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Robust Inference in Risk Elicitation Tasks

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Recent experimental evidence suggests that noisy behavior correlates strongly with personal characteristics. Since decision noise leads to bias in most elicitation tasks, there is a risk of falsely interpreting noise-driven relationships as preference driven. This puts previous studies that found a negative relation between personality measures and risk aversion into perspective and in particular raises the question of how to achieve robust inference in this domain. This paper shows, by way of an economic experiment with subjects from all walks of life, that using structural estimation that models heterogeneity of noise in combination with a balanced design allows us to mitigate the bias problem. Our estimations show that cognitive ability is related to noisy behavior rather than risk preferences. We also find age and education to be strongly related to noise, but the personality characteristics obtained using the Big Five inventory are less related to noise and more robustly correlated to risk preferences.

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1. Introduction

To err is human, as the proverb says, but the empirical fact is that some people are more likely to err than others. Previous research has shown that error propensities are related to observable characteristics such as cognitive ability, education, age and gender (Andersson et al. 2016, Choi et al. 2014, von Gaudecker et al. 2011, Burks et al. 2009, Eckel 1999). Since decision noise leads to bias in most elicitation tasks (see, for example, Crosetto and Filippin 2016), there is a risk of falsely interpreting noise-driven relationships as preference driven. In Andersson et al. (2016), we show that this danger is real by demonstrating that cognitive ability can be both positively and negatively correlated to estimated risk preferences, depending on how the risk elicitation task is constructed. This suggests that the relationship between cognitive ability and risk preferences reported in the earlier literature may be spurious (see, e.g., Benjamin et al. 2013, Dohmen et al. 2010).

The previous evidence shows that decision errors are heterogeneous, which may lead to spurious inference regarding the relationship between risk preferences and personal characteristics. This problem should be taken seriously but it does not necessarily imply that any attempt to measure risk preferences and relating preferences to observable characteristics is futile. Instead, the findings in this paper highlight that using appropriate elicitation tasks and econometric methods may help to overcome this bias. In regard to econometric specifications, it is worth noticing that simple OLS estimations cannot handle such error structures. Instead, we need methods that take the heterogeneity of noise into account. A promising approach is to use "off the shelf" structural econometric specifications that take the heterogeneity of the noise into account in combination with multiple elicitation tasks so that the error structure can be estimated with precision.

In this paper, we demonstrate the usefulness of this approach. In particular, by utilizing data from an experiment with a random sample from the Danish population, we estimate a random parameter CRRA utility function (Apesteguia and Ballester 2018).[1] One appealing feature of structural models is that a range of parameters, including noise parameters, can be estimated jointly and be allowed to correlate with covariates. We estimate the models using experimental data from the iLEE panel, with subjects from the Danish adult population from all walks of life.[2]

[1] Apesteguia and Ballester (2018) show convincingly that random utility models, such as the Luce models with random errors, are not necessarily monotone in risk preferences which may lead to an underestimation of the risk parameters. Their results generalize the insights established in Wilcox (2011).

[2] See http://www.econ.ku.dk/cee/ilee/ for a more detailed description of platform.

To elicit risk preferences, we use two Multiple Price Lists (MPLs) that differ with respect to the implied switch point for a given risk preference, and this difference allows for a precise estimation of the error structure.

We find that cognitive ability is significantly negatively related to risk aversion if we do not allow cognitive ability to correlate with the noise parameters, which corroborates previous findings (e.g., Benjamin et al. 2013, Dohmen et al. 2010, Beauchamp 2017). However, when we do allow for such correlation, we find no significant relationship between risk aversion and cognitive ability. Instead, we observe that cognitive ability is negatively correlated to the amount of noise.[3]

Our analysis corroborates the findings of Andersson et al. (2016) by using structural estimation techniques. In that paper, we showed, using an experimental design, that there is a spurious relation between cognitive abilities and estimated risk preferences due to how preferences are elicited. One potential mechanism behind the spurious relation is noisy decision making. However, as noted by Dohmen et al. (2018) it may still be that cognitive ability is related to risk preferences but that this is masked by decision noise. Hence, we cannot conclude that there is no underlying relation between cognitive ability and risk preferences. By structurally modelling both risk and noise we take the analysis one step further to understand these relationships. Indeed, in the current paper, we find that cognitive abilities are more correlated with noisy behavior than to modelled risk preferences.

The potential problem of spurious relationships naturally extends beyond cognitive ability. To investigate this issue, we use measures of age, gender and personality characteristics (Big Five inventory) of the subjects on whom we elicit risk preferences. Letting these measures correlate with the noise measures as well as the preference parameters, we find that age and education are more closely related to noise than risk preferences. Yet, other variables are much less related to decision noise. In particular, several Big Five personality traits are strikingly robust to our different noise specifications and significantly correlated with risk aversion even after allowing for heterogeneous noise. These findings add to the literature on the relationship between

[3] 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 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.

economic preferences and personality measures (see Almlund et al. 2011). In a study, using a representative sample from the German population, Becker et al. (2012) find that Big Five personality measures, as well as measures of educational attainment, correlate with risk preferences.[4] However, they do not control for noisy decision-making. Our results suggest that only Big Five but not education robustly relates to risk preferences.

One natural question is whether it suffices to use multiple elicitation tasks to mitigate the bias problem without resorting to structural estimations. In this paper, we show that using a balanced design (in our case pooling two skewed MPLs) mitigates the bias somewhat but does not entirely eliminate it. Naturally, it is inherently hard to construct a fully balanced design since subjects' risk preferences are unknown ex ante. Our results highlight that it is important to employ structural estimation techniques that allow noise to depend on covariates (such as age, education and cognitive ability) in addition to using a balanced design. While this approach requires an extensive set of choice tasks, it enables the researchers to obtain signal-to-noise ratios for a given set of choices.

The paper contributes to an old but recently resurrected literature on measurement errors in experiments (see Yariv et al. 2018 for an overview of this literature). However, Yariv et al. (2018) review recent experimental papers published in the top 5 economics journals and show that very few of them try to handle measurement errors. An exception is Beuchamp et al. (2017) who use a latent variable model approach to handle potential measurement errors in estimated risk preferences. They assume homogeneous noise across individuals. However, as we have shown in Andersson et al. (2016), less cognitively able subjects tend to be less consistent; hence it is not clear that homogenous noise is a good assumption. It may improve the precision of aggregate estimates, but is not well suited for inference regarding preference heterogeneity. Another approach is to collect several measures and use an instrumental variable strategy to reduce the effects of measurement error. Recently, Yariv et al. (2018) use such an approach to re-examine the effect of risk preferences on competitive behavior. Both these studies consider homogenous noise (classical measurement error) whereas we allow noise to be heterogeneous. In particular, our results show that only allowing homogenous noise may not be sufficient to control for noise in the estimated parameters. Chapman et al. (2018) propose a dynamic estimation method that tries to minimize the effect of noise on estimated preferences by using Bayesian methods to optimally select decision tasks. They find that the consistency of subject's choices in MPLs

[4] See also Borghans et al. (2009) who find a significant relationship between Big Five measures and risk preferences.

affects the correlation between cognitive abilities and estimated risk preferences which supports the results presented here. When using their proposed method they find that cognitive ability and risk preferences are correlated. However, as with the previous methods, they do not allow noise to be heterogeneous which can potentially explain why our results differ. Finally, in a paper developed subsequently to ours, a factor analysis approach is used in combination with a random parameter utility specification, as in this paper, to reduce noise in preference elicitation (Jagelka 2020). In line with the findings presented here, they find that cognitive ability is mostly correlated with noisy behavior, while their measured psychological traits are correlated both risk preferences and noisy behavior. Unlike us, they do not use multiple MPLs to debias the estimation, which may explain why a significant correlation between cognitive abilities and risk aversion is found.

The rest of the paper is structured as follows. Section 2 explains the basic intuition for why noisy decision making may create biased inference. Section 3 describes the experiments and our measures of cognitive ability and personality. Section 4 presents the results from the main specification and Section 5 concludes.

2. Experimental variation of bias induced by mistakes

This section explains how 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 MPLs used in our study.

Table 1 shows the two price lists used in our study. 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 relatively "high up" (above the middle row) in the list.

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

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

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

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 $1 - e$. A straightforward way to measure risk preferences is 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.[6] Hence, B-types on average appear to be risk averse despite being risk neutral ($2 + 3e > 2$ for $e > 0$). Now, suppose for instance that 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.

The right panel in Table 1 shows the second price list MPL2. It produces a positive (or no) correlation between cognitive ability and risk aversion under the simple error structure described above. 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, if both A- and B-types are moderately risk averse (which is the typical

[6] 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 $2*(1 - 0.5e) + 8*0.5e = 2 + 3e$.

finding in the experimental literature), there is a *positive* relationship between cognitive ability and risk aversion.

The model of errors presented above is referred to as the constant error model, or the tremble model (Harless and Camerer 1994). Our argument above also holds for a broad range of alternative 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 4, we use the more elaborate random parameter error structure suggested by Apesteguia and Ballester (2018) in addition to the tremble parameter. In the Appendix, we also estimate a Luce random-utility model that includes a tremble parameter. The results from that estimation are qualitatively similar to the results reported in the main analysis.

Taken together, the discussion above shows that, for plausible levels of risk aversion, smarter people make more risky choices in MPL1 than others, but make less risky choices in MPL2 than others, if people with high cognitive ability are less prone to noisy behavior. We therefore expect a negative relationship between risk aversion and cognitive ability in MPL1 and positive relation between risk aversion and cognitive ability in MPL2. In Section 4 we demonstrate that the bias is reduced by using a balanced design, i.e., by using a design that combines data from MPL1 and MPL2. However, we argue that using a balanced design might not be sufficient to eliminate the bias, and the balanced design needs to be accompanied by structural estimation techniques aimed at handling heterogeneous noise.

3. Experimental procedures and measures

This section describes the recruitment procedures, the risk task and other measures of interest such as the cognitive ability test. Table 2 shows descriptive statistics for the background variables and measures that we include in our analysis. The description in the following paragraphs tracks the one in Andersson et al. (2016) very closely since we use the same experiment.

1.1. Recruitment procedures

We use an online platform called iLEE (internet Laboratory for Experimental Economics) developed at the University of Copenhagen. Recruitment was carried out by asking Statistics Denmark (the Danish National Bureau of Statistics) to invite a random sample of adults (aged

18-80) residing in Denmark.[7] Invitation letters were sent out using regular mail. The recipients were informed that they were randomly selected to participate in a scientific study in which they could earn money (earnings were transferred via electronic bank transfer). They were provided with a personal identification code and asked to use it to log on to the webpage of the study.

Our data comes from two experiments. In 2008, 2,334 participants participated in the first experiment which included MPL1 and about one year later the same participants were invited to participate in a second experiment which included MPL2. A total of 1,396 participants completed the second experiment. The response rate was around 11% percent for MPL1 and around 60% for MPL2, which is similar to other online experiments.[8] In our analysis, we restrict attention to the 1,396 participants that completed both MPL1 and MPL2. The experiments also contained other modules in addition to the ones we use in this paper (e.g., a public good game, a trust game and survey questions).[9]

1.2. Risk elicitation tasks

The two risk elicitation tasks, MPL1 and MPL2, used different payoffs (see Table 1), but were otherwise identical. In both experiments, subjects were informed that they would be asked to make a series of choices between gambles and that one of the gambles would be selected for payment after the experiment. The main difference between the tasks is that the switch point of a risk neutral agent (printed in bold text in Table 1), comes further up in MPL1 compared to MPL2. In line with the discussion in Section 2, a noisy risk-neutral participant will appear more risk averse in MPL1 compared to MPL2. Screenshots and translations of the instructions are available in the Appendix.

The results of Dave et al. (2010) show that participants with low level of numeracy have difficulties in understanding MPL formats with varying probabilities. Hence, to make the tasks easy to comprehend, which seemed important given the broad sample we targeted, we used fixed 50-50 probabilities and instead varied the prizes (similar to Binswanger 1980 or Tanaka, Camerer

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[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).

[8] Hoogedorn and Daalmans (2009) show that the overall total sample rate (essentially the share of people who effectively participate as a share of recruited people) is 11.5 percent for the Center Panel at the University of Tilburg which is also an internet-based panel used for online experiments as ours. Von Gaudecker et al. (2012) investigate selection effects in the Center Panel and report that self-selection appears to have a minor impact on estimated risk preferences.

[9] iLEE has been used for studies on a broad range of topics such as cooperation behavior (Thöni et al. 2012 and Fosgaard et al. 2014), eliciting social preferences (Hedegaard et al. 2018), political attitudes (Morton et al. 2016), and risk taking on behalf of others (Andersson et al. 2013).

and Nguyen 2010). By keeping probabilities fixed, we do not address potential effects from probability weighting (Quiggin 1982; Fehr-Duda and Epper 2012).

1.3. Measures of cognitive ability and personality

To measure cognitive ability, we employ a module of a standard intelligence test called "IST 2000 R". The test items resemble Raven's Progressive Matrices (Raven 1938), and it provides a measure of fluid intelligence which does not depend much on verbal skills or other kinds 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 the Appendix 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.[10]

The subjects also completed a Big Five personality test (administered after MPL1 but before the current experiments) which is arguably 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.[11] It takes most participants 10 to 15 minutes to complete the test. In our regressions, for each of the measures, we use a dummy that takes the value one if the subject a reported personality trait that is above the median in the sample.

4. Results

The results in Andersson et al. (2016) provide evidence that cognitive ability is related to mistake propensities rather than to risk preferences. In this section, we demonstrate the usefulness of combining a balanced design with econometric methods that allow mistakes propensities to be heterogeneous. Indeed, we find no relation between risk preferences and cognitive ability when we use a more balanced experimental design (by merging the data from MPL1 and MPL2) together with an econometric specification that allows noise to depend on covariates. Consistent

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

[11] 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.

with our argument, we find a strong association between cognitive ability and the noise parameters. Other covariates such as education and age are also related to noise. However, all covariates do not correlate with the noise parameter and are, hence, more stable across specifications.

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 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

$$\Delta EU = EU(L) - EU(R) \ . \tag{3}$$

Acknowledging the stochastic nature of the decision making process, we follow Apesteguia and Ballester (2018) who show that random parameter models represent a more robust alternative compared to random utility models as they do not violate the monotonicity assumption.[12] Assuming that the risk aversion parameter γ is randomly affected by noise that follow a logistic distribution, the probability of choosing L is given by

$$Pr(L) = (1-2\omega)\frac{e^{\tau\gamma^{(L,R)}}}{e^{\tau\gamma^{(L,R)}} + e^{\tau\gamma}} + \ \omega \ , \tag{4}$$

where $\gamma^{(L,R)}$ is the value at which ΔEU is equal to zero, and τ is a precision parameter, determining the size of the random noise affecting γ and ω a tremble probability capturing the probability of making a random choice (see Apesteguia and Ballester 2018 for details about the estimation procedure).

The OLS analysis in Andersson (2016) revealed a spurious relationship between risk aversion

[12] In Table A4 the Appendix, we also estimate random utility models with the Luce (1959) error structures. Results are qualitatively robust to using these specifications instead.

and many of our control variables such as cognitive ability. The results of the structural model corroborate these results and shed new light on the underlying correlation structure when properly correcting for heterogeneous noise.[13] Table 2 reports summary statistics for the control variables used in the analysis.

Table 2: Summary statistics of control variables

Variable	# Obs	Mean	Std. Dev.	Min	Max
Cognitive ability	1,396	8.833	3.200	0	19
Female	1,396	0.478	0.500	0	1
Age	1,396	47.128	14.761	18	80
Education1	1,396	0.266	0.442	0	1
Education2	1,396	0.463	0.499	0	1
Education3	1,396	0.168	0.374	0	1
Big5a	1,396	0.502	0.500	0	1
Big5c	1,396	0.571	0.495	0	1
Big5e	1,396	0.554	0.497	0	1
Big5n	1,396	0.509	0.500	0	1
Big5o	1,396	0.521	0.500	0.000	1.000

Notes: The sample consists of subjects completing both MPL1 and MPL2. Cognitive ability measured using the IST test. 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 dummies determined by the median of the scores of the Big Five personality dimensions.

For the sake of space and readability we report the full set of results in the Appendix. In the Appendix we also estimate our model without heterogeneous noise and tremble specifications (i.e., the noise and tremble terms only estimated with a constant) and only using MPL1 or MPL2. The results are presented in Table A2 and Table A3 respectively.

[13] 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 a mean CRRA estimate of 0.7.

Table 3: Summary of coefficients from Table A2 and A3 in the Appendix

	Homogenous noise	Heterogeneous noise		
	γ	γ	τ	ω
Cognitive ability	-0.00843*	-0.00626	0.0198**	-0.00884***
	[0.00477]	[0.00430]	[0.00909]	[0.00144]
Female	0.0286	0.0336	-0.0217	0.0253***
	[0.0302]	[0.0283]	[0.0550]	[0.00933]
Age	-0.00133	-0.00147	-0.00062	0.00265***
	[0.00101]	[0.000926]	[0.00190]	[0.000332]
Education1	0.00215	0.039	-0.065	-0.0365**
	[0.0534]	[0.0482]	[0.103]	[0.0155]
Education2	-0.0223	0.0101	-0.123	-0.0305**
	[0.0547]	[0.0496]	[0.106]	[0.0149]
Education3	-0.0583	-0.0217	0.00991	-0.0714***
	[0.0554]	[0.0503]	[0.114]	[0.0164]
Big5a	0.0778***	0.0724***	-0.106**	0.0083
	[0.0284]	[0.0268]	[0.0538]	[0.00903]
Big5c	0.0494*	0.0388	-0.000721	-0.0026
	[0.0273]	[0.0249]	[0.0514]	[0.00879]
Big5e	-0.0441	-0.0437*	0.061	0.0095
	[0.0287]	[0.0261]	[0.0550]	[0.00870]
Big5n	0.0602**	0.0514*	-0.107*	0.0114
	[0.0287]	[0.0266]	[0.0549]	[0.00903]
Big5o	0.0514*	0.0559**	-0.0632	0.0155*
	[0.0288]	[0.0266]	[0.0600]	[0.00884]

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. The models also include median-split dummy variables for each of the Big Five personality dimensions. Robust standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

To get a better overview of our main results, Table 3 summarizes the coefficients from the estimations reported in Table A2 and A3 in the Appendix. The leftmost column shows the estimated coefficients for the risk aversion parameter using both MPLs but only allowing for homogeneous noise (therefore we exclude these parameters). The three rightmost columns show estimated coefficients for the risk and noise parameters when allowing for heterogeneous noise. The insignificant relation between cognitive ability and risk preferences in the latter specification corroborates our previous findings in Andersson (2016), indicating a spurious relationship.[14]

With a more appropriate specification of the noise structure, we are better able to uncover the underlying correlations between our control variables and the parameters of the model.[15] We do not find that gender is related to risk preferences in Table 3. 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 et al. (2007) find no statistically significant gender differences in risk aversion. However, in our study gender seems to be insignificant because our specifications include personality variables which are known to systematically vary with gender (see, e.g., Schmitt et al. 2008). If we exclude the Big 5 variables, being female is significantly and positively related to risk aversion and to the noise parameter (available upon request). 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. Older subjects display more noisy behavior, and the highly educated exhibit less noisy behavior. Similar results have been reported by von Gaudecker et al. (2011) in a study of risk preferences, and by Choi et al. (2014) in a study of optimal consumer choice. These studies 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. In line with these results Bonsang and Dohmen (2015) find that the relationship between risk preferences and age is weak and turns insignificant once controls for cognitive ability measurement error are introduced.

Education appears to be mostly related to noise in our setting. 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.

Another remarkable result of our structural estimations is that the significant relations between the Big 5 personality variables and risk aversion are almost unaffected by allowing noise to

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[14] Table A3 in the Appendix further shows the importance of using multiple MPLs. When only using data from MPL1 allowing for heterogeneous noise is not enough to eliminate the bias created by noisy behavior.

[15] One should however be cautious to interpret these correlations as causal relations or true determinants of risky behavior. For instance, some facets of Big 5 personality measures capture important aspects of risk preferences, but it is impossible to say something about the direction of causality. And although cognitive abilities are mainly formed in younger years they have shown to increase with educational attainment (Ritchie 2018).

depend on these observed characteristics. This indicates that the risk-aversion estimates robustly relate to the subjects' personalities. Previous studies have found significant relationships between Big Five items and risk preferences (see Frey et al. 2017 for a comprehensive study). Our results add to this literature by showing that these are robust to allowing for heterogeneous noise. This appears intuitive as we have no strong reason to believe that personality traits are strongly connected to noisy decision making. Rather, our results suggest that risk preferences are robustly linked to the subjects' personalities (as captured by the Big Five variables). Borghans et al. (2008) similarly conclude that personality traits and cognitive ability are interrelated, but that it is possible to econometrically separate them. This result adds to the literature on the relation between personality measures and risk preferences (see Almlund et al. 2011 for a review). Almlund et al. (2011) report that in the data of Dohmen et al. (2010) agreeableness and openness correlate with risk preferences, a result that we show holds even when controlling for heterogeneous noise.

Related to the findings presented here, Crosetto and Filippin (2016) argue that decision noise leads to bias in most elicitation tasks. Supporting evidence for this finding is presented by Vieider (2018) who shows that the proposed relationship between violence and a preference for certainty, suggested by Callen et al. (2014), appears to be spurious and driven by differences in noisy decision making rather preferences. Bruner (2017) argues that risk aversion causes lower decision errors, which goes counter to the noise argument we propose. Their estimation method builds on a two-step procedure where risk aversion is first estimated and then this measure is correlated against propensities to choose dominated options in a second step. However, the paper fails to recognize the argument made here, that the risk aversion estimate may be biased by decision errors itself. That is, the risk preference measures from the first step are also prone to bias. Indeed, in their elicitation task it can be shown that, for risk-averse decision makers, higher error propensity leads to an overestimation of risk aversion in the first step, implying that the direction of causality may go in the other direction.

5. Conclusion

Establishing relationships between preferences and observable characteristics is inherently difficult since observed choices may be driven by both preferences and bounded rationality. In this paper, we corroborate previous results showing that behavioral noise causes biased inference in risk elicitation tasks. Since such noise is strongly related to many important individual characteristics such as education, age, and cognitive ability, the bias can lead to spurious inference concerning the relationship between measured preferences and these characteristics.

We have argued that two central ingredients in any attempt to remedy the problem are: *i)* a balanced design that involves multiple choice tasks, and *ii)* econometric techniques that allow for heterogeneous noise. In particular, structural estimation with heterogeneity taken properly into account is commendable. Our results show that using balanced designs (in our case pooling the two skewed pricelists from Experiment 1 and Experiment 2) mitigates the bias but may not 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 et al. 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.

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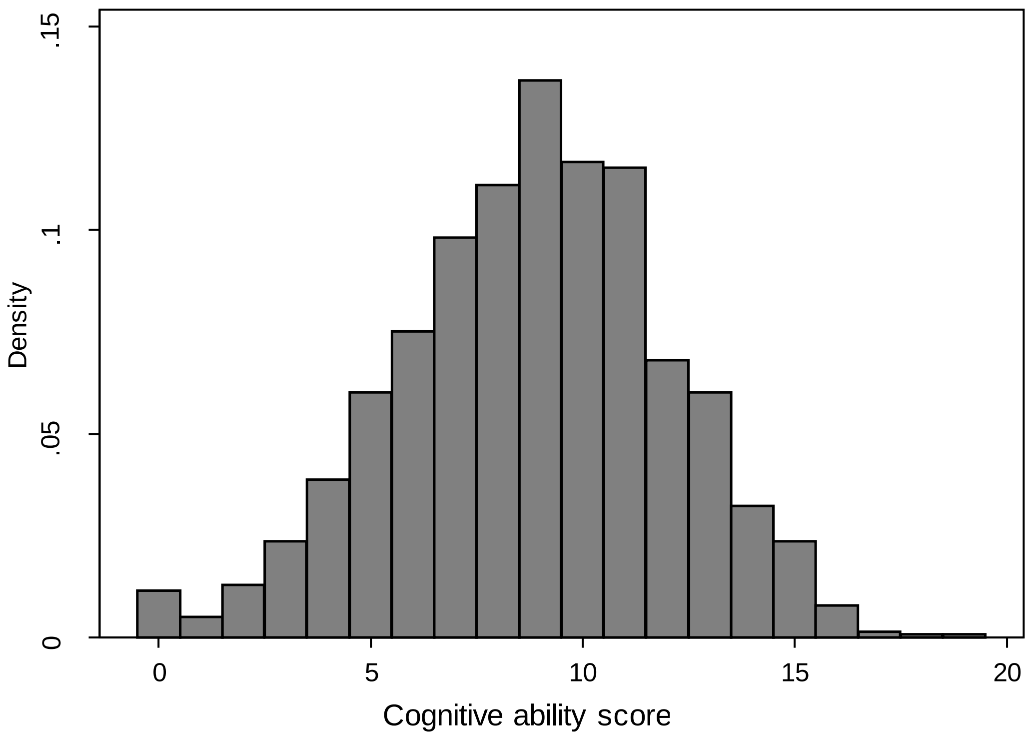
Appendix

This document provides supplementary information to the paper "Robust inference in risk elicitation tasks using structural estimation techniques". The Appendix is organized into two parts. The first part (A) provides some ancillary descriptive statistics of the variables we use in our analysis and additional estimation results. The second part (B) contains screenshots and translations of the instructions.

A. Estimations using random utility models

Figure A1. Distribution of the cognitive ability score (IST)



Notes: The histogram is based on the subjects used in our main analysis. Number of observations = 1,396; Mean cognitive ability score = 8.8; Median cognitive ability score = 9.

Detailed structural estimation results

We estimate our baseline results such that risk aversion only depends on cognitive ability. In a second step, we also allow for heterogeneity in the noise and tremble parameters τ and ω. The results are presented in Table A2 and Table A3 respectively. In these Tables we illustrate the effect of using multiple MPLs or only allowing for homogenous noise. We report results from structural estimations without a heterogeneous noise and tremble specifications (i.e., the noise and tremble terms only estimated with a constant) and using only data from MPL1 or MPL2. When performing the latter we confirm our previous observations in Andersson (2016) of opposite signs of the correlation between cognitive ability and risk aversion (albeit non-significant in the latter estimation).

Table A2: RPM estimates of risk preferences without heterogeneous noise

	MPL1			MPL2			MPL1 + MPL2		
	γ	τ	ω	γ	τ	ω	γ	τ	ω
Cognitive ability	-0.0139***			0.000887			-0.00843*		
	[0.00464]			[0.00332]			[0.00477]		
Female	0.0546*			-0.0101			0.0286		
	[0.0314]			[0.0212]			[0.0302]		
Age	-0.00126			-0.000680			-0.00133		
	[0.00108]			[0.000749]			[0.00101]		
Education1	0.0199			-0.0134			0.00215		
	[0.0547]			[0.0416]			[0.0534]		
Education2	0.0155			-0.0310			-0.0223		
	[0.0540]			[0.0397]			[0.0547]		
Education3	-0.0839			-0.0207			-0.0583		
	[0.0577]			[0.0436]			[0.0554]		
Big5a	0.0518*			0.0574***			0.0778***		
	[0.0302]			[0.0203]			[0.0284]		
Big5c	0.0593**			0.0175			0.0494*		
	[0.0301]			[0.0207]			[0.0273]		
Big5e	-0.0341			-0.0197			-0.0441		
	[0.0307]			[0.0214]			[0.0287]		
Big5n	0.0706**			0.0185			0.0602**		
	[0.0317]			[0.0211]			[0.0287]		
Big5o	0.0768**			0.0182			0.0514*		
	[0.0310]			[0.0204]			[0.0288]		
Constant	0.336***	1.710***	0.154***	0.111*	2.815***	0.304***	0.262***	2.076***	0.255***
	[0.102]	[0.0452]	[0.00735]	[0.0655]	[0.0547]	[0.00506]	[0.0960]	[0.0242]	[0.00460]
Observations	13,960	13,960	13,960	13,960	13,960	13,960	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 dummies determined by the median of the scores of the Big Five personality dimensions. Robust standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3: RPM estimates of risk preferences with heterogeneous noise

	MPL1			MPL2			MPL1 + MPL2		
	γ	τ	ω	γ	τ	ω	γ	τ	ω
Cognitive ability	-0.0130***	-0.00327	-0.00762***	0.0018	-0.0164	-0.00973***	-0.00626	0.0198**	-0.00884***
	[0.00429]	[0.0202]	[0.00260]	[0.00356]	[0.0285]	[0.00155]	[0.00430]	[0.00909]	[0.00144]
Female	0.0608*	0.0312	0.006	-0.00567	0.0376	0.0278***	0.0336	-0.0217	0.0253***
	[0.0312]	[0.159]	[0.0201]	[0.0216]	[0.131]	[0.00997]	[0.0283]	[0.0550]	[0.00933]
Age	-0.00285***	-0.0105**	0.00205***	-0.000398	-0.003	0.00305***	-0.00147	-0.00062	0.00265***
	[0.00106]	[0.00490]	[0.000727]	[0.000837]	[0.00488]	[0.000369]	[0.000926]	[0.00190]	[0.000332]
Education1	0.0272	-0.383	-0.101***	0.00465	0.032	-0.0207	0.039	-0.065	-0.0365**
	[0.0575]	[0.270]	[0.0320]	[0.0422]	[0.206]	[0.0177]	[0.0482]	[0.103]	[0.0155]
Education2	0.0151	-0.408*	-0.0672**	-0.0158	0.105	-0.0330**	0.0101	-0.123	-0.0305**
	[0.0608]	[0.241]	[0.0279]	[0.0428]	[0.214]	[0.0167]	[0.0496]	[0.106]	[0.0149]
Education3	-0.05	-0.273	-0.128***	-0.0082	0.0877	-0.0413**	-0.0217	0.00991	-0.0714***
	[0.0623]	[0.229]	[0.0273]	[0.0464]	[0.238]	[0.0191]	[0.0503]	[0.114]	[0.0164]
Big5a	0.0465	-0.112	-0.00102	0.0547**	-0.0735	0.0170*	0.0724***	-0.106**	0.0083
	[0.0298]	[0.121]	[0.0160]	[0.0235]	[0.187]	[0.00979]	[0.0268]	[0.0538]	[0.00903]
Big5c	0.0429	-0.0198	0.000734	0.0108	0.0189	-0.0126	0.0388	-0.000721	-0.0026
	[0.0289]	[0.0991]	[0.0151]	[0.0215]	[0.137]	[0.00989]	[0.0249]	[0.0514]	[0.00879]
Big5e	-0.0347	0.114	0.0273*	-0.0242	-0.000839	0.00353	-0.0437*	0.061	0.0095
	[0.0286]	[0.0964]	[0.0154]	[0.0251]	[0.207]	[0.00980]	[0.0261]	[0.0550]	[0.00870]
Big5n	0.0539*	-0.152	-0.00292	0.0102	-0.117	0.00997	0.0514*	-0.107*	0.0114
	[0.0305]	[0.105]	[0.0168]	[0.0237]	[0.159]	[0.0103]	[0.0266]	[0.0549]	[0.00903]
Big5o	0.0533*	-0.246	0.0112	0.0206	-0.0115	-0.00473	0.0559**	-0.0632	0.0155*
	[0.0297]	[0.174]	[0.0251]	[0.0219]	[0.164]	[0.00949]	[0.0266]	[0.0600]	[0.00884]
Constant	0.425***	2.780***	0.184***	0.0834	3.114***	0.255***	0.224***	2.126***	0.212***
	[0.0946]	[0.560]	[0.0674]	[0.0669]	[0.469]	[0.0335]	[0.0863]	[0.188]	[0.0297]
Observations	13,960	13,960	13,960	13,960	13,960	13,960	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 dummies determined by the median of the scores of the Big Five personality dimensions. Robust standard errors in brackets. *** p < 0.01, ** p < 0.05, * p < 0.1.

Structural estimation using random utility models

This section presents estimates from a random utility model building on the Luce error structure (introduced by Luce 1959 and popularized by Holt and Laury 2002), adding a tremble parameter that captures the interpretation of errors laid out in Section 2 of the paper.

In the example in Section 2, we introduced noise as a probability to randomly choose between the options. We here estimate this particular noise model explicitly using maximum likelihood techniques. More precisely, we assume that with probability ω an individual chooses at random between the two lotteries Left (L) and Right (R) and with probability (1- ω). In addition the individual evaluates the utility difference with an error that follows a type I extreme value distribution (Luce 1959), i.e a random utility model. This gives rise to the following probability of choosing L:

$$Pr(L) = (1 - \omega)\frac{EU(L)^{1/\tau}}{EU(L)^{1/\tau} + EU(R)^{1/\tau}} + \frac{\omega}{2}$$

We estimate these two specifications using maximum likelihood, including data from both MPL1 and MPL2 and the results are presented in Table A4. Again, in the first model in each table, only the risk aversion parameter γ depends on cognitive ability and other covariates. Again, we observe that γ is significantly related to cognitive ability when we do not let the noise parameter depend on cognitive ability. When we allow also the noise parameters to depend on the cognitive ability, we confirm our previous findings. Cognitive ability is significantly related to the noise parameters but not to the risk aversion parameter. In particular, cognitive ability appears to be strongly related the tremble parameter ω.

Table A4: Estimates of risk preferences and noisiness, Luce model with trembles

	(1)			(2)		
VARIABLES	γ	ω	τ	γ	ω	τ
Cognitive ability	-0.0122***			-0.00571	-0.0176***	-0.00233*
	[0.00438]			[0.00407]	[0.00443]	[0.00126]
Female	0.0356			0.0203	0.0464*	0.00104
	[0.0295]			[0.0283]	[0.0238]	[0.00718]
Age	0.000469			-0.00143	0.00559***	0.000610*
	[0.00114]			[0.00111]	[0.000853]	[0.000321]
Education1	-0.00354			0.0462	-0.0295	-0.0207
	[0.0529]			[0.0715]	[0.0442]	[0.0159]
Education2	-0.00801			0.0357	-0.0389	-0.0103
	[0.0543]			[0.0765]	[0.0444]	[0.0163]
Education3	-0.0789			-0.00631	-0.0886**	-0.0333**
	[0.0573]			[0.0748]	[0.0444]	[0.0156]
Big5a	0.0830***			0.0809***	-0.0182	0.0101
	[0.0273]			[0.0287]	[0.0233]	[0.00811]
Big5c	0.0646**			0.0541*	0.0174	-0.0140
	[0.0283]			[0.0279]	[0.0249]	[0.00860]
Big5e	-0.0520*			-0.0574**	-0.00644	0.00843
	[0.0287]			[0.0289]	[0.0249]	[0.00754]
Big5n	0.0737**			0.0602**	0.0267	0.00204
	[0.0302]			[0.0291]	[0.0265]	[0.00870]
Big5o	0.0783***			0.0666**	0.0438*	-0.00353
	[0.0288]			[0.0295]	[0.0232]	[0.00736]
Constant	0.238***	0.254***	0.127***	0.237**	0.168**	0.123***
	[0.0880]	[0.0207]	[0.00762]	[0.102]	[0.0764]	[0.0258]
Observations	27,920	27,920	27,920	27,920	27,920	27,920

Notes: The sample consists of subjects completing both MPL1 and MPL2. The estimations are based on the CRRA utility function. Cognitive ability measured using the IST test. 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 dummies determined by the median of the scores of the Big Five personality dimensions. Robust standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B. Experimental instructions and screen shots

Screenshot S1: Experiment1, Risk Preference Elicitation Task, Instructions


iLEE Internet Laboratoriet for Eksperimentel Økonomi

Hjælp

Instruktioner - Plat eller krone spillet

På de næste to skærme bedes du gentagne gange vælge mellem to spil.

Du bedes angive, om du foretrækker spillet til VENSTRE eller til HØJRE. Hvert spil har to mulige udfald: PLAT eller KRONE. Chancen for begge udfald er lige stor, dvs. at der i hvert spil er 50% chance for, at udfaldet er PLAT og 50% chance for, at udfaldet er KRONE. Hvis udfaldet bliver plat, får du PLAT-udfaldet af det spil, du har valgt, og hvis det bliver krone, får du KRONE-udfaldet. **Der er ikke nogen rigtige eller forkerte svar. Vælg blot det spil, du foretrækker.**

Eksempel:

			Jeg foretrækker			
	SPIL VENSTRE				SPIL HØJRE	
	PLAT	KRONE	Spillet til venstre	Spillet til højre	PLAT	KRONE
Beslutning 1	Vinder 30 kr.	Vinder 50 kr.	◯	◯	Taber 10 kr.	Vinder 80 kr.

Hvis du vælger spillet til VENSTRE i eksemplet ovenfor, *vinder* du 30 kroner, hvis mønten lander på PLAT, og du *vinder* 50 kroner, hvis den lander på KRONE. Hvis du vælger spillet til HØJRE, *taber* du 10 kroner, hvis mønten lander på PLAT, hvorimod du *vinder* 80 kroner, hvis den lander på KRONE.

På de følgende to skærme kommer to tabeller, hvor du i hver række bedes vælge mellem spil, der ligner dem i eksemplet. Du skal i alt foretage 17 valg.

Når du har truffet alle valg, vil én af de 17 rækker i de to tabeller tilfældigt blive udvalgt. Alle rækker har samme chance for at blive udvalgt. I den udvalgte række vil det spil, du har valgt, blive spillet – det vil sige, at der vil blive slået plat eller krone om det pågældende spils udfald. Herefter bliver din gevinst føjet til din indtjening. Nogle af rækkerne kan imidlertid medføre tab. Hvis den udvalgte række medfører et tab, vil det tabte beløb blive trukket fra din totale indtjening i eksperimentet.

Fortsæt

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Translation S1: Experiment 1, Risk preference elicitation task, Instructions

Instructions - The heads or tails game.

In the two following screens, please choose between two lotteries.

Please state, whether you prefer the lottery to the LEFT or to the RIGHT. Each lottery has two possible outcomes: HEADS or TAILS. The chances of getting either one are equally big, i.e. each lottery has a probability of 50 percent for HEADS and a probability of 50 percent for TAILS. If the outcome is HEADS, you will receive the HEADS outcome of your chosen lottery. If the outcome is TAILS, you will receive the TAILS outcome of your chosen lottery. **There is no right or wrong answer. Just choose the lottery you prefer.**

For example:

			I prefer			
	LEFT LOTTERY				RIGHT LOTTERY	
	HEADS	TAILS	The Left Lottery	The Right Lottery	HEADS	TAILS
Decision 1	Win 30 kr.	Win 50 kr.			Lose 10 kr.	Win 80 kr.

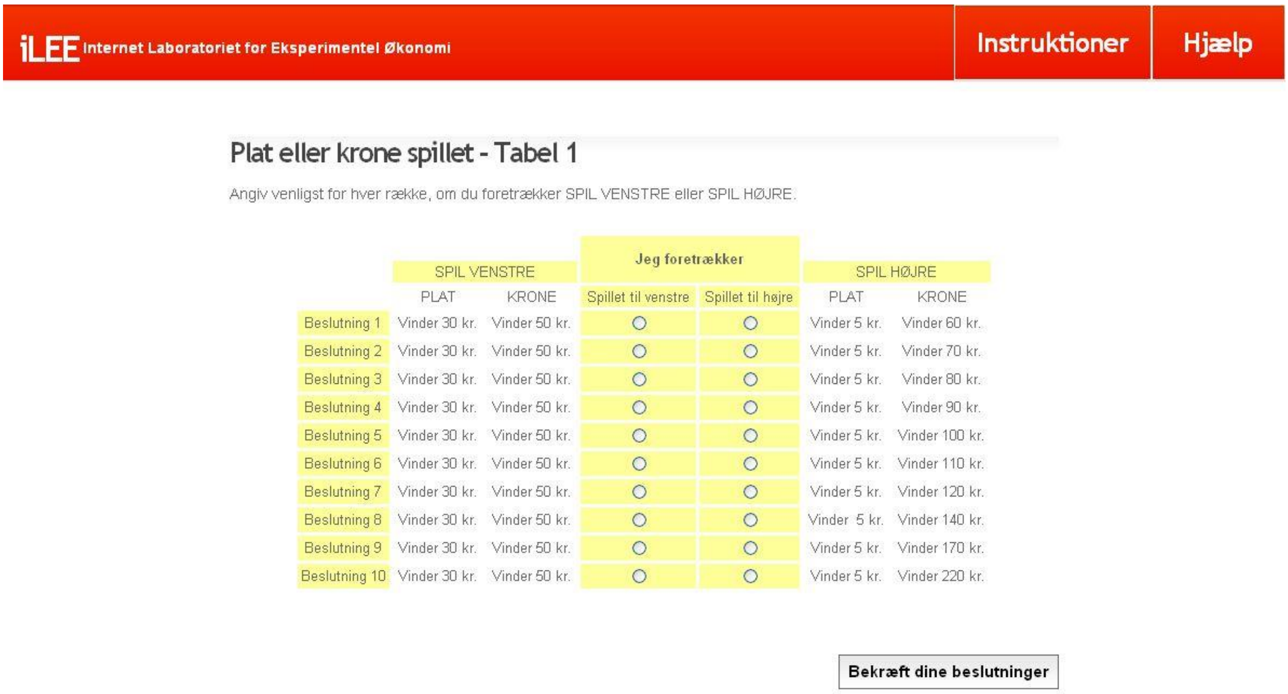
If you choose the lottery to the left in the example above: you will *win* 30 kroner if the coin shows HEADS; and you will *win* 50 kroner if the coin shows TAILS. If you choose the lottery to the right: you will *lose* 10 kroner if the coin shows HEADS; and you will *win* 80 kroner if it shows TAILS.

In the following two screens, there will be two tables, where you will be asked to choose between lotteries similar to the ones in the example. In total, you have to make 17 choices.

When you have made all you choices, one of the 17 rows will be randomly selected. All the rows have the same probability of being chosen. In the selected row, the lottery you have chosen will be played out – which means a coin will be flipped to determine the outcome of the lottery. Thereafter, your earnings will be added to your income. However, some of the rows can bring losses. If the selected row induces a loss, that loss will be deducted from your total income in the experiment.

Continue

Screenshot S2: Experiment 1, Risk Preference Elicitation Task, Price List 1



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Plat eller krone spillet - Tabel 1

Angiv venligst for hver række, om du foretrækker SPIL VENSTRE eller SPIL HØJRE.

	SPIL VENSTRE		Jeg foretrækker		SPIL HØJRE	
	PLAT	KRONE	Spillet til venstre	Spillet til højre	PLAT	KRONE
Beslutning 1	Vinder 30 kr.	Vinder 50 kr.	○	○	Vinder 5 kr.	Vinder 60 kr.
Beslutning 2	Vinder 30 kr.	Vinder 50 kr.	○	○	Vinder 5 kr.	Vinder 70 kr.
Beslutning 3	Vinder 30 kr.	Vinder 50 kr.	○	○	Vinder 5 kr.	Vinder 80 kr.
Beslutning 4	Vinder 30 kr.	Vinder 50 kr.	○	○	Vinder 5 kr.	Vinder 90 kr.
Beslutning 5	Vinder 30 kr.	Vinder 50 kr.	○	○	Vinder 5 kr.	Vinder 100 kr.
Beslutning 6	Vinder 30 kr.	Vinder 50 kr.	○	○	Vinder 5 kr.	Vinder 110 kr.
Beslutning 7	Vinder 30 kr.	Vinder 50 kr.	○	○	Vinder 5 kr.	Vinder 120 kr.
Beslutning 8	Vinder 30 kr.	Vinder 50 kr.	○	○	Vinder 5 kr.	Vinder 140 kr.
Beslutning 9	Vinder 30 kr.	Vinder 50 kr.	○	○	Vinder 5 kr.	Vinder 170 kr.
Beslutning 10	Vinder 30 kr.	Vinder 50 kr.	○	○	Vinder 5 kr.	Vinder 220 kr.

Bekræft dine beslutninger

Translation S2: Experiment 1, Risk Preference Elicitation Task, Price List 1

The Head or Tails game – Table 1

For each row, please state if you prefer the LEFT LOTTERY or the RIGHT LOTTERY.

	LEFT LOTTERY		I prefer		RIGHT GAME	
	HEADS	TAILS	The left lottery	The right lottery	HEADS	TAILS
Decision 1	Win 30 kr.	Win 50 kr.			Win 5 kr.	Win 60 kr.
Decision 2	Win 30 kr.	Win 50 kr.			Win 5 kr.	Win 70 kr.
Decision 3	Win 30 kr.	Win 50 kr.			Win 5 kr.	Win 80 kr.
Decision 4	Win 30 kr.	Win 50 kr.			Win 5 kr.	Win 90 kr.
Decision 5	Win 30 kr.	Win 50 kr.			Win 5 kr.	Win 100 kr.
Decision 6	Win 30 kr.	Win 50 kr.			Win 5 kr.	Win 110 kr.
Decision 7	Win 30 kr.	Win 50 kr.			Win 5 kr.	Win 120 kr.
Decision 8	Win 30 kr.	Win 50 kr.			Win 5 kr.	Win 140 kr.
Decision 9	Win 30 kr.	Win 50 kr.			Win 5 kr.	Win 170 kr.
Decision 10	Win 30 kr.	Win 50 kr.			Win 5 kr.	Win 220 kr.

Confirm your decisions

Screenshot S3: Experiment 1, Raven progressive matrices – instruction

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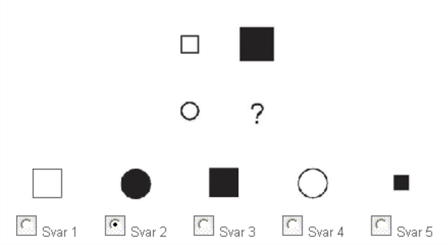
Instruktioner - Logiske Opgaver

Du er næsten færdig med eksperimentet. Det sidste, vi vil bede dig om, er at løse nogle logiske opgaver.

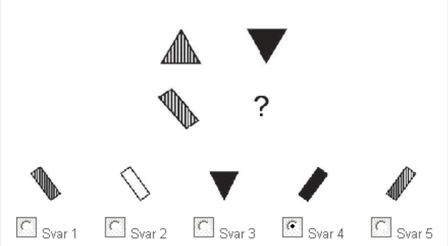
På hver af de følgende opgaver vil du øverst se et billede, som mangler en figur. Under billedet ser du fem figurer, hvoraf én fuldender billedet. Du bedes finde ud af, hvilken af de fem valgmuligheder, som skal indsættes i stedet for spørgsmålstegnet i billedet.

Eksempel 1



I den øverste række af billedet i eksempel 1 bliver den lille hvide firkant til en stor sort firkant. Derfor må den lille hvide cirkel i nederste række blive til en stor sort cirkel. Det korrekte svar i eksempel 1 er altså "Svar 2".

Eksempel 2



I eksempel 2 bliver trekanten i øverste række af billedet spejlet horisontalt (trekanten bliver vendt på hovedet) og bliver sort. Derfor skal rektanglet i nederste række også spejles horisontalt og blive sort. Det korrekte svar i eksempel 2 er altså "Svar 4".

Hver opgave har én logisk korrekt løsning. For hver opgave skal du klikke på den svar mulighed, du mener er den rigtige, herefter skal du trykke på Bekræft svar for, at dit svar bliver registeret.

Du har præcis **10 minutter** til at løse så mange af opgaverne som muligt; derefter afsluttes del 3 automatisk. **Forvent ikke at nå at løse alle opgaverne**. I løbet af de 10 minutter kan du **gå frem og tilbage mellem opgaverne, og du har mulighed for at ændre dine svar.** Du kan gå frem og tilbage i opgaverne på to måder. 1) Inden for de 10 minutter vil du kunne se en oversigtslinje i bunden af skærmen. Ved at trykke på tallene på den linje, kan du komme til den ønskede opgave 2) I hver ende af oversigtslinjen kan du også trykke på enten frem eller tilbage pilene.

Du kan til enhver tid forlade de logiske opgaver, selvom de 10 minutter ikke er gået. Skulle du ønske dette, trykker du blot på Afslut opgaverne.

Når du er klar til at gå i gang med at løse opgaverne, tryk da Start opgaver. Når de 10 minutter er gået, afsluttes de logiske opgaver automatisk. Bemærk, at såfremt du logger ud undervejs og vender tilbage senere, vil du ikke have mulighed for at fortsætte de logiske opgaver, men vil komme videre til afslutningen af eksperimentet.

Start opgaver

Translation S3: Experiment 1, Raven progressive matrices – instructions

Instructions - Logical problems.

You are almost done with the experiment. The last task we ask of you is to solve some logical problems.

At the top of each of the following problems, you will see a picture that is missing a figure. Below the picture you will see five figures, one of which completes the picture. Please determine which one of the five possible answers should be inserted to replace the question mark in the picture.

Example 1

In the top row of the picture in example one, the small white square becomes a big black square. Thus the small white circle in the bottom row will become a big black circle. The correct solution in example 1 is therefore “Answer 2”

Example 2

In example 2, the triangle in the top row was mirrored horizontally (the triangle was turned upside down) and colored black. Thus, the rectangle in the bottom row should also be mirrored horizontally and colored black. The correct solution example in example 2 is therefore “Answer 4”

Each problem has one logical solution. In each problem you have to click on the answer you believe is correct, and then press Confirm Solution for your answer to be registered.

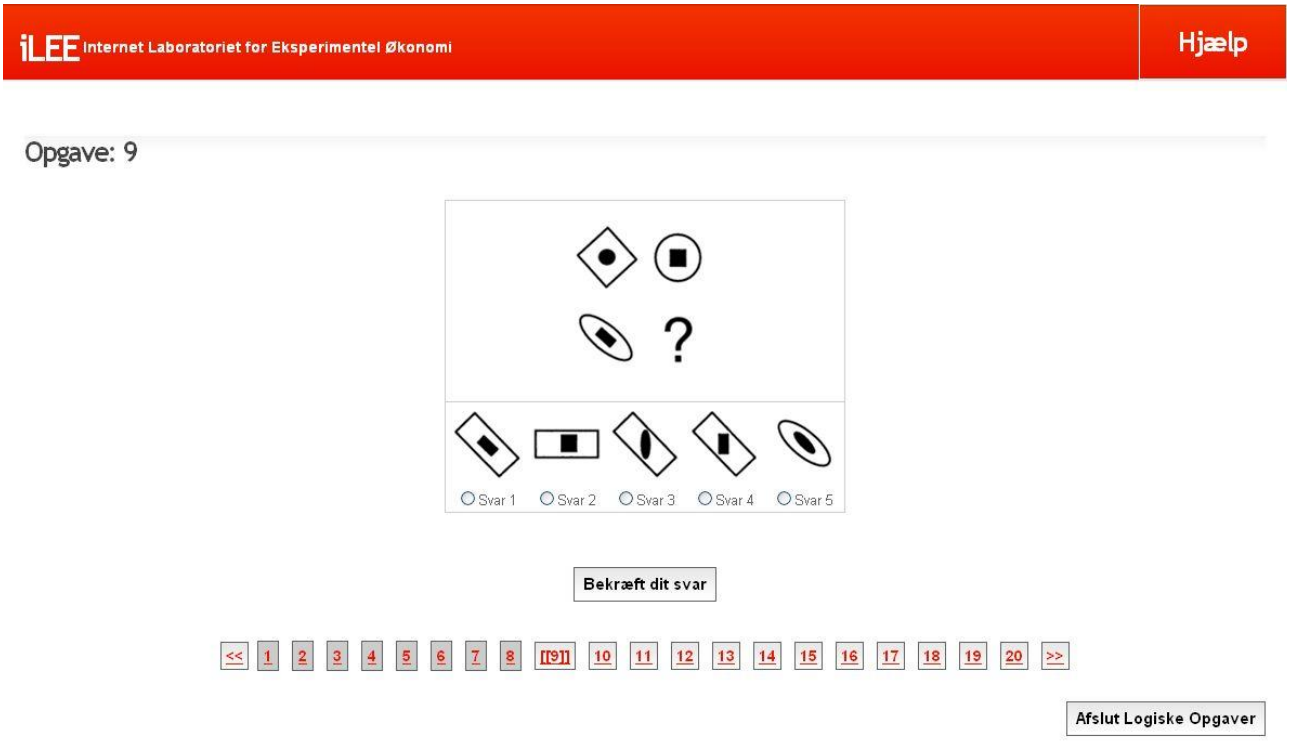
You have exactly **10 minutes** to solve as many of the problems as possible, and then part 3 will be automatically finished. **Do not expect to solve all the problems**. During the 10 minutes, you **can skip back and forth between the problems and you have the possibility of changing your answers.** You can skip between the problems in two ways. 1) During the 10 minutes you will see an overview line at the bottom of the screen. By pressing the numbers on that line, you can jump to the desired problem. 2) At the ends of the overview line you can press either the forward or back arrows.

You can leave the logical problem anytime you wish, even though the 10 minutes have not passed. Should you wish to do so, just press Finish Problems.

When you are ready to start solving the problems, press Start problems. When the 10 minutes have passed, the problems will end automatically. Note, that if you log out on the way and return later, you will not be able to continue the logical problems, but will be taken to the finish the experiment stage.

Start Problems

Screenshot S4: Experiment 1, Raven progressive matrices – decision



Translation S4: Experiment 1, Raven progressive matrices – decision

Confirm you answer

<< 1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20 >>

Finish Logical Problems

Screenshot S5: Experiment 1, Personality traits

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Hjælp

Nogle udsagn om dig

På denne og de følgende to skærme finder du en række udsagn. Læs hvert udsagn omhyggeligt og marker, hvor godt det passer på dig.

Sæt en markering i:

"Meget uenig"	hvis udsagnet er 100 % forkert, eller du er meget uenig.
"Uenig"	hvis udsagnet stort set er forkert, eller hvis du er uenig.
"Neutral"	hvis udsagnet hverken er særlig rigtigt eller forkert, eller hvis du er i tvivl eller er neutral over for udsagnet.
"Enig"	hvis udsagnet stort set er rigtigt, eller hvis du er enig.
"Meget enig"	hvis udsagnet er 100 % rigtigt, eller du er meget enig.

Der er ingen rigtige eller forkerte svar, og besvarelse af spørgsmålene forudsætter ingen særlig viden. Besvar alle spørgsmål og beskriv dig selv så ærligt og præcist som muligt.

	Meget uenig	Uenig	Neutral	Enig	Meget enig
Jeg er kendt for min dømmekraft og sunde fornuft	○	○	○	○	○

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Nogle mennesker anser mig for at være kold og beregnende	○	○	○	○	○
	Meget uenig	Uenig	Neutral	Enig	Meget enig

Bekræft dine beslutninger

Translation S5: Experiment 1, Personality traits

Some statements about you

In this and the following screens, you will find a number of statements. Read each of the statements carefully and mark how well they fit you.

Mark either:

“Disagrees a lot” if the statement is 100 percent incorrect or you disagree a lot.

“Disagrees” if the statement is wrong on the whole or if you disagree.

“Neutral” if the statement is neither very wrong nor right, or if you are in doubt or neutral towards the question.

“Agrees” if the statement is correct on the whole, or if you agree.

“Agrees a lot” if the statement is 100 percent correct, or if you agree a lot.

There are no right or wrong answers, and the completion of the questions does not presume any special knowledge. Answer all the questions and describe yourself as honestly and precisely as possible.

	Disagrees a lot	**Disagrees**	**Neutral**	**Agrees**	**Agrees a lot**
.....					
	Disagrees a lot	Disagrees	Neutral	Agrees	Agrees a lot

Confirm your decisions

Screenshot S6: Experiment 2, Risk Preference Elicitation Task, Instructions

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Hjælp

Valg mellem plat eller krone-spil

I tredje del af sidste års eksperiment skulle du gentagne gange foretage valg mellem to forskellige spil plat eller krone. Denne øvelse ønsker vi nu at gentage med nogle andre udfald. Her kommer en genopfriskning af instruktionerne:

Angiv, om du foretrækker spillet til VENSTRE eller spillet til HØJRE. Hvert spil har to mulige udfald, PLAT eller KRONE. Udfaldet afgøres tilfældigt, og begge udfald er lige sandsynlige. Hvis udfaldet er PLAT, får du resultatet angivet neden under PLAT. Hvis udfaldet er KRONE, får du resultatet neden under KRONE.

Der er ingen rigtige eller forkerte svar. Du skal blot vælge de spil, som du foretrækker.

I alt vil du blive bedt om at foretage 20 valg. En af de 20 rækker vil blive tilfældigt udvalgt til betaling. Alle rækkerne har samme sandsynlighed for at blive udvalgt. For den udvalgte række vil dit foretrukne spil blive spillet, og udfaldet PLAT eller KRONE vil bestemme din indtjening. Nogle af rækkerne kan udløse tab, som i givet fald vil blive trukket fra din samlede indtjening i eksperimentet.

Her kommer et eksempel.

EKSEMPEL

	VENSTRE		Jeg foretrækker		HØJRE	
	KRONE	PLAT	Spillet til VENSTRE	Spillet til HØJRE	KRONE	PLAT
Beslutning 1	Vind 25 kr.	Vind 45 kr.	○	○	Vind 2 kr.	Vind 40 kr.

Hvis du vælger spillet til VENSTRE, vinder du 25 kr., hvis udfaldet er KRONE, og 45 kr., hvis udfaldet er PLAT. Hvis du vælger spillet til HØJRE, vinder du 2 kr., hvis udfaldet er KRONE, men vinder 40 kr., hvis udfaldet er PLAT.

Fortsæt >>

Kommentar

Translation S6: Experiment 2, Risk preference elicitation task, Instructions

Choose between Heads and Tails lotteries

In the third part of last year's experiment, you made a series of choices between two lotteries. We now would like you to repeat this task, but with somewhat different outcomes. There follows a repetition of the instructions.

Please state, whether you prefer the lottery to the LEFT or to the RIGHT. Each lottery has two possible outcomes: HEADS or TAILS. The outcome is randomly determined, and each outcome is equally likely. If the outcome is HEADS, you will receive the outcome stated below HEADS. If the outcome is TAILS, you will receive the outcome stated below TAILS.

There is no right or wrong answer. Just choose the lottery that you prefer.

You will be asked to make a total of 20 choices. One of the 20 rows will be randomly selected for payment. All rows have the same probability of being chosen. In the selected row, the lottery you have chosen will be played out and the outcome HEADS or TAILS will determine your earnings. Some of the rows can bring losses, which will be deducted from your total income in the experiment.

Here is an example:

			I prefer			
	LEFT LOTTERY				RIGHT LOTTERY	
	HEADS	TAILS	The Left Lottery	The Right Lottery	HEADS	TAILS
Decision 1	Win 25 kr.	Win 45 kr.			Win 2 kr.	Win 40kr.

If you choose the LEFT lottery, you will *win* 25 kroner if the coin shows HEADS, and 45 kroner if the coin shows TAILS. If you choose the RIGHT lottery, you will *win* 2 kroner if the coin shows HEADS, but you will *win* 40 kroner if the outcome is TAILS.

Continue

Screenshot S7: Experiment 2, Risk Preference Elicitation Task


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Valg mellem plat eller krone-spil (1/2)

Angiv dine foretrukne spil.

	VENSTRE KRONE	VENSTRE PLAT	Jeg foretrækker: Spillet til VENSTRE	Jeg foretrækker: Spillet til HØJRE	HØJRE KRONE	HØJRE PLAT
Beslutning 1	Vind 25 kr.	Vind 45 kr.			Vind 2 kr.	Vind 40 kr.
Beslutning 2	Vind 25 kr.	Vind 45 kr.			Vind 2 kr.	Vind 50 kr.
Beslutning 3	Vind 25 kr.	Vind 45 kr.			Vind 2 kr.	Vind 55 kr.
Beslutning 4	Vind 25 kr.	Vind 45 kr.			Vind 2 kr.	Vind 60 kr.
Beslutning 5	Vind 25 kr.	Vind 45 kr.			Vind 2 kr.	Vind 65 kr.
Beslutning 6	Vind 25 kr.	Vind 45 kr.			Vind 2 kr.	Vind 70 kr.
Beslutning 7	Vind 25 kr.	Vind 45 kr.			Vind 2 kr.	Vind 75 kr.
Beslutning 8	Vind 25 kr.	Vind 45 kr.			Vind 2 kr.	Vind 95 kr.
Beslutning 9	Vind 25 kr.	Vind 45 kr.			Vind 2 kr.	Vind 135 kr.
Beslutning 10	Vind 25 kr.	Vind 45 kr.			Vind 2 kr.	Vind 215 kr.

Indsend svar

Translation S7: Experiment 2, Risk Preference Elicitation Task

Choose between Head or Tails lotteries – (1/2)

Please state which lotteries you prefer.

	LEFT LOTTERY		I prefer		RIGHT GAME	
	HEADS	TAILS	The left lottery	The right lottery	HEADS	TAILS
Decision 1	Win 25 kr.	Win 45 kr.			Win 2 kr.	Win 40 kr.
Decision 2	Win 25 kr.	Win 45 kr.			Win 2 kr.	Win 50 kr.
Decision 3	Win 25 kr.	Win 45 kr.			Win 2 kr.	Win 55 kr.
Decision 4	Win 25 kr.	Win 45 kr.			Win 2 kr.	Win 60 kr.
Decision 5	Win 25 kr.	Win 45 kr.			Win 2 kr.	Win 65 kr.
Decision 6	Win 25 kr.	Win 45 kr.			Win 2 kr.	Win 70 kr.
Decision 7	Win 25 kr.	Win 45 kr.			Win 2 kr.	Win 75 kr.
Decision 8	Win 25 kr.	Win 45 kr.			Win 2 kr.	Win 95 kr.
Decision 9	Win 25 kr.	Win 45 kr.			Win 2 kr.	Win 135 kr.
Decision 10	Win 25 kr.	Win 45 kr.			Win 2 kr.	Win 215 kr.

Confirm your decisions