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Risk aversion relates to cognitive ability: Fact or Fiction?

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Abstract

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. Structural estimation allowing for heterogeneity of noise yields no significant relation between risk aversion and cognitive ability. Our results suggest that cognitive ability is related to random decision making rather 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) fails to account for the heterogeneous nature of the propensity to make mistakes, which may lead to biased inference about preferences for risk from observed choices.

Specifically, we show 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. We find that such errors are correlated with cognitive ability 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, we choose two risk-elicitation tasks such that one produces a positive correlation and the other a negative correlation of risk aversion and cognitive ability. Taken together, these results indicate that an observed correlation between risk preferences and cognitive ability is task-contingent, and therefore spurious.

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] Choices are ordered such that as we move down the list, the risky lottery becomes more attractive. A rational (error-free) individual therefore starts choosing the relatively safe lottery, and then switches at some point to the more risky lottery. For such a subject, observing few "safe" and many "risky" choices leads to the correct inference that the individual is not very risk averse, and vice versa.

To illustrate, 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

[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).

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 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. This correlation is spurious because errors cause a bias towards overestimation of risk aversion in this task, as explained above. 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.

In our experiment we use the MPL format, but the problem is not confined to this particular elicitation method. Indeed, all methods that employ discrete or restricted choice sets are to varying degrees susceptible to similar problems of false inference as those demonstrated here. The upside with the MPL format is that subjects make many decisions which enables estimation of the error component in the decisions. In contrast, many other risk-preference elicitation tasks involve only one decision (see Harrison and Rutström 2008 and Charness, Gneezy and Imas 2013 for discussions and comparisons). Hence, estimation of the error component is not feasible, which makes it hard to evaluate the size of the resulting bias when using those tasks.

While our contribution has clear implications for positive economics (the measurement of risk preferences), it also relates to some deep and difficult issues in normative economics (see the discussion in Caplin and Schotter 2008). Intuitively, the question of whether the relation between risk aversion and cognitive ability is a "fact or fiction" matters because the policy implications sharply differ in the two cases. If low cognitive ability is correlated with risk preferences ("fact"), policy interventions meant to increase risk taking among groups with low cognitive ability seem unwarranted because choices may simply reflect their preferences. However, if decision makers with low cognitive ability just seem to be risk averse ("fiction") and tend to shy away from risky choices because of mistakes, policy interventions may increase welfare.

Consider the example of stock market participation. Accumulating evidence suggests that people with low cognitive ability (and low financial literacy) are less likely to hold stocks, controlling for observables like wealth and education (e.g. Grinblatt, Keloharju and Linnainmaa 2011, Angrisani and Casanova 2011, van Rooij, Lusardi, and Alessie 2011). The existence of differences in risk preferences between high and low cognitive ability groups would speak against policy interventions (e.g. financial education campaigns addressed to the elderly (e.g. Banks 2010) or regulators requesting particularly transparent financial products). We find no support for such a preference-based explanation of the gap in stock market participation, which implies that policy interventions may indeed be warranted.

A positive implication of our research concerns the experimental measurement of risk preferences. 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) is futile. We think a fruitful approach is to combine a balanced elicitation design (e.g. several price lists with varying switch points for given risk preferences) together with econometric specifications that take the structure of the noise into account. We demonstrate the usefulness of this approach by estimating a structural model of choice in which we allow both preferences and noise to vary with covariates. In particular, we estimate a CRRA utility function with a contextualized version (Wilcox 2011) of the Fechner error structure (Hey and Orme 1994). We find that cognitive ability is negatively related to risk aversion if we do not allow cognitive ability to correlate with the noise parameter. But when we do allow for such correlation, we find no relation between risk aversion and cognitive ability. We instead find that cognitive ability is negatively correlated to the amount of noise. These findings are robust to different utility specifications and error structures.

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

The evidence from non-experimental studies on how risk aversion relates to cognitive ability is somewhat mixed. Such studies do not normally measure risk preferences in purpose-designed tasks but observe risky behavior or simply ask for risk attitudes. Most of these studies seem to suggest that people with low cognitive ability are *more* likely to engage in risky behavior like committing crimes, smoking and out-of-wedlock births (Goto et al. 2009, Frisell, Pawitan and Långström 2012). In line with this interpretation, a survey of the psychological development literature (Boyer 2006, p. 334) concludes that “the probability of risk-taking behaviors decreases as cognitive capacities and emotional regulation skills improve”. Grinblatt et al. (2011) find that individuals with high cognitive ability hold portfolios that tend to be less risky. However, those with low cognitive ability, in particular low numeracy, tend to participate less in the stock market (van Rooij, Lusardi and Alessie 2011, Angrisani and Casanova 2011, Christelis, Jappelli and Padula 2010). Booth and Katic (2013) find no relation between cognitive ability and risk preferences (measured by self-assessment) in Australian birth-cohort data. In all of these studies, risky behavior is (also) shaped by factors other than cognitive ability that are often difficult to control for or measure. The evidence from non-experimental studies is therefore at best suggestive of a causal relation between cognitive ability and risk preferences.

Experimental studies using incentivized tasks, such as the multiple price list (MPL) to measure risk, promise avoiding such confound, and the emerging consensus from a recent wave of such studies seems to be that people with low cognitive ability tend to be more averse to risk (and would thus be *less* likely to engage in risky behavior, ceteris paribus).[2] For example, Dohmen et al. (2010) find such a relation in a representative sample of the German population, Benjamin et al. (2012) 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

[2] We focus on studies using the MPL because the main bulk of the papers claiming a relation between cognitive ability and risk aversion use this measure, and because MPL are ideally suited to address the issue of how noise biases preference estimates. This is more difficult with other measures such as the hypothetical risk question used, for example, in the robustness analysis of Dohmen et al. (2010), because they are typically not repeated or varied within a subject. Similarly, when letting subjects choose between certain (hypothetical) payments and (hypothetical) gambles, as in Frederick (2005), subjects with low cognitive ability may choose the safe option for the sake of computational simplicity rather than as a result of risk aversion. In our design, both options include computations, so such effects are unlikely to play a role.

to the presentation of the task and to changes in the choice set. A series of 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] However, the main pattern is also consistent with choice simply being noisy which implies that MPLs with many decisions on the risk-averse domains lead to increased risk aversion estimates and conversely that many decisions in the risk-averse domain reduce risk-aversion estimates. The prevalence of such 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).

The main argument of this paper is that behavioral noise can bias estimates of risk aversion, and that the direction of the bias depends on the risk-elicitation task at hand. In particular, we show that noise causes underestimation of risk aversion in a risk-elicitation task containing many decisions on the risk-loving domain, but causes overestimation in a task containing many options on the risk-averse domain (see Section 3). If those with low cognitive ability are more likely to be noisy, a spurious correlation between cognitive ability and risk aversion obtains.[4]

[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 (2008) 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 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.

[4] Evidence showing that those with low cognitive ability are more prone to make errors is abundant and, perhaps unsurprisingly, rather clear. For example, Eckel (1999) finds that students with lower cognitive ability (measured by GPA

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 et al. 2012, and Burks et al. 2009) might be spurious. The reason is that these studies happen to have used MPL with choice sets in which noise, according to our argument, causes underestimation of risk aversion. Thus, the choice sets of the MPL 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 explain some other findings reported in the literature. For example, the study of Burks et al. (2009) includes several MPL. In two of these, noise causes overestimation of risk aversion, but creates the opposite bias in the third one. Using the latter MPL, they indeed obtain a positive relation between cognitive ability and risk aversion (Figure 3B in Burks et al. 2009). 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.[5] That the bias can go either way depending on the task at hand is clearly seen in Sousa (2010). He uses a battery of six MPL and finds no relation between cognitive ability and risk aversion. Overall, this finding is again consistent with our claim since the price lists used are balanced, in the sense that half of the MPL create an upward bias and half a downward bias. This balanced design may therefore have neutralized the biases so that the noise would not lead to any biased inference.[6]

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.

[5] 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).

[6] Brañas-Garza et al. (2008) also find no relation between math skills, as measured by a sub-sample of the quantitative section of the GRE test, in conjunction with additional questions concerning probability judgments and risk aversion. However, the number of subjects in this study is rather small. They divide the total sample into three groups. The groups with low and high cognitive ability have only 19 subjects each.

In a recent study, Beauchamp, Cesarini and Johannesson (2013) find a negative relation between cognitive ability and survey-based measure of risk aversion among male Swedish twins.[7] The authors argue that the predictive power of these estimates increases when econometrically controlling for mistakes. However, the authors do not allow mistakes to be heterogeneous which may substantially moderate the strength of the relation. One of our main results is that once we (econometrically) control for such heterogeneity, the relation between cognitive ability and risk preferences disappears.

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 our argument that noisy decision making may bias estimates of risk preferences is tested 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 may also be prone to the same type of problems. In addition, we think the general insight also extends to studies that relate risky choices "in the wild" (i.e. in non-experimental settings) to experimentally elicited preferences. For instance, a recurrent finding is that the relation between elicited preferences and behavior outside the lab is stronger when these elicitations properly control for behavioral noise (see e.g. Jacobsen and Petrie 2009 and Anderson and Mellor 2009).

[7] These authors also find that such measures predict risky behavior such as investment decisions, entrepreneurship and health behaviors such as smoking and drinking. This contrasts with Sutter et al. (2013) who find no relation between cognitive ability (measured by maths grades) and risk aversion in sample of children and adolescents in Austria, and that the experimental risk measures are at best weak predictors of field behavior such as smoking and drinking.

III. Experimental variation of bias induced by mistakes

This section explains how the errors in decision making and the elicitation procedure interact to create a bias. Depending on the choice task used, noise can bias estimates of risk preferences either way. We illustrate this with reference to the two MPL used in our experiments, and state our testable hypotheses.

Table 1 shows MPL1, the choice task used in our Experiment 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 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 list 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).[8] The switch point of a risk neutral decision maker is printed in bold face and relatively "high up" (above the middle row) in the list.

To illustrate the bias induced by noise in MPL1, assume that there are two types of individuals, A and B, who are heterogeneous in their likelihood to make errors. For the sake of exposition, we assume a simple error structure in which A-types are perfectly error-free, but B-types make a mistake with probability $e > 0$ (and then pick between Left or Right at random), and choose the lottery that maximizes expected utility with $1 - e$.[9] A straightforward way to measure risk preferences is

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

[9] This model of errors is referred to as the constant error model, or the tremble model (Harless and Camerer 1994). Our argument is robust to a broad range of error structures. For example, similar results obtain if we assume that B-types are consistent in the sense that they do not switch back and forth between the two lotteries, but their choice of switch point is stochastic. The same goes for assuming that B-types switch at a random row with probability *e* and switch at their preferred row with probability 1-*e*. In the structural estimation of section 5 we use the more elaborate error structure suggested by Wilcox (2011). In this framework error propensities are not constant but depend on the utility difference between the lotteries. In Online Appendix C we also estimate other error models including an extended version of the Wilcox (2011) model that contains a tremble parameter.

to count how often the decision maker chooses the (relatively safe) Left lottery. When both types are risk neutral, it is optimal for everyone to switch at decision 3, meaning that A-types make 2 safe choices while B-types make $2 + 3e$ safe choices in expectation.[10] Hence, B-types on average appear to be risk averse despite being risk neutral ($2 + 3e > 2$ for $e > 0$). Now, suppose cognitive ability is correlated with being prone to error, i.e. assume A-types have higher cognitive ability than B-types. Then, any method of statistical inference that does not take the heterogeneity of noise into account finds a spurious negative correlation between cognitive ability and risk aversion, despite the fact that both types have the same true risk preferences.

Table 1. Multiple Price List used in Experiment 1 (MPL1)

	Left		Right	
	Heads	Tails	Heads	Tails
Decision 1	30	50	5	60
Decision 2	30	50	5	70
Decision 3	**30**	**50**	**5**	**80**
Decision 4	30	50	5	90
Decision 5	30	50	5	100
Decision 6	30	50	5	110
Decision 7	30	50	5	120
Decision 8	30	50	5	140
Decision 9	30	50	5	170
Decision 10	30	50	5	220

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

[10] On the first two rows, the decision maker chooses the Left gamble with probability $(1 - e)*1 + e*0.5 = 1 - 0.5e$. For the remaining 8 rows, the decision maker chooses Left only when he trembles, which gives a probability of choosing the Left gamble of $0.5e$. Taken together, this gives $2*(1 - 0.5e) + 8*0.5e = 2 + 3e$.

Table 2. Multiple Price List used in Experiment 2 (MPL2)

	Left		Right	
	Heads	Tails	Heads	Tails
Decision 1	25	45	5	40
Decision 2	25	45	5	50
Decision 3	25	45	5	55
Decision 4	25	45	5	60
Decision 5	25	45	5	65
Decision 6	**25**	**45**	**5**	**70**
Decision 7	25	45	5	75
Decision 8	25	45	5	95
Decision 9	25	45	5	135
Decision 10	25	45	5	215

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

Table 2 shows MPL2, the risk elicitation task used in Experiment 2. It produces a positive (or no) correlation between cognitive ability and risk aversion. When all decision makers are risk neutral, error-free A-types switch at Decision 6, implying 5 safe choices. B-types make the same number of safe choices in expectation (but with higher variance). However, when both A- and B-types are moderately risk averse (the typical finding in the experimental literature) a positive relation between cognitive ability and risk aversion results.

The upshot of this discussion is that, for plausible levels of risk aversion, smarter people make more risky choices in MPL1 (Table 1) than others, but make less risky choices in MPL2 (Table 2) than others, if people with high cognitive ability are less prone to noisy behavior. *We therefore expect a negative relation between risk aversion and cognitive ability in Experiment 1 and positive relation between risk aversion and cognitive ability in Experiment 2.*

IV. 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.[11] 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.[12] 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. In Experiment 1, subjects participated in several modules, including two versions of the public good game, a risk elicitation task, 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. Subjects who completed iLEE1 were re-invited to participate in iLEE2 which included the risk elicitation task of Experiment 2 among other modules. 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

[11] 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.

[12] 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).

subjects. Apart from sample selection effects, using the “virtual lab” approach does not seem to affect risk preference estimates compared to standard laboratory procedures.[13]

In total, 2,334 participants completed Experiment 1 and 1,396 completed Experiment 2. 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.[14]

Upon beginning Experiment 1, subjects were informed that they would make a series of choices between two lotteries, as shown in Table 1.[15] 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 Experiment 2 was identical to that of Experiment 1 except for the payoffs in the MPL (see Table 2). The switch point for a risk neutral subject (marked in bold face) comes later in MPL2 than in MPL1. In line with the arguments in Section 2, we therefore expect a positive relationship between estimated risk aversion and cognitive ability in Experiment 1, but a negative relationship in Experiment 2.

The MPL 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

[13] The differences in measured preferences in von Gaudecker, van Soest and Wengström (2012) are due to sample selection rather than the mode of implementation.

[14] 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 Hoogedorn 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.

[15] 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.

have used fixed payoffs and vary probabilities (e.g. Holt and Laury 2002). By keeping probabilities fixed, we disregard potential effects from probability weighting (Quiggin 1982; Fehr-Duda and Epper 2012). 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.

A. 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. Our results are essentially identical if we keep these subjects in the sample, or if we further restrict the sample further by dropping subjects that spend very little time on the task or if we only study subjects with a unique interior switch points (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 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.[16]

Experiment 1 also includes the *Cognitive Reflection Test (CRT)* proposed by Frederick (2005). The test consists of three questions aimed at capturing a specific dimension of cognitive ability. A typical question is as follows: a bat and a ball cost $1.10 in total and the bat costs $1.00 more than the ball. How much does the ball cost? The answer that springs to mind ($.10) is in fact wrong. 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 Experiment 1), 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,[17]with 60 items in total. It takes most participants 10 to 15 minutes to complete.

V. Results

Section A shows that our experimental variation produces opposed correlations between risk preferences and cognitive ability. Section B presents results from

[16] See figure A1 in Online Appendix A for a graph of the distribution of the IST scores in our sample.

[17] 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.

structural estimation showing that cognitive ability is correlated to noisy behavior, but not to risk preferences under the expected utility model. Section C reviews a series of robustness checks of the structural estimations and Section D discusses our findings.

A. Spurious relation between cognitive ability and risk aversion

We provide evidence in support of our claim in three steps. First, by providing simple correlations (without adding any controls), second by linear regression, and third by structural estimation.

Figure 1 visualizes our main result. We find a negative relation between risk aversion and cognitive ability in Experiment 1 (left panel) and a positive relation in Experiment 2 (right panel). Both the negative and the positive correlation are highly significant (Experiment 1: $\rho = -0.073$, *p*-value = 0.002; Experiment 2: $\rho = 0.114$, *p*-value < 0.001, Pearson's correlation coefficients). The same pattern is found if we restrict attention to the subset of subjects that participated in both experiments.[18] Taken together, this suggests that higher cognitive ability is associated with more risky decisions in Experiment 1, but less risky decisions in Experiment 2. However, since the measure of cognitive ability and the set of people on which it is measured are held constant, the correlation must be spurious.

[18] Experiment 1: $\rho = -0.120$, *p*-value < 0.001; Experiment 2: $\rho = 0.084$, *p*-value = 0.012, Pearson's correlation coefficients. The number of observations is 905 (including only subjects that participated in both experiments and switched at least once in each experiment).

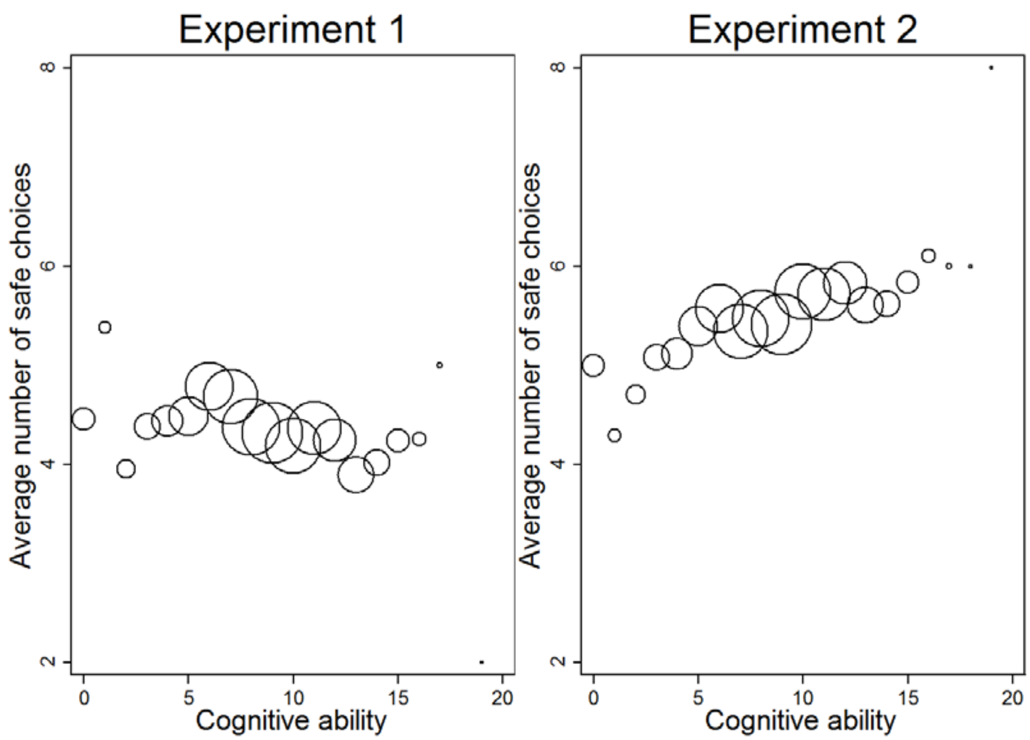

Figure 1: Opposite relation of risk aversion and cognitive ability in Experiment 1 and 2

Notes: Figure shows average switch points in MPL1 (left) and MPL2 (right) by cognitive ability (IST score). The centre 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 = 1,756 in the left panel and 1,142 in the right panel.

This finding 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.

Table 3 reports OLS estimations for Experiment 1 and Experiment 2.[19] 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 Experiment 1

[19] 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).

(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 Experiment 2 (model 4 without controls, model 5 with socio-demographic controls, model 6 with socio-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 of cognitive ability (IST score) by one standard deviation results in a 7 percent of a standard deviation change in the number of safe choices in Experiment 1 (around 0.14 less safe choices), and a 8 to 11 percent of a standard deviation change in the number of safe choices in Experiment 2 (between 0.14 and 0.2 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 Experiments.[20]

[20] In the subsequent structural estimation we elaborate more on other covariates such as gender and personality measures.

Table 3. Correlates of risk preferences

	Experiment 1			Experiment 2		
VARIABLES	(1)	(2)	(3)	(1)	(2)	(3)
Cognitive ability (IST)	-0.045***	-0.043***	-0.043***	0.064***	0.046**	0.045**
	[0.015]	[0.016]	[0.016]	[0.017]	[0.018]	[0.018]
Female		0.412***	0.234**		-0.069	-0.122
		[0.094]	[0.102]		[0.109]	[0.118]
Age		-0.001	-0.001		-0.009**	-0.010**
		[0.004]	[0.004]		[0.004]	[0.004]
Education1		-0.135	-0.102		0.413**	0.395**
		[0.175]	[0.175]		[0.196]	[0.196]
Education2		-0.196	-0.179		0.309*	0.293
		[0.163]	[0.164]		[0.184]	[0.184]
Education3		-0.471**	-0.431**		0.303	0.236
		[0.185]	[0.188]		[0.211]	[0.215]
Big5a			0.034***			0.006
			[0.009]			[0.010]
Big5c			-0.004			0.008
			[0.009]			[0.011]
Big5e			0.009			-0.017*
			[0.009]			[0.001]
Big5n			0.022***			0.003
			[0.008]			[0.009]
Big5o			0.007			0.027***
			[0.008]			[0.009]
Constant	4.759***	4.790***	3.025***	4.956***	5.251***	4.701***
	[0.136]	[0.295]	[0.624]	[0.157]	[0.338]	[0.699]
Observations	1,756	1,756	1,756	1,142	1,142	1,142
R-squared	0.005	0.022	0.036	0.013	0.022	0.032

Notes: OLS regressions. Education1 refers to participants' degrees from high school and vocational school, Education2 represents tertiary education up to 4 years and Education3 tertiary education of at least 4 year. Participants with basic schooling (up to 10 years of schooling) are our baseline category. Big5a to Big5o refer to the scores of the Big five personality dimensions. Standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

An alternative way to analyze the data is to study *variation* in the number of safe choices for those subjects that take part in both Experiment 1 and Experiment 2. Given the structure of the two lists we expect, for a rational individual with a given risk preference, more safe choices in Experiment 2. 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. In Online Appendix C we report robust estimation results that support this prediction.

B. *Structural estimation*

The results in the previous section support our hypothesis and provide evidence that cognitive ability is related to mistake propensities rather than to risk preferences. In this section we corroborate this finding by using structural estimation techniques. Moreover, the results in this section demonstrate the usefulness of combining a balanced design with econometric methods that allow mistakes propensities to be heterogeneous. We find no relation between risk preferences and cognitive ability when we use a balanced experimental design (by merging the data of Experiment 1 and Experiment 2) with an econometric specification that allows noise to depend on cognitive ability.[21] Yet, consistent with our argument, we find a strong association between cognitive ability and the noise parameters.

The behavioral noise of the decision process can be taken into account by estimating the risk parameters using a structural model of choice. We estimate

[21] To balance the design we only include subjects that participated in both experiments in the structural estimations.

such a model under the assumption that individuals have constant relative risk-aversion (CRRA). That is, the utility function has the following form

$$u(x) = \frac{x^{1-\gamma}}{1-\gamma}\ , \tag{1}$$

where γ is the coefficient of relative risk-aversion. The expected utility of a lottery A is simply given by

$$EU(A) = \sum_{a \in A} p(a)u(a)\ . \tag{2}$$

We define the difference in expected utility between the lotteries Left (L) and Right (R) as

$$\Delta \mathrm{EU} = \mathrm{EU(L)} - \mathrm{EU(R)}.$$

Acknowledging the stochastic nature of the decision making process, we assume that individuals evaluate differences in expected utility with some noise. More specifically, we utilize the Fechner errors structure, popularized by Hey and Orme (1994), which states that the L lottery will be chosen if

$$\Delta EU + \tau\varepsilon > 0,\ \text{where } \varepsilon \sim N(0,1), \tag{3}$$

where τ is a structural noise parameter. We follow Wilcox (2011) and normalize ΔEU by dividing with $\mu > 0$, defined as the difference between the maximum utility and the minimum utility over all prizes in each lottery pair. This normalization, known as contextual utility serves to capture lottery-specific heteroskedasticity in the error term and it has recently become popular. See for example Hey, Lotito and Maffioletti (2010), Bruhin, Fehr-Duda and Epper (2010) and Andersen et al. (2013) for studies using this error structure. Given this structure, the probability of choosing left can be written as

$$\Pr(L) = \Phi\left(\frac{\Delta EU}{\tau\mu}\right), \tag{4}$$

where Φ is the cumulative distribution of the standard normal.

We now estimate the CRRA utility function with this error specification using maximum likelihood. The parameters to be estimated are the risk parameter γ and the noise parameter τ. We estimate the model using the pooled data from the two experiments. We cluster the observations at the individual level and estimate average effects, allowing for heterogeneity through the covariates. More specifically, we model the parameters γ and τ as linear functions of the covariates.

The results are reported in Table 4. Model 1 in Table 4 shows a specification, in which only the risk aversion parameter γ to depend on cognitive ability.[22] We find a negative effect of cognitive ability on the risk parameter, suggesting that higher cognitive ability maps into less risk aversion. Yet, when we also allow the noise parameter τ to depend on cognitive ability and other covariates in model 2, the relation between cognitive ability and the risk parameter turns insignificant whereas the relation between cognitive ability and the noise parameter is significant.

[22] The level of risk aversion in our experiment is lower than in most previous studies. From a specification without any covariates, we obtain a γ estimate of 0.25 (0.30 in Experiment 1 and 0.24 in Experiment 2). For example, Holt and Laury (2002) report that most of their subjects fall in the 0.3 to 0.5 range. Like us, Andersen et al. (2008) also uses subjects that are randomly sampled from the Danish population and they obtain an mean CRRA estimate of 0.7.

Table 4 Estimates of risk preferences and noisiness, Contextual utility

	(1)		(2)	
VARIABLES	γ	τ	γ	τ
Cognitive ability (IST)	-0.008*		-0.004	-0.009***
	[0.005]		[0.004]	[0.001]
Female	0.029		0.029	0.018*
	[0.032]		[0.029]	[0.011]
Age	-0.001		-0.002**	0.003***
	[0.001]		[0.001]	[0.000]
Education1	0.009		0.047	-0.024
	[0.045]		[0.051]	[0.019]
Education2	0.009		0.038	-0.020
	[0.042]		[0.040]	[0.019]
Education3	-0.041		0.016	-0.058***
	[0.051]		[0.053]	[0.019]
Big5a	0.008***		0.008***	0.000
	[0.003]		[0.002]	[0.001]
Big5c	0.005		0.005*	-0.001
	[0.003]		[0.003]	[0.001]
Big5e	-0.007**		-0.007***	-0.000
	[0.003]		[0.002]	[0.001]
Big5n	0.001		0.001	0.001
	[0.003]		[0.002]	[0.001]
Big5o	0.008***		0.007***	0.001
	[0.002]		[0.002]	[0.001]
Constant	-0.106	0.228***	-0.076	0.201***
	[0.212]	[0.005]	[0.154]	[0.048]
Observations	27,920	27,920	27,920	27,920

Notes: The estimations are based on the CRRA utility function. Education1 refers to participants degrees from high school and vocational school, Education2 represents tertiary education up to 4 years and Education3 tertiary education of at least 4 years. Participants with basic schooling (up to 10 years of schooling) are our baseline category. Big5a-Big5o refer to the scores of the Big Five personality dimensions. Robust standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

C. Robustness

In Online Appendix C, we present results from a series of robustness checks for the structural estimations. First, to rule out that our results are an artifact of our parametric specification, we estimate our model using the more flexible expo-power utility function that nests CRRA and CARA as special cases (Saha 1993). The results are identical to the ones based on the CRRA utility function. Second, previous research has pointed out that estimates may differ significantly depending on the choice of stochastic model (Wilcox 2008; Harrison and Rutström 2008). We therefore estimate a series of models that use alternative error specifications. To start with, we estimate models building on the Luce error structure (introduced by Luce 1959 and popularized by Holt and Laury 2002). We then extend both the contextual utility model and the Luce model by adding a tremble parameter that captures the interpretation of errors laid out in Section 3. Adding the tremble parameter implies that subjects, in addition to the contextual and Luce errors, have a constant probability of choosing randomly between the lotteries (see for example Harless and Camerer 1994 and Moffatt and Peters 2001). All of the alternative specifications reveal the same pattern and support our previous conclusions. Cognitive ability is related to parameters capturing decision errors, but not to the curvature of the utility function. As an additional robustness check we also estimated the models of Table 4 with a reduced set of covariates and repeated all our analyses (including correlations and OLS regressions) using the results from the cognitive reflection test (Frederick 2005) instead of the IST 2000 R test. Again, we find that our conclusions are robust to these variations.

D. Discussion

Taken together, the results of the structural model are in line with our earlier analysis based on OLS regressions. Apart from cognitive ability, we also note that other covariates such as age and education are related to the noise parameter. Older subjects display more noisy behavior and the highly educated exhibit less noisy behavior.[23] Similar results have been reported by von Gaudecker, van Soest and Wengström (2011) in a study of risk preferences, and by Choi et al. (2011) in a study of optimal consumer choice. These studies also find that the young are more consistent than the old, and (as discussed next) that subjects with high education are more consistent than those with less education.

Interestingly, we find that education appear to be related to noise and risk in a similar way as cognitive ability. The education variables are negatively correlated to the number of safe choices in Experiment 1, but positively related in Experiment 2 (see Table 3). This difference may reflect an important aspect of socialization -- that subjects with a higher educational level have learned to be careful when processing information and that they thus tend to make fewer random choices. This finding is well in line with our interpretation of what the noise term captures, motivating us to take due caution when interpreting results on correlations between education and risk preferences.

A noteworthy pattern in the structural estimates is that age is not significantly related to the risk aversion parameter when we do not let noise depend on age (see Table 4 and the alternative error specifications presented in Online Appendix C).

[23] We do not find that gender is related to risk preferences in Table 4. This may come as a surprise given the earlier literature (see for example Croson and Gneezy 2009 for a survey), but it should be noted that in a previous study on the Danish population, Harrison, Lau and Rutström (2007) find no statistically significant gender differences in risk aversion. However, in our study gender seems to be insignificant because our regressions include personality variables which are known to systematically vary with gender (see e.g., Schmitt et al. 2008). If we exclude the Big5 variables, being female is significantly and positively related to risk aversion and to the noise parameter (see Online Appendix C). That is, in contrast to cognitive ability, gender appears to be correlated with both risk preferences and noisy decision making. This observation suggests that the often presumed gender difference in risk taking may be far more complicated than previously thought.

But, when we allow for age-heterogeneous noise, we observe a significant negative relationship between age and the risk aversion parameter. That is, it appear as if the fact that older subjects behave more nosily, and in particular tremble more, masks an underlying negative relationship between utility curvature and age in our data.

Another remarkable side result of our structural estimations is that the significant relations between the personality variables and cognitive ability are almost unaffected by allowing noise to depend on observed characteristics. The relations are also insensitive to the choice of error structure (see Online Appendix C). This indicates that the risk-aversion estimates not only capture noise, but also relate to the subjects' personalities. This appears intuitive as we have no strong reason to believe that personality traits are strongly connected to noisy decision making, Moreover, we believe that preferences are linked to the subjects' personalities (which are captured by the Big Five variables).[24]

VI. 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.

[24] Borghans et al. (2008) conclude that personality traits and cognitive ability are interrelated, but that it is possible to econometrically separate them. Since our regressions control for cognitive ability, we believe we are more likely to identify "pure" personality dimensions of the Big Five variables. Almlund et al. (2010) reviews the literature relating the personality measures to risk preferences, and the findings are mixed. However, some of the earlier studies are consistent with our results. Almlund et al. (2011) report that in the data of Dohmen et al. (2010) agreeableness and openness are related to risk preferences.

This paper provides supporting evidence for this claim using two approaches. First, 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. Second, we use a structural estimation approach in which we either allow both preferences and noise to vary with covariates or not. If heterogeneity of noise is not taken into account, we find a correlation between cognitive ability and risk preferences, but the correlation disappears if we do allow for such heterogeneity. Once heterogeneity is taken into account, we find that cognitive ability is related to noise, but not to preferences. 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, structural estimation with heterogeneity taken properly into account is commendable. Our results from the structural model show that using balanced designs (in our case pooling the two skewed pricelists from Experiment 1 and Experiment 2) mitigates the bias but may entirely eliminate it. Structural models of choice allowing the noise to depend on covariates (such as age, education and cognitive ability), in particular models that allow the researcher to estimate both individual preference parameters and individual error propensities (see von Gaudecker, van Soest and Wengström 2011 for an example of such models) seem promising. While this approach requires an extensive set of choice tasks, it enables researchers to obtain signal-to-noise ratios for a given set of choices.

Third, 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 includes choice bracketing, the "two-system" approach (e.g. in Dohmen et al. 2010), or noisy utility evaluations (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.

Fourth, 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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