that the results presented in Table 3 are robust to using this measure. We note that, by construction, this measure excludes subjects that tremble and make multiple switches within the same screen. Hence, the fact that we still observe opposing relationships between cognitive ability and risk taking in the two tasks suggests that there is noise occurring at the preference level.

An alternative way to analyze the data is to study the within-subject variation in the number of safe choices for those subjects that take part in both MPL1 and MPL2. In particular, we study the difference in the number of safe choices between MPL2 and MPL1 (i.e. NrSafe MPL2 – NrSafe MPL1). Apart from using within-subject differences, this method differs from the previous analysis in that it keeps the sample constant over the two MPLs. Given the structure of the two lists we expect, for a rational individual with a given risk preference, more safe choices in MPL2. Noise will reduce the difference in safe choices between the two experiments, since it will in both experiments bias the number of safe choices towards the middle of the range. This implies that the number of safe choices in the two experiments will be closer for noisy subjects than for consistent subjects. We therefore expect the difference in the number of safe choices between the experiments to be positively related to cognitive ability. Table 5 reports results from an OLS regression using this difference as the dependent variable. The results strongly support this hypothesis.

Table 4. Correlates of risk preferences. Interval regressions of CRRA

	MPL1			MPL2		
VARIABLES	(1)	(2)	(3)	(1)	(2)	(3)
Cognitive ability	−0.004*	−0.006**	−0.006**	0.022***	0.017***	0.017***
	[0.002]	[0.002]	[0.002]	[0.005]	[0.006]	[0.006]
Female		0.038**	0.013		−0.040	−0.044
		[0.015]	[0.016]		[0.035]	[0.038]
Age 30-39		−0.003	−0.004		−0.018	−0.020
		[0.026]	[0.026]		[0.060]	[0.060]
Age 40-49		0.037	0.037		−0.003	−0.014
		[0.026]	[0.026]		[0.059]	[0.059]
Age 50-64		−0.019	−0.020		−0.064	−0.084
		[0.026]	[0.026]		[0.058]	[0.059]
Age 65+		−0.095***	−0.093***		−0.114	−0.134*
		[0.033]	[0.033]		[0.071]	[0.073]
Education 1		−0.055	−0.052		0.241***	0.236***
		[0.034]	[0.034]		[0.074]	[0.074]
Education 2		−0.043	−0.041		0.275***	0.277***
		[0.033]	[0.033]		[0.075]	[0.075]
Education 3		−0.045	−0.048		0.311***	0.300***
		[0.035]	[0.035]		[0.077]	[0.077]
Education 4		−0.095**	−0.092**		0.358***	0.340***
		[0.037]	[0.037]		[0.085]	[0.085]
Income 2nd quartile		0.009	0.01		−0.093*	−0.083
		[0.023]	[0.023]		[0.058]	[0.055]
Income 3rd quartile		−0.005	−0.003		−0.071	−0.061
		[0.024]	[0.024]		[0.058]	[0.058]
Income 4th quartile		−0.031	−0.019		−0.157***	−0.135**
		[0.025]	[0.026]		[0.060]	[0.061]
Control for Big5	No	No	Yes	No	No	Yes
Constant	0.374***	0.436***	0.140	−0.075	−0.167*	−0.214
	[0.023]	[0.043]	[0.093]	[0.054]	[0.094]	[0.215]
Observations	1,386	1,386	1,386	883	883	883

Notes: OLS regressions. Dependent variable is the CRRA intervals. Education 1 refers to subjects with maximum 12 years of schooling, Education 2 less than 15 years of schooling, Education 3 maximum 16 years of schooling and Education 4 more than 16 years of schooling. Subjects with less than 9 years of schooling constitute the left out category. Income 2nd quartile refers to subjects in the second quartile of the gross income distribution of the sample (yearly income between 207,730 DKK and 322,205 DKK), Income 3rd quartile the third quartile of the distribution (yearly income between 322,205 DKK and 420,779 DKK) and Income 4th quartile the fourth quartile of income distribution (yearly income above 420,779 DKK). Subjects in the first income quartile are the left out category. Control for Big5 refers to the scores of the Big five personality dimensions (coefficients are reported in Online Appendix C). Standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5. OLS Regressions. Difference in number of safe choices

VARIABLES	(1)	(2)	(3)
Cognitive ability	0.089***	0.088***	0.093***
	[0.029]	[0.031]	[0.032]
Female		−0.424**	−0.342
		[0.197]	[0.213]
Age 30-39		0.452	0.442
		[0.334]	[0.332]
Age 40-49		0.228	0.206
		[0.350]	[0.353]
Age 50-64		0.246	0.214
		[0.307]	[0.318]
Age 65+		0.308	0.279
		[0.348]	[0.353]
Education 1		0.024	0.047
		[0.442]	[0.442]
Education 2		0.007	0.032
		[0.441]	[0.441]
Education 3		0.143	0.186
		[0.460]	[0.461]
Education 4		0.803	0.899*
		[0.495]	[0.502]
Income 2nd quartile		−0.177	−0.182
		[0.298]	[0.299]
Income 3rd quartile		−0.472	−0.485
		[0.317]	[0.321]
Income 4th quartile		−0.324	−0.340
		[0.339]	[0.348]
Control for Big5	No	No	Yes
Constant	0.804***	0.875*	2.624**
	[0.282]	[0.527]	[1.136]
Observations	1,374	1,374	1,374
R-squared	0.007	0.018	0.023

Notes: OLS regressions. Education 1 refers to subjects with maximum 12 years of schooling, Education 2 less than 15 years of schooling, Education 3 maximum 16 years of schooling and Education 4 more than 16 years of schooling. Subjects with less than 9 years of schooling constitute the left out category. Income 2nd quartile refers to subjects in the second quartile of the gross income distribution of the sample (yearly income between 207,730 DKK and 322,205 DKK), Income 3rd quartile the third quartile of the distribution (yearly income between 322,205 DKK and 420,779 DKK) and Income 4th quartile the fourth quartile of income distribution (yearly income above 420,779 DKK). Subjects in the first income quartile are the left out category. Control for Big5 refers to the scores of the Big five personality dimensions (coefficients are reported in Online Appendix C).Standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B. Switch points and cognitive ability

The previous analysis suggests that cognitive ability is related to noise which, in turn, causes the opposing relationships in the two MPLs. The fact that this results is obtained also when multiple switchers are weeded out in Table 4 indicates that this bias occurs even in subject pools that pass a standard consistency test (i.e., they have unique switching row in the MPLs). For this purpose it makes sense to investigate the switching behavior in our population.

Figure 4 shows the distribution of the total number of switches in both experiments. It is important to point out that both zero and one distinct switch is consistent with rational behavior. While the bulk of the observations are at zero or one switches, we also see about 15–18 percent of subjects switching more often.

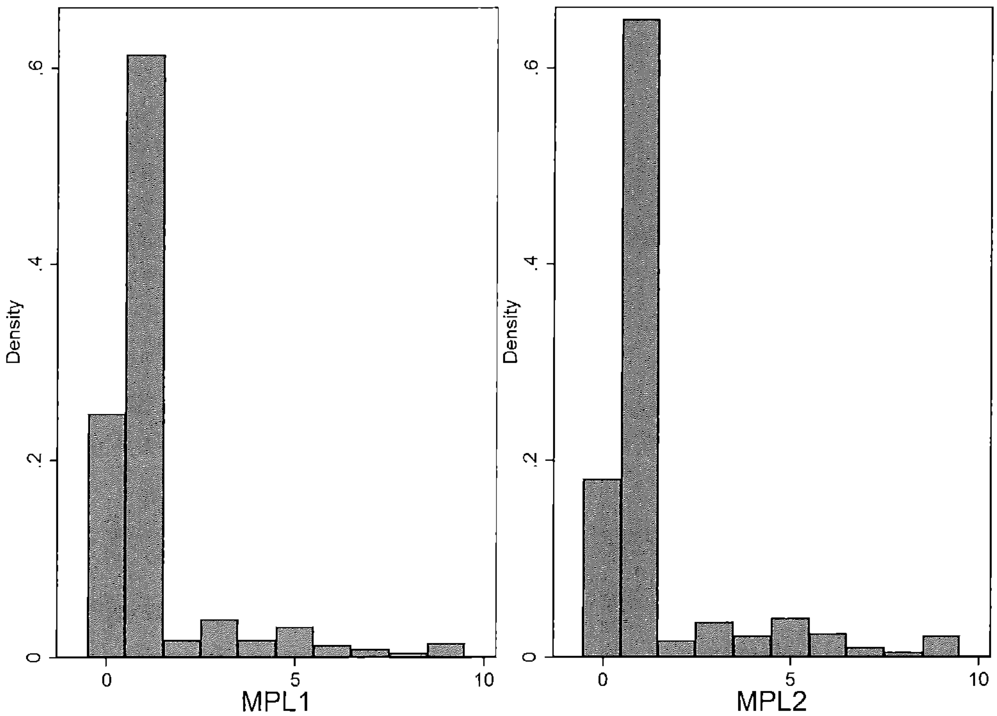

Figure 4: Total number of switches in MPL1 and MPL2

Figure 4 underestimates the extent of non-consistent choices somewhat since a subject may switch only zero or once, but does so in a non-consistent manner. For instance, a subject may have switched once but from the Right to the Left lottery or always chosen the Right lottery in MPL2, including the first one in which the Right lottery is dominated by the Left. For these reasons it makes sense to distinguish between subjects with consistent and non-consistent switching behavior. We define a subject for our purposes as Consistent if her decisions are compatible with rational and monotone preferences and defined as Not Consistent otherwise.

Table 6. Consistency and cognitive ability

	Consistent individuals					
	MPL1			MPL2		
	Not consistent	Consistent	p-value	Not consistent	Consistent	p-value
Cognitive ability	7.27	8.83	0.000	7.52	9.25	0.000
Observations	338	1 951		321	1 053	
	Consistent individuals that switched exactly once					
	MPL1			MPL2		
	Not consistent	Consistent	p-value	Not consistent	Consistent	p-value
Cognitive ability	7.79	9.13	0.000	7.77	9.44	0.000
Observations	903	1 386		491	883	

Notes: The p-values refer to two-sided t-tests comparing mean cognitive ability scores between Consistent and Not Consistent subjects.

Table 6 presents the averages for our measure of cognitive ability for both types of subjects along with p-values from two-sided t-tests. Consistent subjects have significantly higher scores on the cognitive ability tests.[13] Because some of the

[13] This result is in lined with previous evidence showing that those with low cognitive ability are more prone to make errors. For example, Eckel (1999) finds that students with lower cognitive ability

subjects that never switched may have done so out of ignorance, we add subjects that never switched to the Not Consistent category in the bottom half of Table 6. The corresponding tests clearly show that our previous conclusion continues to hold when using this stricter definition of consistency.

Previous studies (see Section II for a discussion) suggest that the difference in correlation between risk preferences and cognitive ability across our MPL may be driven by a heuristic to choose a switch point in the middle of the list. If such a heuristic were to explain our results, we should see a positive correlation between the distance of a choice to the middle of the list (i.e. how many lines above or below the middle row) and cognitive ability.

Figure 7 plots the correlation between the distance from the middle of the list (row 6 in both MPLs) to subjects unique switch point, and cognitive ability. Since we are using each subjects switch point in this figure we are, in line with the predictions of the heuristic, only showing subjects that switched once. Figure 7 together with correlation coefficients show that in MPL1 there is no relationship between the distance to the midpoint and cognitive abilities ($\rho = 0.012$, p-value = 0.644) and in MPL2 the relationship is inverse ($\rho = -0.101$, p-value = 0.003). Hence, we find little support for this heuristic in the data.

To sum up, we find evidence for noise at both the preference level and the decision level. In particular, we show that behavior compatible with maximizing a monotonically increasing utility function is more common among participants with high cognitive ability. Furthermore, our results do not appear to be driven by a tendency of subjects to switch in the middle of the MPL.

(measured by GPA scores) tend to make more inconsistent choices across two measures of risk preferences (abstract vs. context-rich). Similarly, Huck and Weizsäcker (1999) find that subjects with low cognitive ability (measured by math grades) behave more randomly in a lottery-choice experiment. Burks et al. (2009) and Dave et al. (2010) find that subjects with low cognitive ability more often violate monotonicity by switching back and forth when moving down the MPL.

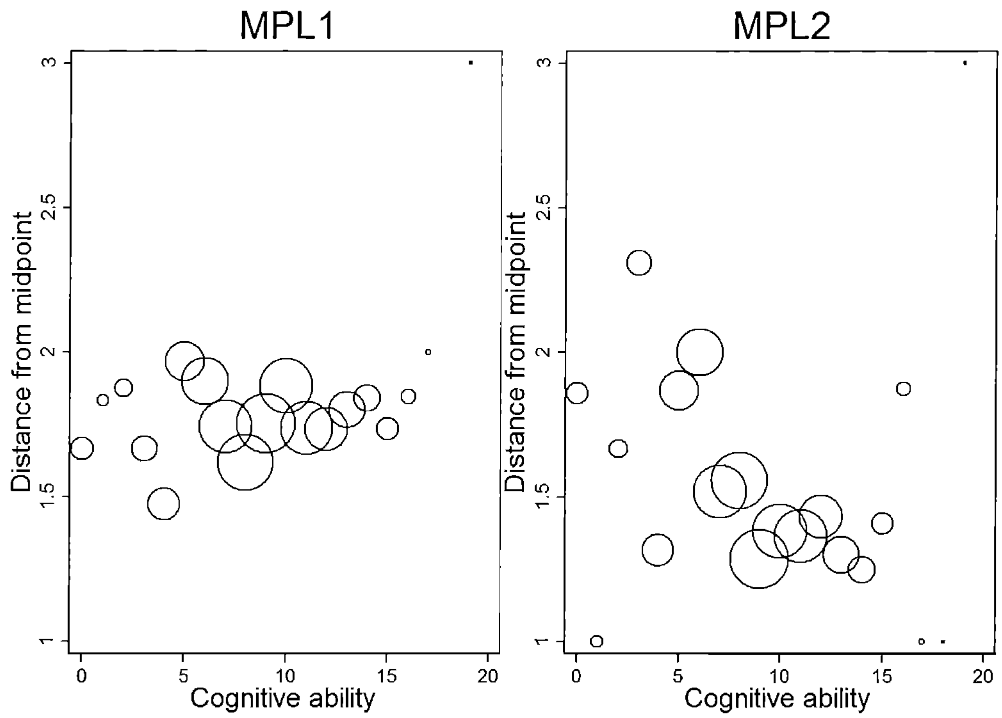

Figure 7: Relation between the distance of switch point to the middle of the list and cognitive ability in MPL1 MPL2

Notes: Only subjects with unique switch point is used in this figure. The figure shows average distance in MPL1 (left) and MPL2 (right) by cognitive ability (IST score). The centre of each bubble indicates the average distance and the size of the bubble the number of observations for each cognitive ability score.

V. Concluding remarks

Inferring preferences from observed choices is fraught with difficulties because both preferences and bounded rationality can drive choices. We have argued that noisy decision making can bias measured risk preferences both upwards and downwards, depending on the risk elicitation task at hand. Because such behavioral noise decreases with cognitive ability, the bias can induce spurious correlation between measured risk preferences and cognitive ability.

This paper provides supporting evidence for this claim. We use experimental variation of the risk elicitation task (the multiple price list, MPL) to produce both a negative and a positive correlation between measured risk preferences and cognitive ability. These correlations obtain for a given set of subjects and a given measure of cognitive ability. Our findings are robust to using a range of alternative specifications and alternative measures of cognitive ability.

These results put recent claims that a relation between risk preferences and cognitive ability is a fact into perspective. In addition, our findings have a number of implications for estimating risk preferences and suggest the following avenues for further research.

First, elicitation studies need to be designed to prevent behavioral noise from causing biased estimates of risk preferences. A straightforward but only partial solution is to use a balanced design, i.e. to include both risk-averse and risk-neutral options into the elicitation task. In addition, given the strong empirical association between cognitive ability and noisy decision making, it is commendable to also elicit a measure of cognitive ability and to use it as a control in the econometric analysis.

Second, our results challenge the explanations offered in the literature for why cognitive ability and risk preferences might be related at all. These explanations invoke "mistakes" in one way or another (see Online Appendix D for a discussion) and include choice bracketing, the "two-system" approach (e.g. in Dohmen et al. 2010), or noisy utility evaluation (in Burks et al. 2009). While these accounts do not seem entirely implausible, they are inconsistent with our finding that the estimated relation between risk preferences and cognitive ability is sensitive to changes in the choice set presented to subjects as part of the risk elicitation task. The observed sensitivity speaks in favor of a more direct interpretation of noise as stochastic decision making.

Third, an interesting avenue for further investigation is to what extent the bias studied in this paper applies to different types of elicitation tasks (see Charness, Gneezy and Imas 2013 for a comparative evaluation along other dimensions). Our demonstration of biased preference elicitation and spurious correlation is based on a particular tool to elicit risk preferences, the multiple price list (MPL), but we think similar results may apply for other tasks. The advantage of the MPL format is that subjects make many decisions which enable an estimation of the error component in the decisions. Such estimation is not feasible if subjects only make one decision as in many other types of elicitation procedures, and the bias may thus remain undetected.

Finally, a promising issue to investigate is whether the spurious relation identified between risk preferences and cognitive ability also holds for other variables. Broadly speaking, our argument is that spurious correlation between a variable x and measured risk preference arises if x is correlated with behavioral noise. Our empirical analysis has focused on the role of cognitive ability. But our estimation results suggest that our argument applies to factors other than cognitive ability. In particular, our estimate of the effect of education on risk preferences (which controls for cognitive ability) appears to be also affected by the construction of the choice set because there is a strong empirical relation between behavioral noise and education.

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