LUND UNIVERSITY
School of Economics and Management

Cognitive Ability and Economic Decision Making

A study comparing cognitive reflection and intelligence quotient in decision time in various economic situations

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Advisor
Erik Wengström

Authors
Laila Bjöörn and Linn Karlsson

Abstract

Cognitive ability can be measured with several different instruments. The first thing that springs to mind is probably IQ or knowledge tests, such as the SAT. In 2005, a new test came out on the market, the cognitive reflection test (CRT). This test was constructed differently, namely to capture cognitive reflection, an ability to use system 2 in an effective way. System 2 is a concept from the dual-process theory, which states that our mind is processed with two main systems, system 1 and 2. System 1 is always active, and can be described as our intuitive system. However, when more difficult tasks need to be dealt with, system 2 needs to be activated. It is more complex, and also slower, than system 1. System 2 is deliberate, and thus, more often generates proper results, while system 1, sometimes can be sloppy. A high score on the CRT is assumed to be related to an active system 2, as the questions are constructed to generate an intuitive but incorrect answer. This study aims to examine whether there is a difference between an ordinary IQ measure and the CRT. We examine four different situations in the field of behavioural economics; decision making between lotteries (with and without losses), the public good game and the dictator game. We purpose to clarify and summarize the effects, as well as differences in effect, for CR and IQ in general, and fill out the gaps where previous research is scarce. This seems to be especially relevant for the decision time analysis, seeing that the CRT is a fairly young measure, in contrast to traditional IQ measures. Hence, our main focus is to examine the differences in decision times from these games, and whether these differences, in turn, are related to better answers and outcomes. The results we obtain do confirm that individuals with high CR have a slower decision speed for some tasks. It also confirms that these individuals make more rational and utility maximizing choices, even more so, than individuals with high IQ. We also found that CR can be a better predictor of behaviour in certain situations. Basically, we can confirm that there exists a difference between these measures, and thus, that they do capture different dimensions of cognitive ability.

Keywords: cognitive reflection test (CRT), intelligence quotient (IQ), decision time, economic decision making, dual process theory

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1 Introduction

Intelligence and cognitive thinking can be interpreted in many different ways, and thus, also be measured differently. The first thing that often springs to mind when hearing the word intelligence is intelligence quotient (IQ). IQ can be measured with several tests, which are often based on logical thinking tasks, made out of illustrations, rather than pure knowledge tasks. However, there are various ways to examine cognitive behaviour, and thus, one person can be “intelligent” in different ways. Kahneman (2013), among others, discusses that a person’s cognitive behaviour consists of two systems, one fast and intuitive (system 1), as well as another slow but deliberate system, which is activated in difficult and more complicated situations (system 2). Frederick (2005) constructed a test to measure this type of cognitive ability, the cognitive reflection test (CRT), which consists of three questions, especially designed to encourage an intuitive, but incorrect, answer. This type of test does not merely evaluate the logical thinking process, but rather the activeness of system 2. In other words, it measures how careful one is when making decisions, which in turn, may lead to making better ones.

According to a larger literature, economic outcomes have shown to be affected by cognitive ability, and it is thus interesting for economists to investigate these measures, in terms of how, and to what extent, their effect is present in different economic settings. Further research in this field is useful to improve understanding of underlying factors that create individual differences in decision making and choice theory, in order to successfully incorporate this information in economic models (Borghans et al. 2008). One field, among others, in which cognitive ability has been widely employed by economists, is the financial markets. By investigating if and how cognitive ability affects choices and their outcomes in this field, economists have observed, for example, that IQ has a large impact on individuals’ participation in financial markets, indicating that a high IQ increases the probability of participation. Additionally, it has been observed that, among those who actually do choose to participate in the financial markets, a higher IQ is, for instance, associated with having a larger stock hold and lower risk (Grinblatt et al. 2011). It has also been found that relatively smart investors, measured in IQ, tend to perform better in trading, than relatively “dumb” investors (Grinblatt el al. 2012). Further on, IQ has been shown to have an impact on mutual fund choice, indicating that individuals with high IQ are less prone to invest in funds with high management fees (Grinblatt et al. 2014).

Linking this to a more general perspective, it is understandable that information concerning cognitive ability in behavioural economics and decision making do have implications for economic and financial policies and regulations. Recent literature proposes that choices are affected by an individual's decision-making ability, which is dependent on whether or not they have acquired a sufficient level of knowledge that is needed to make better choices. Based on this assumption, it further implies that individuals can make choices of different decision-making quality, depending on their level of ability (Choi et al. 2014). Making choices of different character can influence both individual and aggregate economy. For example, if choice quality in fact is related to cognitive ability, which in turn is related to education, this could possibly, to some extent, explain phenomena's such as growing financial segregation in societies. If IQ and/or CR is related to making better choices, as well as to education, it is likely for individuals with high decision-making ability not only to earn more than their counterparts, but also to keep on making better decisions in different financial situations (as noted above), and by doing so keep getting ahead in life, whereas the reverse relationship then could be assumed for their counterparts. This would then imply that inequalities in society could keep on growing, unless accounted for in financial policy and regulations. Given that the CRT is a relatively new measure, in comparison to IQ tests, it is relevant to examine the relation of CR alone, to different fields of decision making, as well as the relation between CR and IQ in these areas, in order to provide further information to this literature.

One of the essential decisions, when it comes to analysis of cognitive ability, is how you choose to measure and define this term, as we mentioned that it can be specified in several ways. Since Frederick (2005) introduced the CRT, ten years ago, the measure has gained a foothold in this research field. However, still most research only takes into account one measure, in reference to cognitive ability, being either cognitive reflection or some other (e.g. IQ). Consequently, we have observed only a few studies examining CR in relation to other measures of cognitive ability, where the research is especially scarce in contrast to the intelligence quotient (IQ), which for long has been viewed as one of the most reliable measures of cognitive ability.

Ergo, in this study we aim to examine the *difference* between CR and IQ measured cognitive ability, when looking at different mechanisms in decision making, such as risk taking and money distribution. Our main focus lies on the time spent on these tasks, and thus, to examine whether there exists a significant difference between these measures. We do believe that this difference exists, because, even though CR and IQ correlate positively, they do not correlate perfectly. Hence, we have incentives to believe that the measures, to some extent, capture different aspects of cognitive ability.

Regarding the general relationship between these measures, prior studies have found that low IQ is related to low CR, whereas high IQ is somewhat more or less independent of the level of CR (Moritz et al. 2014). Keeping this in mind, we could expect our results to head in the same direction, meanwhile, we also need to remember the fact that our vast sample is quite deviating from former studies, and we can thus not be too sure of drawing the same conclusions.

Finally, concerning our main analysis we have chosen to focus on the decision speed, with the purpose of finding a relation between different response times and different levels of CR. If the theory of dual-process systems is truthful, this should be visible in our results. We have not yet seen much research that put their main focus on the time spent on various tasks in relation to CR. Although, it has been shown that response time, as well as CR and IQ, in different extents, correlates with social preferences in different economic games, such as public good and dictator games (see sections 2.3 and 2.4). So, in line with the assumption of dual-process systems, we hypothesize that individuals with high CR should spend more time on making their decisions, than individuals with a lower score, as the former are presumed to be more deliberate and thoughtful in their decision making, and thus, may have a more active use of their system 2.

Unlike most studies conducted in this field, our study differentiates regarding the vast sample data both in terms of size and variation. A majority of prior studies have been examining students, which can cause biases due to lacking variation not only in age, but also in other individual characteristics, that can be assumed to be similar in such a narrow sample of subjects. As our data is consisting of a large and random sample, with a lot of variation among individuals, these kinds of biases should not be as pronounced in this study.

Using various regressions we examine the relations between cognitive ability, in form of CR and IQ, in four different situations; 1) risk aversion decision making, 2) loss aversion decision making, 3) public good game, and 4) dictator game. The first two decision making gambles are basically a series of choices between two lotteries, both with 50/50 chance outcomes. One lottery is considered the safe choice whereas the other is relatively risky. For the loss aversion gamble, the lotteries can also include possible losses. The shift point chosen in these gambles (i.e. the point in the series where the risky lottery is chosen), says something about how efficient individuals are, and we aim to analyse if differences in cognitive ability affect this choice. The third and fourth situation involves distributing money. In the public good game, the participants choose to put some amount of money into a common pot, which will be doubled and split equally among four participants. The dictator game works between two individuals, where the active participant will distribute money between him/her and the other participant, without this passive participant having any influence. These situations say something about fairness, and of course, we are interested in how cognitive ability affects this aspect. However, as mentioned, our primary analysis, concerns the decision times for these situations, as we believe that there exists a difference between the two measures, especially when examining this part.

Correspondingly, from our results, it turns out that it does. We do find that an increase in CR leads to an increase in decision time, at least for some of the analysed situations. At the same time, IQ decreases decision time, implying there to be a difference in these measures. CR is supposed to measure how well an individual can make use of their system 2. If a high CR, in fact, is related to an active system 2 usage, then our findings are reasonable, as system 2 is assumed to be slow. We do not find this relation with IQ, because IQ seemingly does not capture this specific ability.

Finally, we observe that high CR individuals do make more efficient decisions, and therefore conclude that the extra time spent on making the decision, is worthwhile. However, there are studies that show that these results may be spurious, due to biases induced in the decision making tests, a matter discussed further in upcoming sections. Additionally, we find that cognitive ability, both measured as CR and IQ increases the probability of being selfish in the dictator game. We also observe that a high CR decreases the probability of being fair in the same game. These results can be related to the fact that intuitive (short decision time) individuals are fair in a larger extent than non-intuitive (long decision time) individuals (Cappelen et al. 2014), and therefore, a high CR, related to a longer decision time, may decrease the probability of being fair for that reason. If this is true, then it might not be surprising that we find a high CR to be related to unfairness.

1.1 Limitations

We have limited this study to comparing only the cognitive ability measures of CR and IQ. This is mainly due to the fact that the database we used (the Internet Laboratory for Experimental Economics, i.e. iLEE), had not performed any other tests on the participants at the time. If more time was at hand, it would have been particularly interesting to use a newer, extended version of the CRT including further questions, for reasons discussed in upcoming sections. Further on, it would have been interesting to examine additional measures of cognitive ability, especially further measures of intelligence.

1.2 Disposition

The remaining part is organized as follows; first we present earlier studies conducted in this field and their main results. Second follows a theoretical framework of the key concepts from which we have constructed our analysis. Further on we describe the data sample, followed by a systematic report of the method that has been used and the results obtained. Lastly, we derive a discussion of our own findings, in the context of previous research in the field, as well as a discussion of ideas that could be interesting for future researchers.

2 Previous research

2.1 Cognitive ability and risk preferences

As the inventor of the CRT, Frederick (2005) was among the first to study the relationship between CR and risk preferences in decision making. In his study, he found that individuals who scored high on the CRT, i.e. those with relatively high CR, were more prone to choose the risky option, in a gamble between a safe and a relatively risky choice. This result was obtained, regardless of the value of the expected gain. The fact that cognitive ability in this case was measured with the CRT, tells us that the results might, not entirely, be due to skills in calculating expected returns, and thus, not entirely due to mathematical skills, which it might have been if it was tested with a test like the SAT_M[1] or similar. He further observed that this relation does not hold for losses, and concluded that according to his findings, the theory of loss aversion (from prospect theory), i.e. that individuals turn from risk seeking when facing losses, to risk avert when facing gains, does only apply for individuals with relatively low CR. These results have been furtherly confirmed, by using several different measures of cognitive ability, in a great deal of research (e.g. Burks et al. 2009; Dohmen et al. 2010; Benjamin et al. 2013; Cueva et al. 2015).

However, recent evidence argues that the relation found in the above results may be spurious. Andersson et al. (2013) suggest that the effect of cognitive ability on risk preferences is biased by noise, depending on the gamble presented. In their study (based on the same outset of data from iLEE as used in the present study) they found that a bias is definitely at hand. However, they show that cognitive ability decreases how affected an individual is by this noise, and thus, the bias will be less intense. If the less cognitively able individuals were not biased by the structure of the test, they might be as efficient as individuals with higher cognitive ability in their choices. And thus, we cannot say anything about the performance of low cognitive ability individuals from these tests. This, in turn, is what makes the results spurious. We will describe this bias in more detail in section 4.2.4.

[1] The Scholastic Achievement Test for mathematical skills.

2.2 Cognitive ability and gender

In addition, when investigating the CRT, Frederick (2005) found an interesting result regarding the scores and differences in gender. In his analysis, women scored significantly lower than men, even when controlling for SAT scores. This result has gained a lot of attention lately, and has by that been replicated and further validated by a large literature (e.g. Oechssler et al. 2009; Obrecht et al. 2009; Brañas-Garza et al. 2012; Cueva et al. 2015). However, not only did he observe that women, on average, obtained lower scores than men, he also found that the women who had submitted a wrong answer, in further extension than men, tended to give an intuitive response, whereas men who did not manage to find the correct answer, more often, submitted a random response. Supplementary, Cueva et al. (2015) also discovered that women's answers on the CRT were more intuitive than those of men, when considering the incorrectly answered questions. This is a result which, along the line of the dual-process theory, possibly could be explained by the differences in CR between genders, observing that women who tend to obtain a lower CRT score also act more impulsive, than men in the corresponding situation.

When Campitelli and Labollita (2010) examine the relation of CR and the sex variable, their results regarding the correlation between cognitive reflection scores and gender were in line with those of Frederick (2005), though not significantly. On the other hand, they were not able to find any support for the fact that women would be more inclined to make intuitive errors than men, in opposition to the results mentioned above.

Moving on to other measures of cognitive ability, with focus on different IQ tests, in relation to gender, generally, these do not seem to differ particularly between men and women, in the way that CR seemingly does (Halpern et al. 2011). However, a more extensive discussion on this topic will be held in section 3.2.

2.3 Cognitive ability and response time

We have come across several researchers who have investigated response times in different economic settings of decision making (e.g. Rubinstein, 2007; Piovesan and Wengström, 2008; Brañas-Garza et al. 2012; Nielsen et al. 2014; Cappelen et al. 2014). For example, Rubinstein (2007) suggests that "choices made instinctively, that is, on the basis of an emotional response, require less response time than choices that require the use of cognitive reasoning." (p. 1243). By categorizing actions as being cognitive, instinctive and reasonless, he finds support for this idea through a review of several economic games and the response times of the included tasks. Still we have not yet seen research that specifically focuses their analysis on the CRT, as a measure of cognitive ability, in relation to decision speed. This in fact, could be thought of as fairly strange, as CR and the time spent on decision making, are two concepts assumed to be closely related, originating from a dual-process view.

Given that previous research in this specific domain seems to be quite scarce, we have found one analysis, even if more or less out of our context, that discuss this relationship. Studying the influence of individual differences in CRT scores on performance in judgmental time-series forecasting, Moritz et al. (2014) firstly raise some concerns regarding the results of different decision times, by discussing the possibility of under- or over-thinking a decision. As under-thinking may be connected to a more intuitive behaviour, over-thinking in turn is connected to more deliberation and reflection. The authors mean that a reflective behaviour must not be improving decision making at all times, as the phenomenon of over-thinking in some situations rather may decrease it. This is due to the fact that a longer decision time may make it harder for individuals to find proper weighting schemes for different decisions. Interestingly, the authors find that a higher CRT score is linked to a lesser tendency of over- and under-thinking decisions, as the individuals with high CRT consistently spent a more moderate amount of time in making their decisions, in this case meaning that they were closer to the decision time the authors had predicted in advance (Moritz et al. 2014). Thus, they were, in general, not victims of over-thinking, as one could have expected, considering the connection to a more thoughtful behaviour, but instead these individuals managed to overcome this barrier.

Consequently, as the individuals who scored high on the CRT, were consistently more moderate in making their decisions, they found that these individuals displayed a lower variance in decision speed, in contrast to the individuals with lower scores. Further on, they noticed that high CRT scoring individuals performed better forecasts (even when controlling for intelligence as the Wonderlic Personnel Test, WPT[2]). Following, they found that notably long or short decision times produced higher forecast errors than moderate decision times. To conclude, they suggest that manipulating decision times may help to improve decision performance, at least in their specific context of forecasting.

Moving over to response times in relation to intelligence, the field is considerably wider, not surprisingly, regarding the difference in time that these two types of measures have existed. The results seem to be mixed, some prior literature suggests a negative relation

[2] See section 3.2 for a description of the Wonderlic Personnel Test.

between intelligence and decision time (Bates and Stough, 1997), whereas for example Cappelen et al. (2014) find that response times are not driven by differences in cognitive ability, measured as a 20-item progressive matrices test (IQ).

2.4 Cognitive ability and public good and dictator games

The investigation of how social preferences, for example seen as the traits of being fair, cooperative or selfish, are related to one's cognitive ability, has been broadly viewed by researchers in the form of public good and dictator games. The results, regarding of finding evidence of any prediction at all, seem to be quite mixed. For example, Brandstätter and Güth (2002) investigate the relationship between cognitive ability, measured as self-reported intelligence from questions on individual abilities, and choices made in a dictator and ultimatum game. They find that intelligence, for the most part, is not predictive of the participants choices. Additionally, Benjamin et al. (2013) find that cognitive ability does not predict an individual’s giving in a dictator game, implying that there is no connection between cognitive ability and social preferences. However, as mentioned in the previous section, Cappelen et al. (2014) find that response times are not affected by differences in IQ, still they find that selfishness is connected to a longer response time, i.e. a more deliberate behaviour, whereas fairness is strongly connected to a shorter response time, i.e. a more intuitive behaviour. Assuming that IQ and CR measure different dimensions of cognitive ability, and on the basis of dual-process theory, the connection between actions and response times, could make one start wondering if this behaviour was partly due to differences in CR. If believing so, then one could also assume that high CR is associated with selfishness, and low CR with the probability of being cooperative. However, Nielsen et al. (2014) further confirm the previous result, controlling for cognitive ability, both as a progressive matrices test as well as the CRT, and find that the longer response times of free riders is not driven by differences in these measures. Instead they suggest that that their finding is caused by the fact that free riders need more time to deliberate and overcome the moral dilemma of being selfish or not. Nevertheless, they observe a positive relation of being a free rider and CRT scores.

2.5 Cognitive ability and rationality

When we examine individual differences in cognitive functioning by traditional intelligence tests, they do not seem to measure all dimensions of cognitive abilities, and do not include assessment of rational thinking skills (Stanovich et al. 2011). The CRT, on the other hand, has been proven to strongly correlate with this trait (Toplak et al. 2011). Bearing in mind that individual differences in rational thinking are mainly driven by differences in type 2 processing, the former is not surprising, as rationality thereby is linked to a more reflective thinking. In the domain of decision making, economists and cognitive scientists define rational judgement of an individual as making decisions in terms to maximize expected utility, and along this line, also the definition that we will proceed from in our analysis. If one, for some reason, diverges from such behaviour, this individual may be a victim of one or several cognitive biases. One way to assess rationality is then to examine if, and if so, to what degree an individual exhibits any kind of bias that affects rationality in decision making. Going back to the relation to traditional measures of intelligence, as already mentioned above, these are lacking in assessment of this trait as well as related ones, and are therefore bad predictors of rational thinking and behaviour (Stanovich et al. 2011).

3 Theoretical framework

3.1 System 1 and 2

The dual-process system theory, mentioning the terms system 1 and 2, was first presented by Stanovich and West (2000). They announced that our cognitive process can be separated into two different systems. Kahneman (2013), however, really brought the matter to life. In his striking book, he describes system 1 as the fast system, which is basically always switched on as default. System 2, he describes as the slow system, which only comes to use if really necessary. The reason for this difference is that system 2 is very effortful. Unfortunately, system 2 is the "smart" system. It is used for harder tasks and complicated decisions, or whenever more advanced thinking is required. It is slower than system 1, because it needs time to make a decision carefully. However, as mentioned, it tires easily, as it requires a large amount of energy to be active. The basically always active system 1 is the intuitive system; it makes fast decisions that are not very deliberate. It works automatically (like an autopilot), and thus, does not require the same amount of energy as system 2. It often works in moments of danger, because it is highly sensitive, and hence, is constructed of an intuitive nature. The downside of this system is that it is filled with biases, different situation specific errors, in the choices it makes, due to the fast, inconsiderate thinking process. However, it should not be interpreted as a bad system of any sort, because, most of the time, it works perfectly well and does its job. Furthermore, the two systems work in sync in a very efficient way.

One can argue that the use of system 2, or at least the quality of system 2, is somehow connected to cognitive ability. Both systems are connected, of course, because a lot of the intuitive knowledge that system 1 holds is taught and not congenital. It principally consists of common knowledge, which of course increases when an individual undergoes education, and this is often linked to a higher cognitive ability. However, the tasks that system 2 is able to solve, must be connected to cognitive ability on a higher level. It might therefore be relevant to assume that a higher cognitive ability could relate to a better skilled system 2.

The main reason to study this difference is to find out why certain individuals are more prone to be biased in different situations of decision making. Because, if cognitive ability is connected to these systems, and if they generate different outcomes (intuitive and sometimes sloppy, vs. deliberate and accurate), it could explain why some individuals behave in a more biased way than others. It would additionally help solve the mystery of rationality in humanity. According to Stanovich (2012), intelligence is not the same as rationality. Being intelligent, in the sense of having a high IQ, does not mean having immunity to biases in decision making. And therefore, studying other areas of the cognitive ability in humans, such as cognitive reflection, might give us added information about the differences in decision making and why some individuals are more prone to be biased than others. Kahneman (2013) also suggests further research in this field and concludes that *"Time will tell whether the distinction between intelligence and rationality can lead to new discoveries."* (p. 49).

Evans and Stanovich (2013) collect criticism of the different dual-system theories and summarize a discussion about these in an article, which basically describes the situation today. Most of the critique regards the lacking clarity of the definition, a concern that already has been raised by many (e.g. Keren & Shul, 2009), and some also have empirical evidence against some of the statements that the theories make. Many find the terminology of system 1 and 2 to be confusing, because it is in fact the same system working, however, different ways of processing information. That is why a majority of those who have used this terminology have gone back to use the former terms of type 1 and 2 processing instead. They conclude, that all the defining features originally made, might not necessarily hold. However, they do believe that type 1 processing is linked with autonomous processing and type 2 with, what Evans and Stanovich (2013) call *"...the ability to sustain the decoupling of secondary representations..."* (p. 237). They also agree on this field still being under development, especially with all the recent research proving and disproving the different aspects of the theories.

3.2 Intelligence Quotient

One of the primarily used ways of measuring cognitive ability is by the intelligence quotient (IQ). The modern approach of this intelligence testing originates from the work of Alfred Binet, a French psychologist assigned by the French Ministry of Education to detect less talented students in a fast and low-cost way, to make division into different classes more effective, after the introduction of universal primary education in France, during the 20th century. His work was later developed by William Stern, among others, who is considered to be the creator of the original intelligence quotient, which according to him represented an individual's mental age divided by his or her chronological age (Mackintosh, 2011). Later on, Sterns work has also been revised by many, and today there exist several different types of tests to measure this quotient. One of the most commonly used IQ-tests today, is the latest version of those invented by David Wechsler; The Wechsler Adult Intelligence Scale (WAIS) IV (Urbina, 2011). In contrast to Sterns description of the IQ score, Wechsler refined the definition so that his tests measured the "deviation IQ", a comparison between the IQ score of an individual and the corresponding average obtained by others in the same age (Mackintosh, 2011). Thus, it is worth to keep in mind, that the IQ score is only a rank of your position in terms of cognitive ability in relation to all other individuals, rather than a grading score. This is the typical way to score tests today, where the mean score of most tests is at 100, with a standard deviation of 15-16 (Urbina, 2011).

As there exist more than a few different IQ-measures, we cannot discuss all of them in this essay, but we have chosen to mention two additional test. These are also commonly used among researchers who examine cognitive ability, and are the ones we have encountered the most during our research; The Wonderlic Personnel Test and Raven's Progressive Matrices. The WPT consists of 50 questions that have to be completed in 12 minutes. The problems are based on various fields of knowledge such as mathematical and verbal ability, to mention a few, and are thereby considered to be a good estimate of general cognitive ability (Matthews and Lassiter, 2007). Raven's Progressive Matrices, on the other hand, is constructed of a series of visual problems, where the participant is supposed to determine which out of several alternative images is missing, in order to solve an incomplete puzzle (Raven, 2000). There exists several versions of this test and it is untimed. Raven's Matrices is considered to measure non-verbal cognitive ability, which means that it is not influenced by cultural differences due to verbal skills (Urbina, 2011, p. 29).

Although there exists all these different measures of IQ, most of them are strongly correlated (Borghans et al. 2008). Moving over to general correlations to IQ, beyond the relations to risk preferences, as mentioned in section 2.1, IQ scores have been found to be related to numerous of other economic preferences, as well as several different individual characteristics, such as mortality, income, wealth, etc. (Sternberg and Kaufman, 2011). Regarding economic preferences, it has also been shown to relate to time preferences, implying that higher intelligence is connected to higher patience (Burks et al. 2009; Dohmen et al. 2010).

On the other hand, IQ does not seem to be specifically related to gender. Research has shown that men and women possess divergent abilities when it comes to different fields of tasks. For example, men generally perform better than women in mathematical domains, whereas women, on the other hand, on average, perform better on tasks that examine verbal skills. Today, as most IQ tests are designed in order to be adjusted from overall gender differences, meaning that they do not have any particular bias towards a specific gender, there is, in most circumstances, no difference to be found in average IQ between men and women

(Halpern et al. 2011). This relation, in itself, is a considerable issue, beyond the scope of this essay. Therefore, as only a small branch of our study, it will be overseen in a general perspective, and we will not go any further into the discussion of underlying factors.

Moving over to a discussion about IQ and age, several interesting relations have been found. In short, it is difficult to assess intelligence in childhood, as children express a huge variation in their behaviour, and thus, also in intelligence, during their early years. Most intelligence tests are constructed to measure *stable* cognitive skills, and are therefore not applicable on very young individuals (Rose & Fischer, 2011). When we later reach adulthood, a majority of research is consistent with the fact that, in general, most traits of, and thus overall, cognitive ability seems to decline as we are aging. One of the traits where the largest differences can be observed is in processing speed (Hertzog, 2011).

Finally, in this study, the Intelligence-Structure-Test 2000 R, a test which is closely related to Raven's Progressive Matrices, has been used as a measure of IQ. For further description and motivation of this test, view section 4.2.3.

3.3 The Cognitive Reflection Test

Frederick (2005) constructed the three item "Cognitive Reflection Test" (CRT) for one type of cognitive ability, that he suggested measured "cognitive reflection", which he defined as; *"…the ability or disposition to resist reporting the response that first comes to mind."* (p. 35). The idea behind the test is based on the theory of a dual-process system, consisting of system 1, using a fast and intuitive processing, and system 2, using a more deliberate and thoughtful processing, when performing different tasks. The CRT is created such that the questions are supposed to first generate an intuitive and incorrect answer, triggered by system 1, which then can be driven away by a deeper reflection, and thus, through an activation of system 2. This in turn implies that people with a higher CR, use their system 2 more frequently than others, when deciding on their response, and thus, also have a *better* response rate (Moritz et al. 2014).

As already discussed in section 2.2, CR seems to differ between genders. However, there does not seem to exist equally strong evidence that CR would differ between age groups. Campitelli and Labollita (2010) examine the relation of these variables and find the correlation to be significant only at the ten percent level. Considering that other measures of cognitive ability have been found to decline with age, as mentioned in section 3.2, it is not impossible to assume that the same relation holds for CR, as it has proven to positively correlate with several other measures of cognitive ability, such as academic achievement as well as various measures of IQ. For example, Frederick (2005) found a positive correlation between CRT scores and the Wonderlic Personnel Test (WPT), the Need For Cognition scale (NFC)[3], self-reported Scholastic Achievement Test (SAT) and American College Testing (ACT) scores. Cueva et al. (2015), as well as Obrecht et al. (2009) provide further support to the findings regarding academic achievement, as the former observe that GPA (Grade Point Average) is positively correlated to the CRT, and in the same direction, the latter detect a correlation of 0.45[4] between CRT performance and SAT scores. The relation between CR and different kinds of IQ measures will be discussed further in section 3.4.

Regarding the relation of CR and social preferences, some have investigated how the CRT is related to traits of the Big-five personality test, for a further discussion of the implications of this test, see section 4.2.2. For example, Cueva et al. (2015) find that CRT scores are negatively correlated to Extraversion and Neuroticism. Similarly, Cokely et al. (2012) add to the finding of CRT scores being negatively related to Extraversion, as well as to Openness. Finally, to mention a few, some other variables that have been found to relate to CR are; working memory (Toplak et al. 2011), numeracy (Obrecht et al. 2009), time preferences (Frederick, 2005) and rational thinking (Toplak et al. 2011).

As earlier studies have shown that CR is related to numeracy, as well as academic achievement, this may also suggest that the impact of CR in decision making could be due to the correlation with these abilities (Frederick, 2005). Convincingly, Campitelli and Labollita (2010) offer evidence in dispute to this proposal, examining whether individual differences in these types of general knowledge (i.e. numeracy and academic achievement) could be the cause of CRs effect on decision making. They conclude that this effect is neither due to differences in numeracy, as they still were able to find an effect when investigating tasks that did not need any mathematical figuring, nor due to differences in academic achievement. Thus, in line with Frederick (2005), they conclude, regarding the effect of CR, that there exists at least an indication of some individual strength in the CR measure, which affects performance in decision making.

Even though the CRT has been proven as a worthy measure of cognitive ability, it is to some extent lacking in the sense of future application. As the test simply consists of three short questions, it has been vastly exploited in various surroundings since its origin, above all

[3] Need for cognition (NFC) is commonly described as enjoying complex thinking (high NFC), which can be related to a higher cognitive ability (Cacioppo & Petty, 1982).

[4] Correlations are measured as Pearson's correlations coefficients, and range between -1 and +1, where +1 corresponds to perfect positive correlation, -1 to a perfect negative correlation, and 0 to no correlation.

in educational purposes. This implies that future subjects of interest already might be familiar with the obstacles of these questions as well as their correct answers (Toplak et al. 2014). Trying to solve this problem, Toplak et al. (2014) constructed four new questions, in collaboration with Shane Frederick, among others, that have not already been exploited as the original ones. They add these to the initial test, and thus, created a 7 item expansion of the original 3 item CRT. According to their research, the 4 item CRT presented a 0.58 correlation with the 3 item test, as well as it demonstrated a comparable relationship with measures of cognitive ability and various rational thinking tasks.

However, it is worth to keep in mind, that this is only a temporary solution, as these newly created questions in time will face the same destiny as the original ones, and the usage of the CRT will again get weaker in terms of reliability.[5] Therefore we wonder about how good of a solution this really is, as the CRT questions would need to be updated continuously to resist this threat. It would consequently be of interest to study the prospect of CRT usage closer in the future, and to see if and how one could find a more effective proposition. Maybe it is possible to measure the same dimension of cognitive ability, as with the CRT, using a more persistent method.

3.4 Cognitive reflection as a measure of cognitive ability

There have been several thoughts about what the CRT really measures, and how well it actually measures what it is supposed to measure. Campitelli and Gerrans (2014) discuss some of the most debated opinions in their paper, and sort out which of these they believe should have the most support. The primarily debated opinions about the CRT are whether the test measures mathematical ability, rational thinking and/or open-minded thinking. What they find is that the CRT does not measure pure mathematical abilities, however, that it might be a measure of mathematical ability in combination with rational thinking, or mathematical ability in combination with both rational and open-minded thinking. However, Welsh et al. (2013) discuss whether the accomplishment of the CRT is due to the fact that it is just another, more precise, measure of numerical skills rather than a broader measure of cognitive ability. As many others, they prove that the CRT is strongly related to numeracy, and that the effect of CRT largely can be explained by this fact, and accordingly may be redundant. As follows, they suggest in their conclusion; *"...that 'cognitive reflection' may not be*

[5] This, however, is a problem only for the CRT, because the recognition for these questions are much higher than for the IQ tests, for example, as these first of all include a lot more problems, and these are often constructed of illustrations, not as easily remembered as the CRT questions.

metacognitive as Frederick (2005) describes but, rather, measure a person's ability to quickly recognize bad math." (p. 1592).

Frederick (2005) himself also discusses the validity of the CRT, in particular whether it is just another IQ-test on the market, or if it actually does capture another dimension of cognitive ability. As mentioned in section 3.3, he compared the CRT scores with several other cognitive ability test scores, and all were significantly and positively correlated. This result has been further confirmed between CR and several measures of IQ, which are the two types of cognitive abilities that we focus on in this study. For example, Brañas-Garza et al. (2012) found a 0.29 correlation between scoring on the Raven's Matrices and the CRT. Further on, Moritz et al. (2014) discovered a correlation of 0.44 between the WPT and the CRT, in line with Frederick (2005), who found a correlation of 0.43 between the two measures. Looking closer to the cause of the result, they find something interesting; the high correlation of the two measures is basically due to the fact that individuals who reported a low WPT score, extensively also reported a low CRT score. The reverse relationship, on the other hand, was not observed, as they did not find a specific pattern in CRT scores for those who reported a high WPT score, instead their scores could be either high or low with almost the same rate of recurrence. This indicates that low IQ scores are closely related to low CR whereas high IQ scores are not predictive of CR.

Further on, Toplak et al. (2011) found that CRT scores have a 0.4 correlation with the vocabulary and matrix reasoning subtests from the Wechsler Abbreviated Scale of Intelligence (WASI)[6]. Despite to these findings (the considerable correlation with cognitive ability), when examining the unique prediction power of the CRT, they discover that it explained a larger unique variance (in fact more than double) than the IQ measure. Consequently, they conclude that the CRT is a very powerful predictor of heuristics-and-biases tasks, whereas they consider the latter to be merely moderate. This result was also observed by Frederick (2005), who found that the CRT scores gave the best indication of cognitive ability, for a series of decision making tasks, among the different test that he was analysing. Similarly, Moritz et al. (2014) found that CRT scores positively affected performance, independent of IQ. Hence, they conclude that, although they seem to measure, at least partly, an interrelated effect when it comes to decision making, it has been shown that in this domain, CR alone can offer further information beyond IQ.

[6] The Wechsler Abbreviated Scale of Intelligence (WASI) is an abbreviated version of the original Wechsler Adult Intelligence Scale (WAIS) test.

Both CR and IQ have been found to positively correlate with measures such as numeracy, academic achievement and time preferences. However, one of the main differencing variables in relation to these measures, accordingly to previous research (see section 2.2), seems to be gender. As mentioned on this subject, researchers generally do not find any significant differences between male and female average IQ (see section 3.2), whereas a majority of earlier studies, in contrast, have found a conflicting relationship between CRT scores and gender, indicating that men in general would have a higher cognitive reflection than women. This could possibly, to some extent, be explained by the matter that men, on average, seem to perform better than women on tasks of mathematical structure, and thus could benefit from the design of the CRT.

3.5 Risk and loss aversion

Risk aversion is a very well-known phenomenon in economics, and can basically be described as a characteristic that makes an individual choose a safe option before a risky option, even though, the risky option has a better expected outcome (Wilkinson & Klaes, 2012, p. 151-152). A related, but not as known, phenomenon is loss aversion. It was founded by Kahneman and Tversky (1984), and basically means that individuals are more averse towards a loss than an equally sized gain. That is, losing 10 is a worse loss than winning 10 is in gain, even though the amount is the same (10). We will not explain this in detail, but merely wanted to define these concepts, since we, to some extent, will attend to them in this study.

4 Data

4.1 Data selection

In our analysis we use data from the Internet Laboratory for Experimental Economics (iLEE) at Copenhagen University.[7] The iLEE conducts large-scale internet based experiments on randomly selected individuals from the Danish population in the age range 18-80, and has today completed four waves of experiments.

We have used selected data from the first two waves of the experiment, iLEE1 and iLEE2, in our research. We have chosen to include all observations from participants who completed the first wave for the experiments from iLEE1, and data from participants who completed the second wave for the experiments from iLEE2. The first experiment studies cooperation behaviour in relation to features such as characteristics and personality of the participants through a one-shot public good game. In addition to this game, iLEE1 also includes a CRT test, Big-five personality test, Intelligence-Structure-Test 2000 R (I-S-T 2000 R), risk and loss preference examination (decision making) as well as some background questions. The second experiment is based on a real effort dictator game which they use to study sharing and redistribution choices. It also includes similar risk and loss preference tests as the iLEE1. All of these tests will be described closer in section 4.2.

4.1.1 Descriptive statistics of participants

Our final samples from iLEE1 and iLEE2 consist of 2291 and 1340 participants respectively. It should be noticed that all participants in iLEE2 first had taken part in, and completed, iLEE1.

When comparing the characteristics age and gender from our data, with statistics of the general Danish population (Danmarks Statistik, 2015), we find that our samples are not fully representative in these areas. Regarding gender, we find that men are slightly overrepresented in both iLEE1 and iLEE2. Furthermore, concerning the age variable, we find that middle-aged individuals are overrepresented, whereas the young and the old individuals are underrepresented, a result that also holds for both iLEE1 and iLEE2. However, our sample does not differ dramatically from the population, and thus, we find that our results are representable of the population from the factors we have observed.

[7] A complete description of the platform and the implementation of all waves can be found at http://www.econ.ku.dk/cee/ilee/description/.

4.1.2 Dropped data in different games

We have dropped a few observations for some of the analyses in this study. Firstly, in the decision making analysis, we do not include participants who have been irrational in their choices. This is discussed in further detail in section 5.1.4. Secondly, for the time analysis part, we dropped observations from participants who seemed to take more time than necessary to perform the different tasks. We discuss this further in section 5.1.6.

4.2 Description of tests and games

4.2.1 Cognitive reflection test

The CRT consists of the following three questions[8];

(1) A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball. How much does the ball cost? _____ cents (intuitive: $0.10, correct: $0.05)

(2) If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets? _____ minutes (intuitive: 100 min, correct: 5 min)

(3) In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? _____ days (intuitive: 24 days, correct: 47 days)

The results are measured by the number of questions answered correctly. Thus, the scale goes from 0 to 3 (0, 1, 2, 3), where 3 points represents a full score, that is, all questions were answered correctly. Later in this study, we will be separating the test scores into two groups, high and low CR. The high CR group will consist of participants who answered two or more questions correctly, whereas the low CR group will consist of the participants answering 1 or no questions correctly.

4.2.2 Big-five personality test

This test measures personality by five specific traits. *Openness*, which describes how conventional and conservative an individual is. A high score means being open for experience. This trait reflects a person's intellect. *Conscientiousness* reflects the measure of organization a person lives after. If this score is high, the person is probably very dependable, punctual and generally organized in most aspects of his/her life. *Extraversion* is the social trait, and describes how active a person is among other people. *Agreeableness* is a measure of

[8] Intuitive (and incorrect) as well as correct answers are presented in parentheses after each question.

helpfulness, and of a person's beliefs about other people. A high score here means being helpful, and thinking others will be helpful in return. *Neuroticism* is basically the grade of emotional stability. If a person is very neurotic, he/she is emotionally unstable, and thus easily scared, nervous and embarrassed.

The test is constructed by several statements per trait, which all can be answered by a scale of five alternatives, from "This is 100 % wrong, I strongly disagree" to "This is 100% correct, I strongly agree". For every trait one can score from 0 to 48 points.

4.2.3 IQ test

The Intelligence-Structure-Test 2000 R is a "culture-free" test, which means that it is not based on testing verbal knowledge. The test consists of 20 questions, all with pictures of different shapes and forms where the participant must pick the missing illustration from a row of alternatives. The IQ score is measured by the number of questions answered correctly, and thus, ranges from 0 to 20 (0, 1, 2, …, 20). A test score of 9.6 corresponds to an IQ of 100 (the test can measure IQ between 60 and 150). The I-S-T 2000 R is closely related to Raven's Progressive Matrices, which is helpful in our discussion and comparison between results.

As with the CRT, we will later in this study be separating the test scores into two groups, high and low IQ. The high IQ group will be participants who scored 11-20 questions correctly, whereas the low IQ group will be the participants scoring 0-10.

4.2.4 Risk and loss preferences

In this part, the participants have to choose between two series of 50 percent chance lotteries, in which one lottery is riskier than the other, for a total of ten lotteries in the risk gamble, and seven in the loss gamble. The risky choice gets riskier for every lottery in relation to the safe choice. However, the expected payoff for the risky choice increases for each lottery, which implies that a rational individual chooses the risky lottery at some point. A *risk neutral* individual chooses the risky lottery as soon as the expected payoff of that lottery exceeds the expected payoff of the safe lottery. In the risk aversion gamble, only lotteries with gains are presented. The risk neutral individual will then switch to the risky lottery at the third decision. In the loss aversion gamble, both the safe and the risky lottery include a possible loss. The risk neutral individual will then choose the risky lottery at the second decision. The reason why we choose to examine two very similar tasks is that we want to be able to see if individuals are affected by the fact that a loss is possible. It is reasonable to believe that people act differently when choosing between two lotteries that both generate gains, than between lotteries where possible losses are involved. We want to make sure that this possible difference is acknowledged.

The measure of risk and loss preferences is the shift point, that is, at what point the participant chooses the risky lottery over the safe one. If an individual chooses to switch before the risk neutral shift point, it implies risk seeking preferences, if the choice is made after the risk neutral point, it implies risk averse preferences. Since there are 10 choices for the risk gamble, the scale goes from 1 to 11 (11 corresponding to choosing the safe lottery every time, and 1 corresponding to choosing the risky lottery in the first decision), and for the loss gamble, it goes from 1 to 8 (8 corresponding to choosing the safe lottery every time, and 1 corresponding to choosing the risky lottery in the first decision). Notable here is that whenever a rational individual has chosen the risky lottery, he/she will never go back to choosing the safe lottery, since the expected payoff of the risky lottery will increase for later lotteries (see section 5.1.4 for further discussion on this matter).

The description above holds for iLEE1, and the same principle holds for iLEE2, however, there are 10 lotteries for both the risk and the loss gambles in this wave, and also, for the loss aversion gamble, the safe choice only involves gains. In the risk gamble, the risk neutral individual will switch at decision 6, and in the loss gamble, at decision 9. The participants, who have performed the iLEE2, have also performed the iLEE1, and thus, a similar task. However, these tests are constructed differently, with the risk neutral shift points at different positions in the gambles. Andersson et al. (2013) have used the same dataset as in the present study, and found that noise can bias the choice of shift point, and depending on where the risk neutral choice is placed in the gamble, the bias will go in different directions. They show that when the risk neutral choice is placed early in the gamble (as in iLEE1), more available errors will exist later on in the gamble, and therefore, the bias would on average be downwards, that is, the risk is overestimated. And vice versa if the risk neutral choice is placed late in the gamble (as in iLEE2), which will induce an underestimation of the risk. This is very important to keep in mind, because it can imply that the results from these tests are merely spurious. A further discussion on this matter can be found in section 6.2.1.

4.2.5 Public good game

In the public good game, the participants are supposed to make one unconditional choice, regarding an amount of money to contribute (or withdraw) into (from) a pot of money, which will be doubled and then split equally among four group members (including the participant). The participants who completed the iLEE1 were selected into three different categories for the public good game. Two of them were so called givers, that is, they had 50 DKK to start with, and could choose to put any amount of that money into the shared pot. The givers, per se, are divided into the categories *give* and *hypothetical.* The *give* individuals actually got paid the amount resulting from the game, whereas the *hypothetical* group did not, but still, they were asked to play the game as if they were being paid. The last category was *take*; where the participants instead could withdraw money from the pot which then contained 200 DKK to begin with (they could withdraw a maximum amount of 50 DKK). *Takers* also got paid the resulting amount.

4.2.6 Dictator game

In the dictator game, the participants are being told that they are matched with another individual. Both start out with 75 DKK. The active participant is then told to be the dictator, that is, he/she decides how the money is distributed between them. He/she can choose to give any amount of his/her money to the other (passive) individual or take any amount of the passive individual’s money. The active participant can also choose to do nothing, leaving them both with an equal amount. After the dictator has made his/her choice, he/she is paired with another individual and the roles reverse, thus he/she becomes the passive participant. One of these two situations will then be paid to the participants, however, they will of course not know which one in advance.

5 Analysis

We aim to examine the difference between the cognitive ability measures CR and IQ in a series of decision making tasks. First, we want to show the effects of these measures on the actual outcome of the games. This is followed by our main analysis, where we aim to analyse the differences in decision times for each game. We do hypothesise there to be differences, especially in decision time, because the CRT is, unlike IQ tests, based on dual-process theory, and thus, a measure of the ability of system 2. Hence, a high score on the CRT is assumed be related to consideration, deliberation and slower, but often better, decisions. Consequently, we do not only hypothesise high scorers on the CRT to be slower, decision time wise, but also that they will act more efficient than low scorers. This section will first hold a descriptive statistics section, and is then followed by the methods and results of the analyses.

5.1 Descriptive statistics

5.1.1 Correlations

Table 1 presents the correlations between the main variables included in the analysis. This is mainly interesting because it motivates why these variables should be included.

Table 1

Correlations between variables

	crscore	*iqscore*	*big5a*	*big5c*	*big5e*	*big5o*	*big5n*	*age*	*sex*	*edu*
crscore	1.0000									
iqscore	**0.2898*****	1.0000								
big5a	-0.0487**	-0.0568***	1.0000							
big5c	-0.0036	0.0120	0.1057***	1.0000						
big5e	-0.0185	0.1019***	-0.0515**	0.2644***	1.0000					
big5o	0.0858***	0.0753***	0.0161	0.0041	0.2828***	1.0000				
big5n	-0.0787***	0.0127	-0.0429**	-0.4517***	-0.3734***	0.0249	1.0000			
age	-0.0184	-0.3993***	0.1639***	0.0893***	-0.1749***	-0.0189	-0.1210***	1.0000		
sex	-0.1824***	0.0112	0.2527***	0.0099	-0.0186	0.0564***	0.2488***	-0.0596***	1.0000	
edu	0.1512***	0.1024***	0.0279	0.0812***	0.0699***	0.2103***	-0.0741 ***	0.0337	0.0793***	1.0000

Notes: Pearson's correlation coefficients.
**** p<0.01, ** p<0.05, * p<0.1*

All variables correlate significantly with either CR score or IQ score or both (except *big5c*), motivating that they should be included in the regressions, in order to isolate the actual effect that the scores have on the situations we analyse.

Since one of the main focuses in this paper is the difference between CR and IQ, this result is of special interest (marked bold in table 1). The measures significantly correlate positively. It is a medium strong correlation, indicating that they do differ, quite a lot in fact, validating our theory about the tests measuring, and in some extent capturing, different dimensions of cognitive ability. However, the correlation is positive, which is an important observation, because even if they capture cognitive ability in different ways, we still anticipated that they would be positively related to each other. This result, in terms of similar correlations between CR and different measures of IQ, approximately ranging between 0.3-0.45, has been observed by many researchers, as discussed in section 3.4.

Figure 1 illustrates the distribution of individuals with low and high CR and IQ respectively. This is a matter discussed in prior studies, and it has been found that a low IQ relates to a low CR, whereas a high IQ has not been shown relate to a specific level of CR (Moritz et al. 2014). From our sample we can see that it is not obvious that the two measures relate, an individual can be high in CR and low in IQ, and vice versa, however, it seems to be rare to have high IQ and low CR in relation to the other combinations.

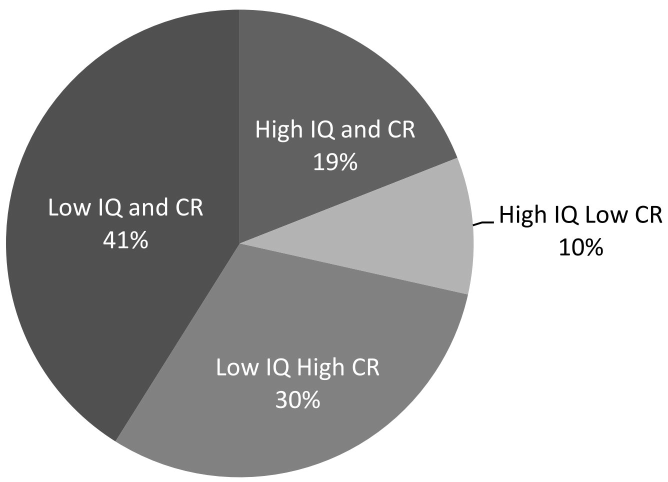

Figure 1

The distribution of high and low CR and IQ respectively amongst participants.

5.1.2 Cognitive reflection

In table 2, we present the average CR scores received by the participants. We also examine the differences in gender, age and education.

Table 2

Average CR scores from the CRT and *t*-values

Total	**Gender**		**Age**			**Education**			
	Men	*Women*	*18-29*	*30-60*	*61-80*	*Basic*	*High school*	*Short Uni*	*Long Uni*
1.473 (1.100)	1.668 (1.074)	1.266 (1.091)	1.489 (1.163)	1.499 (1.090)	1.361 (1.084)	1.210 (1.088)	1.374 (1.101)	1.425 (1.087)	1.914 (1.028)
	t(2289) = 8.874***		*t*(1879) = 0.147		*t*(1954) = 2.289**	*t*(819) = 1.953*	*t*(1652)= -0.906		*t*(1468) = -7.749***

Notes: Average CR scores with standard deviations in parenthesis from the iLEE1. t-test results[9] *presented below the measures tested.*

**** p<0.01, ** p<0.05, * p<0.1*

We found a significant difference in CR scores between the male and female participants. Males scored significantly higher on the CRT than the females. Additionally, we found that the group of elders (61-80 years old) scored significantly lower on the CRT than the middle-age group (30-60). However, we could not find any significant differences between the younger (18-29) and the middle-aged. Further on, we could observe some educational differences, where basic educated individuals scored significantly lower than high school educated, and individuals with a long education at the university scored higher than those with a shorter education at the university. We did not find any difference between high school educated individuals and those with a short education at the university. Table 2 only presents results from the iLEE1, however, since all participants who finished iLEE2 also have finished iLEE1, the observations from iLEE2 is just a sample of the participants in iLEE1, and thus, the results should not differ drastically.

5.1.3 Intelligence Quotient

In table 3, we present the average IQ scores received by the participants. We also examine the differences in gender, age and education.

[9] Two-sample *t*-tests have been performed with Stata 13.0. Degrees of freedom in parentheses. This goes for all the following tests if no other information is given.

Table 3

Average IQ scores from the I-S-T 2000 R test and *t*-values

Total	**Gender**		**Age**			**Education**			
	Men	*Women*	*18-29*	*30-60*	*61-80*	*Basic*	*High school*	*Short Uni*	*Long Uni*
8.688 (3.124)	8.654 (3.185)	8.724 (3.060)	10.397 (2.957)	8.847 (2.949)	6.690 (2.860)	7.889 (3.423)	8.825 (3.226)	8.640 (3.035)	9.109 (2.930)
	t(2289) = -0.537		*t*(1879) = -8.716***		*t*(1954) = 13.251***	*t*(819) = 3.728***	*t*(1652)= 1.156		*t*(1468) = -2.647***

Notes: Average IQ scores with standard deviations in parenthesis from the iLEE1. t-test results presented below the measures tested.

**** p<0.01, ** p<0.05, * p<0.1*

There are no significant differences in IQ scores between men and women. We found that the elders scored significantly lower on the IQ test than the participants in the middle-age group. We also found that the group of young participants scored significantly higher than the middle-age group. Furthermore, we found that basic educated individuals scored significantly lower than high school educated ones, and individuals with a long education at the university scored higher than those with a shorter education at the university. We did not find any difference in IQ scores between high school educated individuals and those with a short education at the university.

5.1.4 Decision making

In the decision making gambles, the participants are supposed to choose between a series of safe and relatively risky lotteries. They are faced with several situations, and each situation has a risky lottery where the expected outcome increases for each situation (see section 4.2.4 for details). The average shift point, where the participants switch from the safe to the risky lottery, is presented in table 4. As can be observed, for the risk aversion gamble, the average risk preference seems to be risk averse (the average switch is made after the risk neutral shift point), in contrast to the loss aversion gamble, where it is risk seeking (the average switch is made before the risk neutral shift point).

Table 4

Average shift points

Risk aversion		Loss aversion	
iLEE1	*iLEE2*	*iLEE1*	*iLEE2*
5.172 (1.966)	6.633 (1.839)	3.298 (1.353)	8.072 (1.191)

Notes: Standard deviations in parenthesis

Table 5

Results from two-sample *t*-tests with rational and irrational participants

		Mean	*t*-value	*p*-value
iLEE1				
CR score	Rational Irrational	1.713 1.189	11.683	0.000
IQ score	Rational Irrational	9.257 8.012	9.693	0.000
iLEE2				
CR score	Rational Irrational	1.683 1.235	7.477	0.000
IQ score	Rational Irrational	9.438 7.810	9.366	0.000

Many participants have behaved irrationally when playing the decision making gambles. That is, they have once or more switched back from the risky choice to choosing the safe lottery again, which does not make any sense, as for each lottery, the expected return of the risky lottery gets higher and higher in relation to the safe lottery. Or, they have not made a switch at all, that is, they have chosen the safe or the risky lottery at all times. These individuals may not have understood the game, not have made enough effort or been doing it on purpose. One interesting finding is that those who are irrational within gambles, have significant lower CR and IQ scores than participants who are rational in their choices. The results of these findings are presented in table 5. For the analysis of decision making, the irrational participants have been dropped, in order to obtain more accurate results.

5.1.5 Public good and dictator game

Table 6 presents the average amount of money the participants chose to share with the group (public good, *give* and *hypo* groups) or take for themselves (dictator game and public good, *take* group).

Table 6

Average amounts of money

Public good			Dictator
Give	*Hypo*	*Take*	
34.862 (14.760)	28.504 (14.453)	35.507 (17.346)	99.168 (32.795)

Notes: Average shares of money (DKK) taken or given by the participants. Standard deviations in parentheses.

We can conclude that participants in the *hypo* group gave less than the participants in the *give* group. This can possibly be due to the fact that the participants in the *hypo* group got the instructions of not getting paid, and therefore did not perform the task as carefully as the other groups, who did get paid.

5.1.6 Decision time

Table 7 presents the average times spent on each game performed. It is however noteworthy that we have dropped some of the data that we considered too extreme to be realistic. Most likely, some participants have forgotten about time, forgot that they had not finished or maybe got a phone call during the task (or similar). This has resulted in some of these values to be extremely large, so we decided to drop them. A sensitivity analysis has been conducted, to ensure that our chosen drop points are valid. This is explained further in section 5.4 and presented in appendix 2.

Table 7

Average decision times

iLEE1				**iLEE2**			
Decision making		***Public good***		***Decision making***		***Dictator***	
Risk aversion	*Loss aversion*			*Risk aversion*	*Loss aversion*		
59079.07 (18762.81)	65000.64 (22641.57)	24120.5 (9826.017)		54893.67 (18845.54)	52532.39 (20099.6)	32371.12 (15887.56)	
		Free rider	*Cooperative*			*Fair*	*Selfish*
		22197.53 (9865.875)	22031.87 (9096.208)			29806.93 (15421.48)	33548.87 (15691.11)

Notes: Time measured in hundredths of seconds (standard deviations in parentheses).

5.2 Method & results

In this section we will present the method and findings from our analyses. First, the effects of CR and IQ on the different outcomes in the games will be presented, in order to get an overview of how these interact. Thereafter, our main analysis, the decision time analysis, is presented. The regressions marked in grey have significant CR and/or IQ score coefficients. This section merely presents the analysis, however, all results will be discussed in detail in section 6.

Most of our regressions are made with the classical ordinary least square (OLS) method, which is a method frequently used when examining relationships between variables. It basically calculates a predicted line that is fitted to the observations, minimizing the distance between this line and all observations, hence the name least squares. In a model with only one regressor, the slope of the line will correspond to the impact of the independent variable on the dependent variable (Verbeek, 2012). It is a powerful method, due to its properties, and, thus, we find it to be a suitable method to use for analysis in this study.

For the analysis of the public good and dictator game, the probit model is used. It is a regression for binary dependent variables, that is, dependent variables that only take the values 1 or 0, which corresponds to a specific event to happen or not. The regression then calculates how the independent variable affects the probability of the dependent variable to take on the value 1. However, the interpretation of the coefficients is not as straightforward as for the OLS model, and thus, the marginal effects must be calculated separately. The sign of the coefficients obtained can be interpreted normally (Verbeek, 2012). In our analysis, we study four different possible situations, and thus, a probit model seems to be the most appropriate model to use.

In the following sections, the regressions used for the analysis are illustrated and explained. The results from these regressions are presented after each methodological description. In all of the regressions below, the variables of interest is the CR score and IQ score. These are independent variables and we examine them and their effect in the different situations. The dependent variable will differ. One thing to note is that we do not aim to *explain* the dependent variable as one would normally do when performing a regression. We simply want to find the *relation* between our variables of interest (CR and IQ scores) and these different situations, and more specifically how these variables of interest differ from each other in the same situation.

We have included various control variables in the regressions that we believe might have an impact on the variation in the dependent variable. The ones that occur in all regressions below are age, education, gender and personality. The first three mentioned are dummy variables in our regressions, allowing for non-linear relations. Age is grouped into *young* (18-30), *youngmiddle* (31-45), *middleold* (46-60) (omitted) and *old* (61-80). Education is grouped into *basicedu* (omitted), which are the participants who only have finished pre high school education, *highschool*, which are the participants who have finished high school but no more, *shortuni*, are participants with university studies up to three years, and *longuni*, are those who have studied at the university for more than three years. Gender is grouped into males (omitted) and females, where the *sex* variable represents females. In section 5.2.2 and 5.2.3 we also include a dummy variable, which indicates to what group the participants belong for the public good game (see section 4.2.5).

All regressions and calculations were made in Stata 13.0.

5.2.1 Decision making

In this section, we seek to find the relation between cognitive ability, in form of CR and IQ, and risky decision making. We will illustrate four regressions in this section, 1) CR and risky decisions excluding losses, 2) IQ and risky decisions excluding losses, 3) CR and risky decisions including losses, and 4) IQ and risky decisions including losses. The first two will capture risk aversion while the second two aim to capture loss aversion (see section 3.5). The regressions are OLS with robust standard errors due to some detection of heteroskedasticity.

1) OLS regression for risk aversion and CR score:

$$shiftpointrisk = constant + \beta_1 crscore + \beta_2 big5a + \beta_3 big5c + \beta_4 big5e + \beta_5 big5n + \beta_6 big5o + \beta_7 sex + \beta_8 highschool + \beta_9 shortuni + \beta_{10} longuni + \beta_{11} young + \beta_{12} youngmiddle + \beta_{13} old$$

where *shiftpointrisk* is the point where the participants choose the risky lottery in the risk aversion gamble, *crscore* is the score from the CRT, *big5a* is the result from the big five test concerning agreeableness, *big5c* is the result from the big five test concerning consciousness, *big5e* is the result from the big five test concerning extraversion, *big5n* is the result from the big five test concerning neuroticism, *big5o* is the result from the big five test concerning openness and *sex, highschool, shortuni, longuni, young, youngmiddle and old* are dummy variables, representing gender, education and age differences.

2) OLS regression for risk aversion and IQ score:

$$shiftpointrisk = constant + \beta_1 iqscore + \beta_2 big5a + \beta_3 big5c + \beta_4 big5e + \beta_5 big5n + \beta_6 big5o + \beta_7 sex + \beta_8 highschool + \beta_9 shortuni + \beta_{10} longuni + \beta_{11} young + \beta_{12} youngmiddle + \beta_{13} old$$

where *iqscore* is the score from the IQ test (I-S-T 2000 R).

3) OLS regression for loss aversion and CR:

$$shiftpointloss = constant + \beta_1 crscore + \beta_2 big5a + \beta_3 big5c + \beta_4 big5e + \beta_5 big5n + \beta_6 big5o + \beta_7 sex + \beta_8 highschool + \beta_9 shortuni + \beta_{10} longuni + \beta_{11} young + \beta_{12} youngmiddle + \beta_{13} old$$

where *shiftpointloss* represents the point where the participants choose the risky lottery in the loss aversion gamble.

4) OLS regression for loss aversion and IQ:

$$shiftpointloss = constant + \beta_1 iqscore + \beta_2 big5a + \beta_3 big5c + \beta_4 big5e + \beta_5 big5n + \beta_6 big5o + \beta_7 sex + \beta_8 highschool + \beta_9 shortuni + \beta_{10} longuni + \beta_{11} young + \beta_{12} youngmiddle + \beta_{13} old$$

We also conducted a two sample *t*-test to map the difference in the average shift point between the participants with low (0-1) and high (2-3) CR scores, first of all, to see whether the participants with high CR differ in risk and loss aversion, but also to be able to combine it with the efficiency discussion. The same was done for low (0-10) and high (11-20) IQ scores, since the average IQ of the population in general is around 100 (corresponding to a score of 9.6) (see section 3.2), we found it reasonable to separate low and high IQ at score 10.

Table 8

Regressions of risk aversion gamble decision switch point

VARIABLES	(1) CR iLEE1	(2) CR iLEE1	(3) IQ iLEE1	(4) IQ iLEE1	(5) CR iLEE2	(6) CR iLEE2	(7) IQ iLEE2	(8) IQ iLEE2
crscore	**-0.319*****	**-0.288*****			**0.128****	**0.124****		
	(0.046)	**(0.048)**			**(0.057)**	**(0.059)**		
big5a		0.037***		0.037***		0.012		0.012
		(0.009)		(0.009)		(0.012)		(0.012)
big5c		-0.008		-0.005		0.000		-0.001
		(0.010)		(0.010)		(0.013)		(0.013)
big5e		0.013		0.016*		-0.011		-0.015
		(0.009)		(0.009)		(0.011)		(0.011)
big5n		0.023***		0.027***		0.007		0.004
		(0.009)		(0.009)		(0.010)		(0.010)
big5o		0.012		0.009		0.018		0.020*
		(0.009)		(0.009)		(0.011)		(0.011)
young		-0.394***		-0.311**		0.373**		0.269
		(0.146)		(0.152)		(0.177)		(0.179)
youngmiddle		-0.096		-0.039		0.336**		0.264*
		(0.132)		(0.135)		(0.159)		(0.159)
old		-0.512***		-0.520***		-0.263		-0.214
		(0.182)		(0.184)		(0.224)		(0.225)
sex		0.059		0.164		-0.095		-0.127
		(0.117)		(0.117)		(0.144)		(0.140)
highschool		-0.031		-0.040		0.687***		0.702***
		(0.188)		(0.190)		(0.264)		(0.262)
shortuni		-0.261		-0.281		0.511**		0.524**
		(0.180)		(0.182)		(0.257)		(0.256)
longuni		-0.306		-0.403*		0.449		0.495*
		(0.205)		(0.207)		(0.278)		(0.277)
iqscore			**-0.036****	**-0.041****			**0.070*****	**0.055****
			(0.017)	**(0.018)**			**(0.022)**	**(0.023)**
Constant	5.699***	3.913***	5.502***	3.574***	6.420***	5.140***	5.971***	5.031***
	(0.093)	(0.605)	(0.171)	(0.622)	(0.124)	(0.786)	(0.230)	(0.815)
Observations	1,399	1,399	1,399	1,399	856	856	856	856
R-squared	0.031	0.065	0.003	0.045	0.006	0.036	0.013	0.038

Notes: OLS regression with CR and IQ scores respectively on decision making, covering risk aversion with data from both iLEE1 (1-4) and iLEE2 (5-8). Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Table 8 presents the results from an OLS regression between CR and IQ scores respectively, on the risk aversion gamble. In regression (1), (3), (5), and (7) the scores are regressed on the decision independently. The other regressions also include control variables (see section 5.1.1 for details). The main findings suggest that higher CR and IQ scores, significantly lower the shift point, that is, the participants who score high on the CRT and/or the IQ test will choose the risky lottery over the safe one earlier in the gamble than those with lower scores. This implies that they are less risk averse, because they choose the risky lottery when the expected outcome is lower than for the lottery which participants with lower scores choose. This result is especially strong for the CR score. However, we only find this relation for the test done in iLEE1. The opposite result is found for iLEE2, where both CR and IQ significantly increase the shift points. Some personality traits, age and education influence these choices as well.

The average shift point for participants with high CR scores (2-3) is 4.900, which differs significantly from the average of those with low scores (0-1), which is 5.526, $t(1397) = 5.980$ (p-value =0.000). We did not find any significant differences in shift point for participants with high (11-20) (average 5.081) and low (0-10) (average 5.218) IQ scores respectively, $t(1397) = 1.233$ (p-value =0.218). These results concern the iLEE1.

Table 9

Regressions of loss aversion gamble decision switch point

VARIABLES	(1) CR iLEE1	(2) CR iLEE1	(3) IQ iLEE1	(4) IQ iLEE1	(5) CR iLEE2	(6) CR iLEE2	(7) IQ iLEE2	(8) IQ iLEE2
crscore	**-0.091*****	**-0.077*****			**0.105*****	**0.098*****		
	(0.029)	**(0.030)**			**(0.024)**	**(0.025)**		
big5a		0.011*		0.011*		0.001		-0.000
		(0.006)		(0.006)		(0.004)		(0.005)
big5c		0.007		0.008		-0.002		-0.002
		(0.007)		(0.007)		(0.006)		(0.006)
big5e		0.009		0.010		0.002		0.000
		(0.006)		(0.006)		(0.005)		(0.005)
big5n		0.017***		0.018***		0.008*		0.007
		(0.006)		(0.006)		(0.004)		(0.004)
big5o		0.013**		0.013**		0.003		0.004
		(0.006)		(0.006)		(0.005)		(0.005)
young		0.121		0.164		0.115*		0.118*
		(0.102)		(0.107)		(0.067)		(0.068)
youngmiddle		0.018		0.051		0.085		0.084
		(0.079)		(0.080)		(0.060)		(0.062)
old		-0.061		-0.071		-0.077		-0.074
		(0.096)		(0.097)		(0.079)		(0.080)
sex		-0.006		0.021		-0.111*		-0.150***
		(0.073)		(0.072)		(0.057)		(0.057)
highschool		0.018		0.022		0.037		0.048
		(0.123)		(0.123)		(0.103)		(0.103)
shortuni		-0.009		-0.012		-0.002		0.021
		(0.117)		(0.117)		(0.101)		(0.101)
longuni		-0.125		-0.148		0.036		0.080
		(0.133)		(0.133)		(0.110)		(0.110)
iqscore			**-0.010**	**-0.021***			**0.012**	**0.003**
			(0.010)	**(0.011)**			**(0.008)**	**(0.008)**
Constant	3.443***	1.872***	3.391***	1.852***	7.480***	7.248***	7.541***	7.422***
	(0.057)	(0.401)	(0.099)	(0.404)	(0.052)	(0.303)	(0.077)	(0.308)
Observations	1,791	1,791	1,791	1,791	1,132	1,132	1,132	1,132
R-squared	0.005	0.023	0.001	0.021	0.018	0.034	0.002	0.019

Notes: OLS regression with CR and IQ scores respectively on decision making, covering loss aversion with data from both iLEE1 (1-4) and iLEE2 (5-8). Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Table 9 presents the results from an OLS regression between CR and IQ scores respectively, on the loss aversion gamble. In regression (1), (3), (5), and (7) the scores are regressed on the decision independently. The other regressions also include control variables. This gamble differs from the risk aversion gamble, as it is possible to make losses. This, of course, will affect the choice. Again, we find that a higher CR and/or IQ score relates to an earlier shift point, indicating less loss aversion. However, on the contrary, a high CR score will delay the choice in the iLEE2, that is, these participants will choose the risky lottery later in the gamble than participants with lower scores. We can still see that personality has a role in this, but we also find a gender difference, where females actually tend to choose the risky lottery earlier in the gamble than men, however only for the iLEE2.

We found that individuals with high CR scores had a significantly lower shift point (average 3.225) than individuals with low CR scores (average 3.385), $t(1789) = 2.498$ (p-value =0.013). The same result was found for high (average 3.190) and low (3.348) IQ scores, $t(1789) = 2.305$ (p-value =0.021). These results concern the iLEE1.

In section 5.1.4, we discuss rationality within the gambles in the risk and the loss aversion gambles. We define rationality as not switching back from a risky to a safe lottery, once the first switch from the safe to the risky lottery has been made. The reason for this is, as mentioned, the fact that the risky lottery will get more attractive for every new lottery choice, that is, at lottery 1, the risky lottery will have the lowest expected outcome in relation to the safe lottery, so once a switch has been made, it would be unreasonable to switch back again. We have established that this kind of rational individuals, has significantly higher cognitive ability.

Furthermore, we also examined consistency between gambles, that is, individuals having the same risk preferences in both iLEE1 and iLEE2. For example, if an individual has been risk averse (chosen to switch after the risk neutral shift point) in iLEE1 as well as in iLEE2, he/she is consistent between gambles. A majority of individuals participating in both iLEE1 and iLEE2 have been consistent. Of course, we only examine the individuals who have been rational within both gambles, because otherwise, we assume that they have not understood the task or have not made a real effort (as described in section 5.1.4). Consequently, we found that consistent individuals exhibit significantly higher cognitive ability (average CR = 1.937 and IQ = 9.935), both in form of CR and IQ, than inconsistent individuals (average CR = 1.661 and IQ = 9.301), $t(604) = -3.172$ (p-value =0.002) for CR and $t(604) = -2.597$ (p-value = 0.010) for IQ.

Furthermore, we have examined the individuals that presented an *optimal* behaviour, i.e. those who have been rational, consistent AND risk neutral in their choices, that is, those who have maximized expected outcome, and hence, their utility. These individuals have an astonishing average CR of 2.360 compared to risk seeking or risk averse individuals (1.808), which is significantly higher, $t(365) = -4.445$ (p-value = 0.000). They also exhibit a significantly higher IQ (10.477 compared to 9.767), $t(365) = -2.051$ (p-value = 0.041).

5.2.2 Public good and dictator games

This section holds two different dependent variables, the amount of money shared in the public good game and the dictator game respectively. This section will hold four probit regressions; 1) CR and public good choice, 2) IQ and public good choice, 3) CR and dictator choice, and 4) IQ and dictator choice.

For the public good game, we examine two situations; a) the probability of the participant being a *free rider*, that is, keeping everything for him-/herself, and b) the probability of the participant being *cooperative*, that is, contributing everything to the common pot.

1) Probit regression for public good game and CR score:

$$situation\ a\ or\ b = constant + \beta_1 crscore + \beta_2 big5a + \beta_3 big5c + \beta_4 big5e + \beta_5 big5n + \beta_6 big5o + \beta_7 sex + \beta_8 highschool + \beta_9 shortuni + \beta_{10} longuni + \beta_{11} young + \beta_{12} youngmiddle + \beta_{13} old + \beta_{14} hypothetical + \beta_{15} take$$

where *situation a or b,* is a binary variable, that is it can only take the value 1 or 0, and a or b are the situations described above, and the variables *hypothetical, give* (omitted) and *take* are dummy variables which represent the different tasks the individuals are grouped into.

2) Probit regression for public good game and IQ score:

$$situation\ a\ or\ b = constant + \beta_1 iqscore + \beta_2 big5a + \beta_3 big5c + \beta_4 big5e + \beta_5 big5n + \beta_6 big5o + \beta_7 sex + \beta_8 highschool + \beta_9 shortuni + \beta_{10} longuni + \beta_{11} young + \beta_{12} youngmiddle + \beta_{13} old + \beta_{14} hypothetical + \beta_{15} take$$

For the dictator game, we examine two situations; c) the probability of the participant being a *fair*, that is, giving half of the money to the other player, and d) the probability of the participant being *selfish*, that is, taking the all money for him-/herself, leaving the passive participant with nothing.

3) Probit regression for dictator game and CR score:

$$situation\ c\ or\ d = constant + \beta_1 crscore + \beta_2 big5a + \beta_3 big5c + \beta_4 big5e + \beta_5 big5n + \beta_6 big5o + \beta_7 highschool + \beta_8 shortuni + \beta_9 longuni + \beta_{10} young + \beta_{11} youngmiddle + \beta_{12} old$$

where *situation c or d,* is a binary variable, that is it can only take the value 1 or 0, and c or d are the situations described above

4) Probit regression for dictator game and IQ score:

$$situation\ c\ or\ d = constant + \beta_1 iqscore + \beta_2 big5a + \beta_3 big5c + \beta_4 big5e + \beta_5 big5n + \beta_6 big5o + \beta_7 highschool + \beta_8 shortuni + \beta_9 longuni + \beta_{10} young + \beta_{11} youngmiddle + \beta_{12} old$$

Table 10 presents the results from the public good game probit regressions in two different situations. The *free rider* (1-4) is a participant who keeps all money to him-/herself and does not share anything with the common pot. The second situation, *cooperative* (5-8), is where the participant puts all their initial money in the common pot. We have regressed CR and IQ scores on the probability of one of these situations happening. Regressions with even numbers have control variables included. Keep in mind that these coefficients cannot be interpreted as numbers, but only as signs of directions. The marginal effects can be found in section 5.3.

We find a relation between high CR and being a *free rider*, that is, scoring high on the CRT will increase the probability of free riding in the public good game. We do not observe this relation with IQ at all. A high score on the CRT will also increase the probability of being *cooperative*, however, we only find this in the regression without the control variables. IQ does not affect this situation significantly either.

Several control variables have an impact on the regression, as seen in table 10. For the *free rider* situation, which is the only situation where CR has an impact when the control variables are included, we can see the following (regression 6): First of all, some personality traits affect this choice. Agreeableness (big5a) significantly lowers the probability of being a free rider, while conscientiousness (big5c) significantly increases this probability.

Furthermore, the young (18-30) and the old (61-80) seem to have a higher probability of free riding in the public good game, compared to the middle-old participants (46-60). We can also see an educational effect, where participants with a long college education tend to be free riders with a higher probability than those who have not. Also, we can see that those in the *take* group tend to free ride more.

Table 10

Regressions of public good game money distribution

VARIABLES	(1) Free rider CR	(2) Free rider CR	(3) Free rider IQ	(4) Free rider IQ	(5) Cooperative CR	(6) Cooperative CR	(7) Cooperative IQ	(8) Cooperative IQ
crscore	**0.111*** **	**0.084***			**0.059** **	**0.017**		
	(0.040)	**(0.044)**			**(0.024)**	**(0.026)**		
big5a		-0.037***		-0.037***		0.012**		0.012**
		(0.008)		(0.008)		(0.005)		(0.005)
big5c		0.016*		0.016*		-0.012**		-0.012**
		(0.009)		(0.009)		(0.006)		(0.006)
big5e		-0.008		-0.009		0.005		0.005
		(0.008)		(0.008)		(0.005)		(0.005)
big5n		0.004		0.003		-0.011**		-0.012**
		(0.008)		(0.008)		(0.005)		(0.005)
big5o		-0.013		-0.012		0.007		0.007
		(0.008)		(0.008)		(0.005)		(0.005)
young		0.352***		0.351***		-0.230***		-0.232**
		(0.128)		(0.130)		(0.088)		(0.090)
youngmiddle		-0.100		-0.098		0.065		0.062
		(0.118)		(0.120)		(0.068)		(0.069)
old		0.212*		0.202		-0.036		-0.038
		(0.125)		(0.127)		(0.079)		(0.080)
sex		-0.158		-0.187*		-0.223***		-0.229***
		(0.101)		(0.099)		(0.060)		(0.060)
highschool		0.060		0.066		0.125		0.127
		(0.173)		(0.172)		(0.102)		(0.102)
shortuni		0.159		0.176		0.135		0.138
		(0.164)		(0.163)		(0.096)		(0.096)
longuni		0.321*		0.372**		0.352***		0.361***
		(0.181)		(0.179)		(0.111)		(0.110)
hypo		0.234		0.227		-0.534***		-0.535***
		(0.195)		(0.194)		(0.137)		(0.137)
take		0.395***		0.393***		0.359***		0.359***
		(0.091)		(0.091)		(0.059)		(0.059)
iqscore			**0.008**	**0.002**			**0.001**	**0.001**
			(0.013)	**(0.015)**			**(0.008)**	**(0.009)**
Constant	-1.750***	-0.907*	-1.648***	-0.749	-0.336***	-0.510	-0.260***	-0.486
	(0.078)	(0.536)	(0.123)	(0.545)	(0.045)	(0.345)	(0.078)	(0.347)
Observations	2,291	2,291	2,291	2,291	2,291	2,291	2,291	2,291

Notes: Probit regression with CR and IQ score respectively on the share of money (DKK) given to (or taken from) the common pot in the public good game. Regression 1-4 is the probability of the participant being a free rider. Regression 5-8 is the probability of the participant of being cooperative. Robust standard errors in parentheses

**** p<0.01, ** p<0.05, * p<0.1*

Table 11 presents the results from the dictator game probit regressions in two different situations. The *fair* situation (1-4), is where the participants share half of the money he/she originally has with the other player. The *selfish* (5-8) is a participant who keeps all money to him-/herself and does not share anything with the other player. We have regressed CR and IQ scores on the probability of one of these situations happening. Regressions with even numbers have control variables included. Keep in mind that these coefficients cannot be interpreted as numbers, but only as signs of directions. The marginal effects can be found in section 5.3.

Table 11

Regressions of dictator game money distribution

VARIABLES	(1) Fair CR	(2) Fair CR	(3) Fair IQ	(4) Fair IQ	(5) Selfish CR	(6) Selfish CR	(7) Selfish IQ	(8) Selfish IQ
crscore	**-0.099*****	**-0.099*****			**0.219*****	**0.201*****		
	(0.031)	**(0.033)**			**(0.035)**	**(0.037)**		
big5a		0.021***		0.021***		-0.023***		-0.022***
		(0.007)		(0.007)		(0.007)		(0.007)
big5c		-0.009		-0.008		-0.004		-0.006
		(0.007)		(0.007)		(0.008)		(0.008)
big5e		-0.016**		-0.014**		0.009		0.004
		(0.006)		(0.006)		(0.007)		(0.007)
big5n		0.000		0.001		-0.006		-0.010
		(0.006)		(0.006)		(0.007)		(0.007)
big5o		0.021***		0.020***		-0.016**		-0.014**
		(0.006)		(0.006)		(0.007)		(0.007)
young		-0.516***		-0.491***		0.513***		0.383***
		(0.111)		(0.113)		(0.116)		(0.118)
youngmiddle		-0.234***		-0.212**		0.284***		0.185*
		(0.090)		(0.092)		(0.098)		(0.099)
old		0.100		0.094		-0.168		-0.100
		(0.097)		(0.098)		(0.116)		(0.117)
sex		-0.011		0.029		-0.031		-0.105
		(0.079)		(0.077)		(0.087)		(0.086)
highschool		0.071		0.062		0.146		0.182
		(0.132)		(0.131)		(0.156)		(0.154)
shortuni		0.035		0.021		0.219		0.254*
		(0.123)		(0.123)		(0.149)		(0.147)
longuni[10]		-0.075		-0.119		0.470***		0.557***
		(0.143)		(0.142)		(0.165)		(0.163)
iqscore			**-0.040*****	**-0.014**			**0.088*****	**0.066*****
			(0.011)	**(0.012)**			**(0.012)**	**(0.013)**
Constant	0.181***	-0.198	0.381***	-0.286	-1.029***	-0.217	-1.483***	-0.259
	(0.059)	(0.456)	(0.101)	(0.457)	(0.069)	(0.489)	(0.117)	(0.498)
Observations	1,34	1,34	1,34	1,34	1,34	1,34	1,34	1,34

Notes: Probit regression with CR and IQ score respectively on the share of money (DKK) taken to keep in the dictator game. Regression 1-4 is the probability of the participant to choose to be fair. Regression 5-8 is the probability of the participant being selfish. Robust standard errors in parentheses

**** p<0.01, ** p<0.05, * p<0.1*

[10] No data for the generous situation (regression 9-12) because there are no generous participants with a long university education in the dataset.

The dictator game differs from the public good game because it is a game between two individuals (compared to the public good game where four players are involved), where one participant has all the power. Therefore, we also expect the results to differ, and as we can observe, they do. First of all, cognitive ability seems to have a greater impact on these specific situations overall in the dictator game, seeing that we have much more significance present. Scoring high on the CRT decreases the probability of being *fair*, and increases the probability of being *selfish.* We find similar results for participants with high IQ scores. A high score decreases the probability of being *fair*, however, only when no controls are present, and it increases the probability of being *selfish*.

As for the controls, we can again observe that agreeableness (big5a) has a positive impact on both the *fair* and the *selfish* situation, that is, high agreeableness scores are related to higher probabilities of these particular situations happening. Extraversion (big5e) has a negative impact on the *fair* situation, while it does not affect the other situations significantly. Openness affects the *fair* situations positively, but the *selfish* situation negatively. Age matters, the younger groups (18-45) have lower probability than the older of being *fair*, but higher probabilities of being *selfish*. We also observe an educational effect, where the participants with a long university education have a higher probability of being *selfish*.

5.2.3 Time analysis

In this section we examine the relation between cognitive ability and the time spent on performing the different tasks in this study (decision making, public good and dictator game), and in particular, we are interested in the difference between CR and IQ. Again, we only seek to find relations between cognitive ability and response time, not causal effects. Basically we have done the exact same regressions as above, that is we include the same control variables and independent variables (not probit, see appendix 3 for public good and dictator games), but we have replaced the dependent variable with the time it took to perform that specific task (e.g. *shiftpointrisk* is replaced with the time it took for the participant to make his/her risky choice in the risk aversion gamble).

We have chosen to remove some extreme observations (very long time compared to average), as we fear that these are participants who might have left the screen on by accident or by sloppiness. We have done this to get a fairer picture of the relationship between the response time and cognitive ability. However, we have performed a sensitivity analysis of the cutting points in our data, to make sure that these points are appropriate and do not change the results remarkably. See section 5.4 for a detailed description of this analysis. Each cut off point is also presented in the table notes as they differ for every regression.

Table 12 holds the results from the OLS regressions with CR and IQ scores respectively on the time spent on making decisions in the risk aversion gamble. The table holds data from both iLEE1 and iLEE2.

Table 12

Regressions of decision time for risk aversion gamble

VARIABLES	(1) CR iLEE1	(2) CR iLEE1	(3) IQ iLEE1	(4) IQ iLEE1	(5) CR iLEE2	(6) CR iLEE2	(7) IQ iLEE2	(8) IQ iLEE2
crscore	**1,902.993***** **(511.641)**	**1,975.814***** **(507.047)**			**541.730** **(621.805)**	**637.644** **(604.525)**		
big5a		295.152*** (98.449)		304.009*** (99.673)		217.138* (117.198)		208.229* (116.052)
big5c		149.363 (111.743)		160.616 (112.516)		28.677 (132.449)		38.977 (131.490)
big5e		-201.687** (100.803)		-233.402** (100.763)		-79.724 (127.766)		-61.022 (127.478)
big5n		-74.455 (98.367)		-108.567 (98.258)		125.411 (102.019)		139.818 (101.562)
big5o		276.921*** (93.277)		307.591*** (93.975)		20.616 (109.452)		27.108 (110.184)
young		-9,012.108*** (1,678.986)		-7,982.205*** (1,779.012)		-12,364.847*** (1,755.823)		-11,297.053*** (1,785.017)
youngmiddle		-6,910.657*** (1,381.032)		-6,352.171*** (1,402.911)		-7,807.441*** (1,604.888)		-7,005.954*** (1,605.835)
old		5,436.038*** (1,889.010)		4,730.835** (1,868.949)		12,040.209*** (2,331.913)		11,802.227*** (2,331.020)
sex		400.566 (1,230.874)		-446.753 (1,209.723)		-123.303 (1,397.776)		-621.630 (1,368.866)
highschool		77.567 (2,139.704)		202.566 (2,169.100)		1,750.789 (2,430.056)		1,510.618 (2,441.693)
shortuni		529.019 (2,147.781)		700.669 (2,176.661)		2,500.110 (2,367.473)		2,444.551 (2,374.459)
longuni		-2,010.363 (2,386.125)		-938.310 (2,402.794)		1,481.913 (2,665.705)		1,619.568 (2,641.476)
iqscore			**-838.762***** **(189.855)**	**-397.470**** **(192.835)**			**-1,236.110***** **(224.333)**	**-539.247**** **(221.059)**
Constant	55,960.947*** (974.805)	45,635.246*** (6,803.715)	66,809.166*** (1,902.287)	52,330.875*** (7,057.213)	53,689.597*** (1,235.243)	47,549.543*** (8,299.851)	66,478.516*** (2,313.571)	52,518.145*** (8,300.085)
Observations	1,072	1,072	1,072	1,072	738	738	738	738
R-squared	0.013	0.117	0.019	0.108	0.001	0.175	0.041	0.180

Notes: OLS regression on CR and IQ scores respectively on the time spent on the decision making gamble covering risk aversion (no losses possible). Data from iLEE1 (1-4) and iLEE2 (5-8). Robust standard errors in parentheses. Cut off point: 100,000 for iLEE1 and iLEE2.
**** p<0.01, ** p<0.05, * p<0.1*

These regressions show that there is a rather huge difference between CR and IQ when examining the time spent on a decision making task. A higher CR score increases the time spent on this task significantly, while a high IQ score does the exact opposite, it decreases the decision time. For the iLEE2 we could only find a significant (negative) relation for IQ scores.

Table 13 holds the results from the OLS regressions with CR and IQ scores respectively on the time spent on making decisions in the loss aversion gamble. The table holds data from both iLEE1 and iLEE2.

Table 13

Regressions of decision time for loss aversion gamble

VARIABLES	(1) CR iLEE1	(2) CR iLEE1	(3) IQ iLEE1	(4) IQ iLEE1	(5) CR iLEE2	(6) CR iLEE2	(7) IQ iLEE2	(8) IQ iLEE2
crscore	**3,083.595*** (506.836)**	**2,918.842*** (518.791)**			**1,642.158*** (575.070)**	**1,618.350*** (573.233)**		
big5a		200.752** (100.950)		195.587* (102.799)		-94.068 (118.952)		-114.395 (119.294)
big5c		232.667** (113.640)		221.532* (114.010)		134.092 (114.595)		145.829 (114.838)
big5e		-203.074** (102.995)		-237.303** (103.587)		-61.341 (107.769)		-74.192 (107.403)
big5n		-20.530 (99.267)		-59.262 (100.206)		-202.356* (104.576)		-216.845** (105.396)
big5o		271.012*** (97.238)		316.617*** (98.180)		62.341 (99.550)		97.190 (100.335)
young		-5,007.527*** (1,713.591)		-4,581.210** (1,795.512)		-10,848.703*** (1,715.424)		-10,059.452*** (1,761.718)
youngmiddle		-4,396.224*** (1,391.895)		-4,375.232*** (1,427.600)		-5,609.881*** (1,531.121)		-5,155.708*** (1,578.632)
old		4,720.277*** (1,787.300)		4,032.086** (1,800.096)		8,496.478*** (1,945.498)		8,088.809*** (1,964.062)
sex		-1,257.634 (1,238.609)		-2,283.196* (1,239.846)		1,285.491 (1,356.666)		543.046 (1,337.609)
highschool		603.479 (2,251.839)		814.017 (2,307.306)		4,324.535* (2,300.814)		4,482.771* (2,321.957)
shortuni		2,346.588 (2,141.206)		2,914.256 (2,188.461)		4,330.248** (2,201.297)		4,714.986** (2,220.441)
longuni		1,768.573 (2,493.944)		3,463.729 (2,505.698)		2,702.848 (2,453.822)		3,345.879 (2,470.240)
iqscore			**-444.369** (184.970)**	**-100.169 (196.543)**			**-901.119*** (194.669)**	**-278.068 (200.942)**
Constant	60,054.645*** (973.476)	46,223.673*** (7,140.969)	68,908.885*** (1,812.045)	52,655.113*** (7,320.002)	49,649.256*** (1,093.606)	50,637.910*** (7,713.083)	60,485.627*** (1,962.375)	55,489.627*** (7,719.936)
Observations	1,547	1,547	1,547	1,547	981	981	981	981
R-squared	0.023	0.066	0.004	0.047	0.008	0.116	0.021	0.111

Notes: OLS regression on CR and IQ scores respectively on the time spent on the decision making gamble covering loss aversion (losses possible). Data from iLEE1 (1-4) and iLEE2 (5-8). Robust standard errors in parentheses. Cut off point: 120,000 for iLEE1 and 100,000 for iLEE2.
**** p<0.01, ** p<0.05, * p<0.1*

The regressions above basically only give significant results for the CR analyses. We see that a higher CR score in fact will increase the time spent on the task. We can observe one significant result for the IQ analysis, however, this is without control variables present. The relation is negative, that is, a higher IQ score decreases the time spent on the loss aversion gamble. The most relevant control here is age, and we can clearly observe that the younger groups (18-45) are faster than the older groups. These results hold for both iLEE1 and iLEE2.

Table 14

Regressions of decision time for public good and dictator games

VARIABLES	(1) CR PG	(2) CR PG	(3) IQ PG	(4) IQ PG	(5) CR D	(6) CR D	(7) IQ D	(8) IQ D
crscore	**-412.874***	**-180.636**			**-550.237**	**-220.054**		
	(214.852)	**(213.302)**			**(438.165)**	**(451.475)**		
big5a		95.528**		96.756**		108.884		106.119
		(44.433)		(44.391)		(85.122)		(84.784)
big5c		70.718		75.327		8.535		17.334
		(45.888)		(46.107)		(88.959)		(88.300)
big5e		-12.048		-8.624		-8.498		9.673
		(43.607)		(43.047)		(79.274)		(78.524)
big5n		37.004		38.791		-41.666		-28.854
		(40.884)		(40.836)		(79.446)		(78.989)
big5o		-30.912		-26.902		-126.726*		-124.210*
		(39.465)		(39.512)		(75.145)		(74.994)
young		-1,685.769**		-1,110.620		-2,774.074**		-1,884.929
		(710.965)		(725.744)		(1,405.634)		(1,419.810)
youngmiddle		-1,863.786***		-1,485.010***		-3,091.653***		-2,455.643**
		(536.921)		(541.066)		(1,146.047)		(1,155.040)
old		5,502.063***		5,145.037***		5,820.852***		5,242.574***
		(731.344)		(732.043)		(1,309.268)		(1,325.616)
sex		216.807		258.221		1,133.160		1,113.236
		(500.974)		(489.609)		(1,013.867)		(979.922)
highschool		-1,366.577*		-1,374.897*		-1,612.409		-1,566.091
		(819.806)		(816.649)		(1,674.783)		(1,677.726)
shortuni		-1,930.742**		-1,869.930**		-4,434.066***		-4,244.447***
		(762.616)		(757.210)		(1,535.349)		(1,541.321)
longuni		-1,979.460**		-1,901.913**		-3,705.367**		-3,574.743*
		(927.513)		(916.753)		(1,835.076)		(1,826.827)
hypo		331.985		449.628				
		(935.633)		(930.840)				
take		-345.107		-345.211				
		(501.672)		(499.814)				
iqscore			**-520.046*****	**-260.918*****			**-780.625*****	**-424.051*****
			(74.123)	**(75.949)**			**(148.271)**	**(150.375)**
Constant	24,614.755***	21,045.824***	28,617.988***	22,418.426***	32,968.476***	35,970.189***	39,147.444***	38,040.185***
	(389.219)	(2,944.747)	(704.529)	(2,929.089)	(781.755)	(5,748.274)	(1,437.579)	(5,769.486)
Observations	1,743	1,743	1,743	1,743	1,123	1,123	1,123	1,123
R-squared	0.002	0.080	0.028	0.086	0.001	0.059	0.025	0.065

Notes: OLS regression on CR and IQ scores respectively on the time spent on the public good (1-4) and dictator games (5-8). Robust standard errors in parentheses. Cut off point: 50,000 for public good and 75,000 for dictator game.
**** p<0.01, ** p<0.05, * p<0.1*

Table 14 presents the results from the public good (1-4) and dictator game (5-8) analyses. CR and IQ scores are regressed on the time spent on deciding the amount of money to give (or take) to (or from) the other player(s). As the results show, CR does not have a significant impact on the time spent on these tasks (except for regression 1, without controls). However, when we look at IQ, we observe that an increase in IQ score significantly decreases the time spent on both the public good game and the dictator game. As for the control variables, the *youngmiddle* group (31-45) seems to be significantly faster than other age groups, while the *old* group (61-80) seems to be significantly slower than the other age groups.

Table 15

Regression of decision time in public good game for free riders and cooperative separately

VARIABLES	(1) CR Free rider	(2) CR Free rider	(3) IQ Free rider	(4) IQ Free rider	(5) CR Cooperative	(6) CR Cooperative	(7) IQ Cooperative	(8) IQ Cooperative
crscore	**-1,126.044**	**-1,026.311**			**-427.542**	**-249.482**		
	(893.063)	**(1,117.474)**			**(296.347)**	**(301.561)**		
big5a		87.312		130.717		91.882		92.214
		(181.392)		(183.393)		(63.518)		(63.129)
big5c		-111.240		-114.191		38.097		49.241
		(239.801)		(248.291)		(66.506)		(66.762)
big5e		160.998		223.989		-41.364		-30.536
		(190.107)		(179.998)		(64.960)		(64.185)
big5n		506.926**		552.736**		40.598		46.559
		(222.867)		(218.907)		(58.721)		(58.681)
big5o		131.509		140.569		60.504		58.340
		(170.210)		(170.206)		(55.901)		(55.613)
young		-4,094.583		-3,690.158		-593.644		-4.286
		(3,255.964)		(3,350.829)		(1,132.767)		(1,150.647)
youngmiddle		-3,119.463		-3,125.616		-658.795		-295.901
		(2,902.485)		(2,927.522)		(761.783)		(764.624)
old		3,740.961		2,955.230		5,607.814***		5,298.738***
		(3,023.304)		(2,907.980)		(1,007.999)		(1,000.032)
sex		2,363.062		1,820.975		-731.363		-636.158
		(2,358.054)		(2,268.501)		(740.528)		(711.711)
highschool		22.909		267.910		574.175		464.007
		(3,715.948)		(3,435.757)		(1,172.624)		(1,159.305)
shortuni		-2,415.216		-2,315.215		-337.766		-404.404
		(4,109.565)		(3,728.847)		(1,047.499)		(1,032.663)
longuni		5,070.062		4,565.637		-1,291.829		-1,297.484
		(4,360.545)		(3,974.606)		(1,206.435)		(1,187.153)
hypo		-3,592.741		-2,814.441		2,400.767		2,763.762
		(5,171.852)		(5,065.328)		(1,721.398)		(1,717.692)
take		-584.145		-468.961		-588.826		-560.688
		(2,294.169)		(2,330.141)		(672.113)		(670.284)
iqscore			**-605.007**	**-244.765**			**-474.957*****	**-277.476****
			(385.523)	**(396.495)**			**(112.794)**	**(115.555)**
Constant	24,157.682***	8,561.684	27,836.793***	4,929.219	22,696.749***	17,263.787***	26,225.748***	18,407.469***
	(1,776.993)	(15,684.661)	(3,716.418)	(16,341.959)	(546.682)	(4,028.837)	(1,047.587)	(3,957.451)
Observations	81	81	81	81	753	753	753	753
R-squared	0.016	0.273	0.033	0.269	0.003	0.078	0.025	0.084

Notes: OLS regression on CR and IQ scores respectively on the time spent on the public good game for free riders (1-4) and cooperative individuals (5-8). Robust standard errors in parentheses. Cut off point: 50,000
**** p<0.01, ** p<0.05, * p<0.1*

In order to truly be able to separate the different situations in the public good and dictator games, we have chosen to regress the decision time separately for the free riders and the cooperative in the public good game, which is presented in table 15, and for fair and selfish individuals in the dictator game, presented in table 16.

Table 16

Regression of decision time in dictator game for fair and selfish individuals separately

VARIABLES	(1) CR Fair	(2) CR Fair	(3) IQ Fair	(4) IQ Fair	(5) CR Selfish	(6) CR Selfish	(7) IQ Selfish	(8) IQ Selfish
crscore	**-288.873**	**-210.072**			**-1,001.297**	**-644.679**		
	(605.763)	**(611.193)**			**(892.171)**	**(937.966)**		
big5a		81.187		81.166		204.230		195.120
		(113.596)		(113.342)		(178.995)		(176.186)
big5c		30.285		33.858		-55.811		12.774
		(110.853)		(110.248)		(183.803)		(174.493)
big5e		-129.805		-118.444		-25.464		85.374
		(99.575)		(98.314)		(176.584)		(170.817)
big5n		-91.147		-86.111		-3.601		116.527
		(101.151)		(101.357)		(172.250)		(167.336)
big5o		-94.548		-88.553		-124.606		-200.344
		(99.763)		(99.111)		(164.362)		(167.379)
young		-2,720.580		-2,217.156		-3,718.392		-1,621.127
		(2,108.677)		(2,108.602)		(2,753.580)		(2,767.427)
youngmiddle		-4,503.554***		-4,131.134***		-351.030		1,236.353
		(1,460.827)		(1,469.375)		(2,540.475)		(2,409.472)
old		7,294.695***		7,023.071***		2,343.415		-88.956
		(1,617.142)		(1,648.778)		(3,643.834)		(3,393.901)
sex		925.590		946.907		1,422.191		1,139.757
		(1,347.795)		(1,294.796)		(2,141.290)		(2,091.383)
highschool		-2,818.343		-2,724.295		-2,259.393		-2,862.602
		(2,299.121)		(2,295.868)		(3,978.982)		(4,073.115)
shortuni		-4,788.339**		-4,687.346**		-4,013.288		-3,654.597
		(2,181.971)		(2,186.729)		(3,899.270)		(4,015.872)
longuni		-3,091.066		-3,052.901		-5,396.131		-4,949.505
		(2,619.571)		(2,622.938)		(4,114.886)		(4,146.126)
iqscore			**-724.180*** **	**-249.276**			**-1,374.811*** **	**-1,371.132*** **
			(195.923)	**(190.088)**			**(318.314)**	**(344.136)**
Constant	30,211.640***	37,539.611***	35,997.119***	38,476.860***	35,419.716***	38,325.140***	47,462.369***	44,501.148***
	(1,042.558)	(7,200.247)	(1,824.260)	(7,210.509)	(1,762.129)	(11,902.330)	(3,420.151)	(11,439.789)
Observations	606	606	606	606	266	266	266	266
R-squared	0.000	0.100	0.023	0.103	0.005	0.037	0.060	0.083

Notes: OLS regression on CR and IQ scores respectively on the time spent on the dictator game for fair individuals (1-4) and selfish (5-8). Robust standard errors in parentheses. Cut off point: 75,000
**** p<0.01, ** p<0.05, * p<0.1*

For the public good game, we find that IQ significantly lowers the decision time for cooperative individuals, that is, these individuals act and decide faster than low IQ cooperative individuals. The only control variable that seems to have a significant effect on this result is the age variable, old cooperative individuals have spent much more time on this task. We could not find any relations for the CR score, neither could we for the free rider situation.

In the dictator game we, once again, only find relations for IQ. We find that a higher IQ is related to a shorter decision time for selfish individuals. We also find that a higher IQ shortens the decision time for fair participants, when regressing without control variables.

5.3 Marginal effects

It is not obvious how to interpret the different effects of the CR and IQ scores, because the scales vary considerably. The CR scale only goes between 0 and 3, while the IQ scale goes from 0 to 20. One step on the CR scale therefore represents several steps on the IQ scale. For that reason, we will also present the marginal effects, that is, the effect of an increase with one standard deviation, of CR and IQ respectively, in order to actually be able to compare the two effects. These have been calculated by multiplying the actual coefficients received for CR and IQ with each of their standard deviations. For the probit models, we multiplied the marginal effects (one unit change effect on the dependent variable) with the standard deviations, in order to get a comparable measure and proper interpretation.

The tables below present marginal effects of an increase of *one standard deviation* for CR and IQ respectively. The effects are calculated from the results *including* control variables. Table 17 presents the marginal effects of CR and IQ on each of the above analysed games. Table 18 shows the marginal effect of CR and IQ on the decision times for each task. These effects are discussed in detail in section 6.2.

Table 17

Marginal effects in standard deviations

	Risk aversion		**Loss aversion**	
	iLEE1	*iLEE2*	*iLEE1*	*iLEE2*
CR	-0.314	0.135	-0.084	0.106
IQ	-0.123	0.167	-0.063	0.010
	Public good		**Dictator**	
	Free rider	*Cooperative*	*Fair*	*Selfish*
CR	0.009	0.007	-0.044	0.067
IQ	0.001	0.002	-0.019	0.064

Notes: Effects of one standard deviation increase in CR and IQ scores respectively, for all games presented in the sections above.

Table 18

Marginal effects in standard deviations for time variables

	Risk aversion		Loss aversion	
	iLEE1	*iLEE2*	*iLEE1*	*iLEE2*
CR	2157.589	692.481	3199.051	1751.055
IQ	-1194.795	-1635.536	-302.811	-882.310
	Public good		**Dictator**	
CR	-198.670		-241.179	
	Free rider	*Cooperative*	*Fair*	*Selfish*
	-1136.125	-276.177	-232.130	-712.370
IQ	-815.108		-1362.052	
	Free rider	*Cooperative*	*Fair*	*Selfish*
	-762.443	-864.338	-782.727	-4305.354

Notes: Effects of one standard deviation increase in CR and IQ scores respectively on the time spent on each of the games presented in the sections above.

5.4 Robustness checks

In order to validate our regressions, we have performed several robustness checks. First of all, we have chosen to use the variables age and education as dummy variables in our regressions, separating them into different groups. This allows for non-linear relations when running an OLS. We present all regressions with the ordinary variables for age and education in appendix 1. When comparing these with the results obtained in our analysis, we could not find any notable differences. This justifies our decision to use the dummy variables in our analysis.

Furthermore, as mentioned before, we have chosen to drop some data from the time variables, since we had some serious outliers. In order to make sure that our cut point in the data is valid, we have performed a sensitivity analysis for each task. The results from this analysis can be found in appendix 2. We present regressions with the original cut point and two additional points, one below and one above the chosen cut point, in order to check that the chosen point does not change the results dramatically. These points were chosen after a visual analysis of the distribution of the data. When examining these regressions, we expect there to be some differences, because there is approximately 3 minutes difference between the cut points that are included. However, for most of the regressions, the results of the main regressors do not change dramatically, and most importantly, they do not change signs. The regression that might be discussable is the loss aversion decision time (table 29) where the signs do change for IQ score. However, the signs change in the right direction, since the effect of the IQ score gets smaller when the cut point increases, and between the actual cut point and the last cut point, the effect gets even more negative. Otherwise, our cut points seem legit according to this analysis.

When analysing the public good and dictator games, we have chosen to use a probit model, because we found this to be an interesting angle to use for examination. However, we have also performed regular OLS regressions, including the same regressors, just to be sure our findings would go in the same direction. These regression outputs can be found in appendix 3. Basically, these regressions suggest that CR significantly increases the amount of money given to the common pot in the public good game, suggesting that CR also would have a positive effect on the *cooperative* situations. We can confirm that our results do go in the same direction. In the dictator game regression, we find from the OLS, that both CR and IQ would increase the amount of money the dictator would keep to him-/herself, however, the effect of CR would be somewhat stronger. This would then imply a possibility of these variables to have a positive effect on the *selfish* situation. We can confirm this, as well as both of them having a negative effect on the *fair* situation.

6 Discussion

This paper examines the differences between cognitive reflection and IQ, primarily focusing on the time spent on performing different tasks, such as decision making under risk and money distribution. We have also mapped out the effects of CR and IQ, separately, in individual's behaviour, when performing these tasks. Furthermore, we sought to summarize research concerning cognitive ability, and different types of cognitive ability measures, in one paper, in order to properly be able to discuss the differences between CR and IQ.

Our hypothesis is that there is a difference between CR and IQ as measures of cognitive ability. Our main hypothesis was that people scoring high on the CRT would be slower when making decisions of importance or difficulty, assuming that they would be more considerate and thorough when making them. This hypothesis is based on the assumption that CR is related to, and supposed to measure, the activeness of system 2 (see section 3.1). A high CRT score then indicates a more active system 2, which means slower, but more considerate, actions.

6.1 Main findings

We can confirm this hypothesis with the results we obtained. We found that a higher CRT score would in fact increase the time spent in several tasks. In the risk aversion gamble, when individuals choose between two lotteries, one riskier than the other (no losses possible), we found that an increase in one CRT score, on average, would increase the decision time with approximately 20 seconds. This result was found to be highly significant. Additionally, we found this relation to be even stronger when examining the same task, however, with a possible loss involved when choosing the risky lottery. The average time spent on this task would then increase with approximately 35 seconds, with an increase of one CRT score. This result was also highly significant. These results are from the tasks in iLEE1, however, they are confirmed by the iLEE2 in the loss aversion gamble, but not in the risk aversion gamble.

Further on, when examining the public good and dictator games, CR does not seem to have an impact on the time spent on these tasks, however, we found that IQ does. We will come back to this result later in this section. Based on the analysis of Moritz et al. (2014) this is somewhat a conflicting result, as they found that CRT scores had an effect on decision speed, where a high CRT score would imply a moderate response time, in between the very long and short ones of low scoring individuals, whereas our findings implies that a high CR results in either a longer response time in some tasks or has no effect at all on the decision time in others. However, assuming that the results (CRT increasing the response time) from the risk and loss aversion gambles are caused by the fact that these individuals actually made better use of their system 2, it does provide further support for Rubinstein's (2007) idea that decisions made on the basis of cognitive reasoning need more time than those of an intuitive nature. Still we do not find this relationship for the public good and dictator games. One possible explanation to why we cannot find any impact of CR on these decisions could be a greater influence of emotion rather than cognitive reasoning, as these choices include decisions that also affect others, not only on an individual level as in the prior gambles, a topic also discussed by Nielsen et al. (2014), who argue that these games are imposing an emotional dilemma for the participants.

When we compare the effect of a high CRT score on response time to the effect of a high IQ score, we anticipated that there would be a difference. Still, we did not know whether the IQ score would increase or decrease the time spent on these tasks, however, we hypothesized that it, at least, would not increase the response time in the same extent as a high CRT score would do. Again, the results obtained confirm our theory. Not only does IQ have a different effect on response time in the risk aversion gamble, it actually decreases the response time with approximately 4 seconds (in iLEE1, 5 seconds in iLEE2), when the IQ score increases with one unit. This result is in line with prior research suggesting a negative correlation between intelligence and response time (Bates and Stough, 1997). However, remember that one additional IQ score is not comparable to one additional CRT score, and thus, the differences in effect seem larger than they actually are. For this reason, we will discuss the marginal effects of one standard deviation change in section 6.2, in order to obtain comparable measures of the effects. In the loss aversion gamble, we did not find any particular impact of IQ when control variables where included.

Further on, in the domain of the public good and dictator games, we found the following; in the public good game, an additional IQ score will decrease the time spent on the task, with approximately 2.6 seconds on average. In the dictator game, the time decreased with approximately 4.2 seconds, again, a result in line with prior studies (Bates and Stough, 1997). We did not find any particular influence of CR on response time for these tasks; a higher IQ on the other hand, will in fact shorten the response time when making decisions on the subject of monetary distribution. Additionally, we found, from the probit regressions on the dictator game, that IQ had an impact on the probability of certain situations (discussed later in this section), which might at least partly explain the shorter time.

Furthermore, we hypothesized there to be a difference in the effect of CR and IQ on the actual results of the games, as we believe that they might be capturing different dimensions of cognitive ability. First of all, we found that when playing the decision making gambles (both risk and loss aversion), CR and IQ both had an equally directed effect on the shift point (when significant). That is, for the risk aversion gamble, a higher CR and/or IQ decreases the shift point, which implies lesser risk aversion. This result is in line with, and supports, a large literature of previous findings regarding cognitive ability and risk aversion (Frederick, 2005; Burks et al. 2009; Dohmen et al. 2010; Benjamin et al. 2013; Cueva et al. 2015). However, in our results, CR does have a somewhat stronger effect than IQ (see section 6.2 for marginal effect comparisons). As for the loss aversion gamble, the same effect was found. A higher score of either CR or IQ decreases the shift point, implying lesser loss aversion in this case. The results for iLEE2 show the opposite effects, however, this was anticipated due to the bias induced by noise, a result found by Andersson et al. (2013). The tests in iLEE1 and iLEE2 are constructed differently, so that the risk neutral shift points are located early in iLEE1 and fairly late in iLEE2, and thus, one can be biased by wanting to choose a shift point somewhere in the middle of the gamble. This is discussed in detail section 4.2.4 and further in section 6.2.1.

If we analyse all of these differences further, we can connect back to the dual-process theory regarding system 1 and 2. The fact that CR has a stronger effect on the shift point in the decision making gamble, could possibly be explained by the fact that a higher CRT score might be an indicator of the system 2 being more active for those individuals. An active system 2 implies that they would be more considerate in the making of these decisions, which requires some extra deliberation in order to be well executed. The fact that a higher CRT score means that these individuals on average would shift earlier in the game, further suggests that they would be less risk averse. To be risk neutral, the participants would shift at point 3 in the risk aversion gamble for iLEE1. Here we found that the average shift point for individuals with a high CRT score (2 or 3) is 4.9. That is, according to a *t*-test we conducted, individuals who scored high on the CRT, shifted significantly earlier than the low scoring (0 or 1) individuals, who shifted, on average, at point 5.5. However, we did not find this relation for participants with high (11-20) or low (0-10) IQ scores respectively. This result could possibly be an indication of the fact that people with high CR in general are more rational, as it is rational to maximize utility (in this case in form of expected outcome), a relationship not found when examining IQ. This is in line with prior findings of CR being strongly correlated to rational thinking, whereas IQ is not (Toplak et al. 2011; Stanovich et al. 2011). Further on, this result relates to those of Campitelli and Gerrans (2014), who did discuss what the CRT actually measures, and found that it might be measuring a combination of both mathematical skills and rationality. In addition, the result itself, could further validate the evidence that CR and IQ are not perfectly correlated, and thus, do in fact measure different dimensions of cognitive ability. When examining the loss aversion gamble, we found that the individuals with high CRT scores did shift significantly earlier, as did the individuals with high IQ scores. That is, higher cognitive ability might be related to less loss aversion.

Moving on to the results of the money distribution games; for the public good game we could not find a particular relationship neither between IQ and the probability of being a free rider nor of being cooperative. A higher CR, on the other hand, would increase the probability of being a free rider, but has no effect on the probability of being cooperative. This result supports those of Nielsen et al. (2014), who also found a positive relation between CR and the probability of being a free rider, but found no relation to IQ. However, we did find that an increased IQ is related to a short decision time for cooperative individuals. The reason for this result may very well be that high IQ individuals realize at a sooner stage, the advantages of being cooperative in the public good game, and therefore do not need as much time to decide, as individuals with low IQ.

In the dictator game, we found that both CR and IQ increase the probability of being selfish. We also found that CR decreases the probability of being fair. This result could be linked to those of Cappelen et al. (2014), who find a strong connection between selfishness and deliberation, which under the assumptions of dual-process theory, possibly could be connected to higher CR. Furthermore, we found that selfish individuals with high IQ were faster in making their money distribution decision than those with lower IQ. Our findings contradict with some prior ones, who have found that cognitive ability, in general, does not predict individual’s choices in dictator games (Brandstätter and Güth, 2002; Benjamin et al. 2013). All in all, regarding the outcomes of the money distribution games, CR seems to be a better indicator of behaviour than does IQ, since we found significant effects from CR for all the various situations that we have analysed, in both games.

6.2 General discussion

In the previous section we discuss the main findings of this study. However, when we compare the effects of CR and IQ, this can be slightly confusing, considering that the scales differ for the CR and IQ scores. In order to make a reasonable comparison of the size of these effects, we have calculated the marginal effects for one standard deviation change in each score.

Starting with time analysis and the risk aversion gamble, we find that a higher CRT score increases the time spent on this task, while a higher IQ score instead decreases the response time. If the CRT score increases with one standard deviation, the time will increase with approximately 21.6 seconds, meanwhile, an increase in one standard deviation for the IQ score will decrease the time with approximately 11.9 seconds. So, not only is the effect from CR twice as strong, but we also see that the measures affect the time spent in opposite directions, as discussed earlier. Additionally, both of these effects were found to be significant. These results hold for iLEE1, and we also found significant results for iLEE2, regarding IQ, however, with a slightly stronger effect than in iLEE1. When examining loss aversion, we only find significant results for CR. We find that an increase in CRT score with one standard deviation increases the decision time with approximately 32 seconds (17.5 for iLEE2). For IQ, the time would slightly decrease, however, not significantly. This implies that when facing losses, in comparison to the risk aversion gamble (where losses are not possible, only smaller and bigger gains) an individual with high CR would be more careful when making the decision, and thus, spend some additional time on it. For the public good and dictator games, we only find significant results for IQ. One standard deviation increase will decrease the time with 8.2 seconds in the public good game and with 13.67 seconds in the dictator game. Nevertheless, we find that CR also would decrease the time, however, not significantly.

Regarding the actual results of the games, we observe that both CR and IQ will decrease the shift point in the risk aversion gamble, that is, a higher score of either or both, relates to less risk aversion. The effect is somewhat stronger for CR than IQ, as one standard deviation increase in CR generates a decrease in shift point with 0.31 and 0.12 for IQ (iLEE1). In the loss aversion gamble, the effects are the same, direction wise, but very small for both CR and IQ. For the iLEE2, as mentioned earlier, we obtain opposite results. An increased CR and/or IQ with one standard deviation will increase the shift point in the risk aversion gamble with 0.14 and 0.17 respectively. This positive effect was found for the loss aversion gamble as well, however, only for CR. However, when comparing individuals with low and high CRT scores (0-1 versus 2-3), there exists a significant difference in shift point in the risk aversion gamble, where the high CR group choose the risky gamble significantly earlier than the low CR group, indicating that individuals with high CR are less risk averse, and therefore in this case more effective, as their average shift point is closer to the risk neutral shift point. So, even though the effect of CR and IQ may be equal, individuals scoring high on the CRT still seem to act more rational and thus be less risk averse, again, a result in line with prior research that confirms a stronger relation between CR and rationality than for IQ (Toplak et al. 2011; Stanovich et al. 2011). This finding can also be related to Moritz et al. (2014), who discuss the phenomenon of under- and overthinking. They found that a moderate thinking time lead to the best choices, and thus, if we assume that the CR high scoring individuals, who spent longer time on average on this gamble, have a moderate time, our results agree. It can then be discussed that individuals scoring low might be under-thinking the matter which results in making worse choices, due to their intuition. This also is in line with the theory about system 1 and 2, which implies that under-thinking might result in non-optimal choices. However, Moritz et al. (2014) also discuss the matter of over-thinking, and argue that this phenomenon might as well generate bad choices. They believe that optimal choices are made when the decision time is moderate. We have not examined over-thinking in this study, but it would certainly be an interesting angle for future research. If we inspect the average shift points for the loss aversion gamble we find that participants, on average, shift after it is optimal to do so. That is, the participants were on average loss averse. This might be due to the fact that the risk neutral point is the second choice, which could induce a downward bias. This is in line with Andersson et al. (2013), who study whether the effect of cognitive ability on risk preferences is biased by noise, depending on the gamble presented. Furthermore, we find that individuals with high CR and/or IQ scores have even earlier shift points than low scorers, which again indicates that higher cognitive ability is related to a more efficient behaviour.

When it comes to the public good game, we cannot really compare the effects between CR and IQ, as we did not find any significant results for IQ. However, we did find this for the dictator game, and especially for the selfish situation. In this case the effects seem to be similar, and increase the probability of being selfish with approximately 6-7 percentages, when either CR or IQ increases with one standard deviation respectively. In addition, we find that an increase in CR decreases the probability of being fair with 4.4 percentages. So here, CR and IQ have an equal effect on the selfish situation, at the same time as a higher CR also is related to a decreased fairness.

One especially interesting thing is that, when participants play the decision making gambles, not all of them would be rational in their choices. That means that once they have made the choice to take the risky lottery, some of them actually changed back, and choose the safe lottery later in the same gamble. This is not reasonable by any means, as the further in the gamble you get, the larger the expected outcome of the risky lottery becomes in relation to the safe lottery. So once an individual chooses the risky lottery, he/she should never change back again. This finding is probably due to some of the participants not quite understanding the task properly, or even maybe just being ignorant. However, we did analyse this phenomenon further, and found that the irrational individuals had scored significantly lower than the rational ones, both on the CRT and the IQ test. Regarding the CRT, this result is not surprising, as it has been found strongly related to this trait (Toplak et al. 2011), but rather for IQ which is considered bad at predicting rational behaviour (Stanovich et al. 2011). So basically, irrational participants were less cognitively able, in general, than the rational ones, a result which might, to some extent, rule out the fact that they were merely ignorant. However, if they were ignorant performing this task, they might as well have been ignorant or sloppy when performing the cognitive ability tests, and thus, have been scoring badly for that reason.

We also examined consistent behaviour in the risk aversion gamble, that is, whether participants have had the same risk preferences in iLEE1 and iLEE2. We found a significant difference in cognitive ability between consistent and inconsistent individuals, where consistent individuals have higher CR and IQ. In addition, we found that individuals who exhibit *optimal* behaviour, that is, rational, consistent and utility (expected outcome) maximizing choices had significantly higher CR and IQ than those with risk seeking or risk averse preferences. That is, higher cognitive ability is in fact related to efficient choices, regardless of whether it is measured with the CRT or an IQ test.

Another matter worth discussing is gender differences. This is a topic reviewed in most research concerning CR, and although it is not our primary focus, we do not want to neglect it. First of all, we did not find any difference between men and women in IQ scores, just as hypothesized, based on past literature (Halpern et al. 2011). However, again anticipated in the light of prior research on CR (Frederick, 2005; Oechssler et al. 2009; Obrecht et al. 2009 etc.), we did find that men, on average, have significantly higher CRT scores. When examining the results from the time analysis, on the other hand, we could not find a significant gender effect in any of the regressions. After all, we can observe that females are somewhat less loss averse, and therefore, will generally choose the risky lottery in the loss aversion gamble, approximately 0.1-0.2 shift points earlier than men (iLEE2). This, in turn, implies that women act less efficient than men in this situation. This can be related to the fact that women scored significantly lower on the CRT than men, and as found by Toplak et al. (2011), higher CR is related to rationality. This is also confirmed by Stanovich et al. (2011) who claim that rationality is driven by type 2 processing. Otherwise, we could not capture any gender effects in any of our regressions where we found significant effects of CR and IQ scores. This might indicate that there actually is no remarkable difference in *the effect* of cognitive ability between men and women when making these different decisions.

Moving on to another variable of interest, we found differences between the age groups. Participants in the ages 61-80 scored lower on both the CRT and the IQ test. We also found that the younger participants, aged 18-29, scored significantly higher than the other groups on both tests. Further on, we do capture these effects in our time analysis, where in most regressions, the younger groups of participants (18-45) are significantly faster, on average. We also observe this for the group of older participants (61-80), who on average are slower when performing these tasks. When relating to the fact that the younger scored higher, and the older scored lower, on both tests of cognitive ability, this fact explains itself. Again this result was anticipated, as it has been shown that cognitive ability typically declines with age (Hertzog, 2011).

6.2.1 Validity and Reliability

As mentioned earlier, Andersson et al. (2013) find supporting evidence for the fact that the relation between cognitive ability and decision making would be biased with noise, and thus making the relationship spurious. It is an interesting topic, and very important to keep in mind, when interpreting the results from this, and all other studies using similar tests and not controlling for this issue, as it highly criticizes the validity and reliability of the decision making tests. And thus, it would also imply that the results found might not actually be true, or at least, cannot be trusted completely until tested with a valid test. However, we found it important to include these results in our study, because it is a very big part of research in this field, and one of our purposes is to summarize and clarify different effects of cognitive ability measures.

To some extent, we have eliminated this bias when examining the behaviour of what we call optimal individuals (rational, consistent and utility maximizing). Because individuals who have been rational *and* consistent have probably understood the task at hand, and thus, might not have been affected by the bias to the same extent as those who have not exhibited this behaviour. And thus, when examining these individuals and their preferences, we found that risk neutral choice individuals did score higher on both cognitive ability tests, and hence, these results might not be as spurious as the other results obtained from the decision making tasks.

6.2.2 Future research

Since we are among the first to examine the difference in time spent on various tasks, concerning decisions in different situation, between CR and IQ (at least, as far as we know), it might be of interest to examine this relation further. A more detailed examination, of each situation separately, would be interesting, as well as extending the comparison to other measures of cognitive ability and control variables. In particular, it would be appealing to explore new versions of the CRT, which contain more questions, and thus, might give the test a stronger reliability, since three questions might be considered too few to estimate an individual's actual CR level. Also, it might be uncertain to compare high and low CR, based on only three questions.

Of course, since the decision making (risk and loss aversion) have been criticized and shown to be biased, it is important to study solutions to this matter, whether it is to control for this bias in different ways, or if it is to construct the tests in a different way so that the bias can be eliminated. Either way, a solution would benefit this field, and future research within the fields of decision making, as this kind of test is a simple way to test for preferences, which is always appreciated by researchers. It does not only simplify the research, but it often generates valid results, since the participants do not tire of participating when the tests are not too long and tedious, especially if it is a sample of great variation of participants.

6.3 Concluding remarks

We have come across some interesting distinctions between the CR and IQ measures in this study. We found that CR is related to slower but more efficient decisions, an effect showed to be the opposite for IQ. This result indicates an activeness of system 2 for high CR individuals, which is important in the sense that we might be able to provide further support for the existence of dual-system processes, as many have questioned their reliability. Furthermore, this result justifies the CRT as a test of its own, and the fact that it is not "just" another IQ test. We also found that both CR and IQ have similar directional effects on some of the tasks (actual choices not decision time). Additionally, we found that both measures of CR and IQ are positively related to rational behaviour. This is a noteworthy result, as economic models generally assume that individuals are rational. Our findings disprove this idea, and rather suggest that this trait depends on an individual's level of cognitive ability, and these measures should therefore be accounted for by economists. We also observe that CR might be a better predictor of behaviour in some situations. Furthermore, the CRT could possibly be used to measure intuition in people, which could be useful. Considering that in some situations, being intuitive is very important, but in others, it can be rather risky, because of the sloppiness that can arise. Consequently, our results imply that a difference between these measures exists, and that they do capture different aspects of cognitive ability.

Hopefully, we have been able to summarize and map the effects of cognitive ability in different forms, in several situations concerning decision making, capturing different aversions and other aspects. As this paper aims to collect and assemble a broad span of tasks and characteristics regarding these measures, up till today based on one of the most vast and varied samples used in this field, we believe that this part of the paper alone, may be a contribution to the existing literature.

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Appendix

Appendix 1

This section holds all regressions made in section 5.2, but with the variables age and education instead of their dummy equivalents.

Table 19

Regressions of risk aversion gamble decision switch point

VARIABLES	(1) CR iLEE1	(2) CR iLEE1	(3) IQ iLEE1	(4) IQ iLEE1	(5) CR iLEE2	(6) CR iLEE2	(7) IQ iLEE2	(8) IQ iLEE2
crscore	**-0.319*****	**-0.286*****			**0.128****	**0.112***		
	(0.046)	**(0.048)**			**(0.057)**	**(0.059)**		
big5a		0.038***		0.038***		0.012		0.012
		(0.009)		(0.009)		(0.012)		(0.012)
big5c		-0.005		-0.003		0.001		-0.000
		(0.010)		(0.010)		(0.013)		(0.013)
big5e		0.013		0.017*		-0.010		-0.014
		(0.009)		(0.009)		(0.011)		(0.011)
big5n		0.023***		0.027***		0.007		0.005
		(0.009)		(0.009)		(0.010)		(0.010)
big5o		0.012		0.009		0.016		0.018
		(0.009)		(0.009)		(0.011)		(0.011)
age		-0.001		-0.004		-0.017***		-0.013***
		(0.004)		(0.004)		(0.005)		(0.005)
sex		0.059		0.168		-0.145		-0.173
		(0.115)		(0.116)		(0.143)		(0.140)
edu		-0.037		-0.048*		0.049		0.050
		(0.026)		(0.026)		(0.034)		(0.034)
iqscore			**-0.036****	**-0.042****			**0.070*****	**0.053****
			(0.017)	**(0.018)**			**(0.022)**	**(0.023)**
Constant	5.699***	3.690***	5.502***	3.574***	6.420***	6.244***	5.971***	5.945***
	(0.093)	(0.616)	(0.171)	(0.645)	(0.124)	(0.767)	(0.230)	(0.823)
Observations	1,399	1,399	1,399	1,399	856	856	856	856
R-squared	0.031	0.056	0.003	0.035	0.006	0.027	0.013	0.030

Notes: OLS regression with CR and IQ score respectively on decision making in covering risk aversion with data from both iLEE1 (1-4) and iLEE2 (5-8). Equivalent to table 8 in section 5. Robust standard errors in parentheses

**** p<0.01, ** p<0.05, * p<0.1*

Table 20

Regression of loss aversion gamble decision switch point

VARIABLES	**(1) CR iLEE1**	**(2) CR iLEE1**	**(3) IQ iLEE1**	**(4) IQ iLEE1**	**(5) CR iLEE2**	**(6) CR iLEE2**	**(7) IQ iLEE2**	**(8) IQ iLEE2**
crscore	**-0.091*****	**-0.081*****			**0.105*****	**0.097*****		
	(0.029)	**(0.030)**			**(0.024)**	**(0.025)**		
big5a		0.012*		0.012*		0.001		0.000
		(0.006)		(0.006)		(0.005)		(0.005)
big5c		0.007		0.008		-0.001		-0.001
		(0.007)		(0.007)		(0.006)		(0.006)
big5e		0.008		0.009		0.002		-0.000
		(0.006)		(0.006)		(0.005)		(0.005)
big5n		0.017***		0.018***		0.007*		0.007
		(0.006)		(0.006)		(0.004)		(0.004)
big5o		0.013**		0.012**		0.003		0.005
		(0.006)		(0.006)		(0.004)		(0.005)
age		-0.004*		-0.006**		-0.005***		-0.005***
		(0.002)		(0.003)		(0.002)		(0.002)
sex		-0.001		0.029		-0.124**		-0.165***
		(0.072)		(0.071)		(0.058)		(0.058)
edu		-0.011		-0.013		0.002		0.008
		(0.015)		(0.015)		(0.012)		(0.012)
iqscore			**-0.010**	**-0.023****			**0.012**	**0.001**
			(0.010)	**(0.011)**			**(0.008)**	**(0.008)**
Constant	3.443***	2.140***	3.391***	2.234***	7.480***	7.529***	7.541***	7.697***
	(0.057)	(0.410)	(0.099)	(0.422)	(0.052)	(0.306)	(0.077)	(0.319)
Observations	1,791	1,791	1,791	1,791	1,132	1,132	1,132	1,132
R-squared	0.005	0.022	0.001	0.020	0.018	0.035	0.002	0.020

Notes: OLS regression with CR and IQ score respectively on decision making in covering loss aversion with data from both iLEE1 (1-4) and iLEE2 (5-8). Equivalent to table 9 in section 5. Robust standard errors in parentheses

**** p<0.01, ** p<0.05, * p<0.1*

Table 21

Regressions of public good game money distribution

VARIABLES	(1) Free rider CR	(2) Free rider CR	(3) Free rider IQ	(4) Free rider IQ	(5) Cooperative CR	(6) Cooperative CR	(7) Cooperative IQ	(8) Cooperative IQ
crscore	**0.111*****	**0.081***			**0.059****	**0.0198**		
	(0.040)	**(0.044)**			**(0.024)**	**(0.0255)**		
big5a		-0.039***		-0.039***		0.0121**		0.012**
		(0.008)		(0.008)		(0.00514)		(0.005)
big5c		0.014		0.014		-0.0102*		-0.010*
		(0.009)		(0.009)		(0.00554)		(0.006)
big5e		-0.008		-0.010		0.00494		0.005
		(0.008)		(0.008)		(0.00502)		(0.005)
big5n		0.004		0.003		-0.0121**		-0.012**
		(0.008)		(0.008)		(0.00480)		(0.005)
big5o		-0.011		-0.010		0.00609		0.006
		(0.008)		(0.008)		(0.00472)		(0.005)
age		-0.002		-0.002		0.00206		0.002
		(0.003)		(0.004)		(0.00198)		(0.002)
sex		-0.183*		-0.215**		-0.241***		-0.249***
		(0.097)		(0.095)		(0.0597)		(0.059)
edu		0.033		0.041*		0.0426***		0.044***
		(0.021)		(0.021)		(0.0130)		(0.013)
hypo		0.223		0.215		-0.529***		-0.530***
		(0.193)		(0.192)		(0.136)		(0.136)
take		0.386***		0.385***		0.359***		0.359***
		(0.091)		(0.090)		(0.0590)		(0.059)
iqscore			**0.008**	**-0.001**			**0.001**	**0.002**
			(0.013)	**(0.014)**			**(0.008)**	**(0.009)**
Constant	-1.750***	-0.701	-1.648***	-0.544	-0.336***	-0.766**	-0.260***	-0.751**
	(0.078)	(0.557)	(0.123)	(0.574)	(0.045)	(0.349)	(0.078)	(0.361)
Observations	2,291	2,291	2,291	2,291	2,291	2,291	2,291	2,291

Notes: Probit regression with CR and IQ score respectively on the share of money (DKK) given to (or taken from) the common pot in the public good game. Regression 1-4 is the probability of the participant being a free rider. Regression 5-8 is the probability of the participant of being cooperative. Equivalent to table 10 in section 5. Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Table 22

Regressions of dictator game money distribution

VARIABLES	(1) Fair CR	(2) Fair CR	(3) Fair IQ	(4) Fair IQ	(5) Selfish CR	(6) Selfish CR	(7) Selfish IQ	(8) Selfish IQ
crscore	**-0.099*******	**-0.100*******			**0.219*******	**0.203*******		
	(0.031)	**(0.033)**			**(0.035)**	**(0.037)**		
big5a		0.021***		0.021***		-0.023***		-0.023***
		(0.007)		(0.007)		(0.007)		(0.007)
big5c		-0.008		-0.008		-0.003		-0.005
		(0.007)		(0.007)		(0.008)		(0.008)
big5e		-0.016**		-0.014**		0.009		0.004
		(0.006)		(0.006)		(0.007)		(0.007)
big5n		0.000		0.001		-0.007		-0.010
		(0.006)		(0.006)		(0.007)		(0.007)
big5o		0.020***		0.019***		-0.015**		-0.012*
		(0.006)		(0.006)		(0.007)		(0.006)
sex		0.006		0.050		-0.066		-0.145*
		(0.078)		(0.076)		(0.086)		(0.085)
edu		-0.007		-0.012		0.058***		0.064***
		(0.017)		(0.017)		(0.019)		(0.019)
age		0.014***		0.013***		-0.016***		-0.011***
		(0.002)		(0.003)		(0.003)		(0.003)
iqscore			**-0.040*******	**-0.012**			**0.088*******	**0.065*******
			(0.011)	**(0.012)**			**(0.012)**	**(0.013)**
Constant	0.181***	-0.906*	0.381***	-0.949**	-1.029***	0.504	-1.483***	0.209
	(0.059)	(0.464)	(0.101)	(0.477)	(0.069)	(0.496)	(0.117)	(0.518)
Observations	1,34	1,34	1,34	1,34	1,34	1,34	1,34	1,34

Notes: Probit regression with CR and IQ score respectively on the share of money (DKK) taken to keep in the dictator game. Regression 1-4 is the probability of the participant to choose to be fair. Regression 5-8 is the probability of the participant being selfish. Equivalent to table 11 in section 5. Robust standard errors in parentheses

**** p<0.01, ** p<0.05, * p<0.1*

Table 23

Regressions of decision time for risk aversion gamble

VARIABLES	(1) CR iLEE1	(2) CR iLEE1	(3) IQ iLEE1	(4) IQ iLEE1	(5) CR iLEE2	(6) CR iLEE2	(7) IQ iLEE2	(8) IQ iLEE2
crscore	**1,902.993*** **	**1,864.919*** **			**541.730**	**572.739**		
	(511.641)	**(506.472)**			**(621.805)**	**(604.765)**		
big5a		291.933***		300.609***		216.515*		208.978*
		(98.184)		(99.209)		(116.573)		(115.323)
big5c		132.087		146.881		-15.337		-2.853
		(110.130)		(110.907)		(132.730)		(131.723)
big5e		-199.866**		-232.368**		-88.758		-68.837
		(100.596)		(100.584)		(128.152)		(127.838)
big5n		-66.978		-99.559		140.757		155.014
		(99.303)		(98.944)		(101.585)		(101.089)
big5o		269.209***		301.633***		7.347		12.584
		(93.610)		(94.272)		(110.012)		(110.510)
age		345.408***		305.069***		501.251***		466.265***
		(41.296)		(44.648)		(46.719)		(48.184)
sex		703.168		-220.304		239.573		-281.074
		(1,229.693)		(1,202.583)		(1,407.736)		(1,374.920)
edu		-243.303		-99.421		113.862		170.516
		(281.499)		(282.957)		(323.744)		(319.345)
iqscore			**-838.762*** **	**-409.245** **			**-1,236.110*** **	**-562.715** **
			(189.855)	**(191.762)**			**(224.333)**	**(222.908)**
Constant	55,960.947***	29,188.212***	66,809.166***	37,116.920***	53,689.597***	24,873.381***	66,478.516***	31,385.571***
	(974.805)	(6,721.096)	(1,902.287)	(7,168.457)	(1,235.243)	(8,164.540)	(2,313.571)	(8,320.712)
Observations	1,072	1,072	1,072	1,072	738	738	738	738
R-squared	0.013	0.111	0.019	0.103	0.001	0.161	0.041	0.167

Notes: OLS regression on CR and IQ scores respectively on the time spent on the decision making gamble covering risk aversion (no losses possible). Data from iLEE1 (1-4) and iLEE2 (5-8). Equivalent to table 12 in section 5. Robust standard errors in parentheses

**** p<0.01, ** p<0.05, * p<0.1*

Table 24

Regressions of decision time for loss aversion gamble

VARIABLES	(1) CR iLEE1	(2) CR iLEE1	(3) IQ iLEE1	(4) IQ iLEE1	(5) CR iLEE2	(6) CR iLEE2	(7) IQ iLEE2	(8) IQ iLEE2
crscore	**3,083.595***** **(506.836)**	**2,849.569***** **(516.271)**			**1,642.158***** **(575.070)**	**1,558.828***** **(574.202)**		
big5a		192.641* (100.478)		185.141* (101.919)		-103.859 (119.219)		-122.809 (119.497)
big5c		216.507* (112.353)		209.548* (112.720)		136.788 (114.737)		149.108 (114.781)
big5e		-189.268* (103.500)		-225.251** (103.872)		-60.706 (107.505)		-73.203 (107.133)
big5n		7.244 (99.283)		-33.987 (100.161)		-189.520* (104.654)		-203.410* (105.312)
big5o		254.938*** (96.650)		303.609*** (97.422)		34.193 (98.227)		69.063 (98.998)
age		248.058*** (41.831)		229.438*** (45.581)		407.314*** (43.768)		378.620*** (46.992)
sex		-1,194.403 (1,232.884)		-2,307.770* (1,229.199)		1,413.509 (1,334.569)		646.521 (1,314.954)
edu		433.849 (280.877)		638.133** (282.669)		286.912 (288.179)		388.069 (288.497)
iqscore			**-444.369**** **(184.970)**	**-96.502** **(198.981)**			**-901.119***** **(194.669)**	**-299.379** **(199.966)**
Constant	60,054.645*** (973.476)	32,422.972*** (7,076.057)	68,908.885*** (1,812.045)	38,789.081*** (7,465.509)	49,649.256*** (1,093.606)	32,301.411*** (7,731.018)	60,485.627*** (1,962.375)	38,363.565*** (7,961.889)
Observations	1,547	1,547	1,547	1,547	981	981	981	981
R-squared	0.023	0.066	0.004	0.049	0.008	0.109	0.021	0.105

Notes: OLS regression on CR and IQ scores respectively on the time spent on the decision making gamble covering loss aversion (losses possible). Data from iLEE1 (1-4) and iLEE2 (5-8). Equivalent to table 13 in section 5. Robust standard errors in parentheses

**** p<0.01, ** p<0.05, * p<0.1*

Table 25

Regressions of decision time for public good and dictator games

VARIABLES	(1) CR PG	(2) CR PG	(3) IQ PG	(4) IQ PG	(5) CR D	(6) CR D	(7) IQ D	(8) IQ D
crscore	**-412.874***	**-228.876**			**-550.237**	**-142.557**		
	(214.852)	**(216.246)**			**(438.165)**	**(453.537)**		
big5a		73.371		75.910*		88.162		86.218
		(44.765)		(44.715)		(84.438)		(84.127)
big5c		55.821		60.685		-2.311		6.245
		(46.727)		(46.838)		(88.458)		(87.712)
big5e		-1.441		1.739		1.792		17.455
		(43.774)		(43.180)		(78.707)		(77.934)
big5n		46.791		48.118		-26.367		-15.046
		(41.464)		(41.347)		(79.532)		(79.031)
big5o		-26.754		-23.744		-102.615		-101.084
		(39.884)		(39.906)		(74.365)		(74.142)
age		156.590***		133.874***		206.714***		172.784***
		(17.920)		(18.987)		(32.548)		(34.313)
sex		189.669		242.706		1,110.016		1,050.765
		(499.958)		(488.853)		(1,017.612)		(980.795)
edu		-341.226***		-319.600***		-821.591***		-770.023***
		(108.416)		(107.437)		(213.780)		(213.377)
hypo		242.750		385.839				
		(950.188)		(946.136)				
take		-254.728		-266.473				
		(506.744)		(505.173)				
iqscore			**-520.046*****	**-267.644*****			**-780.625*****	**-407.789*****
			(74.123)	**(76.899)**			**(148.271)**	**(152.055)**
Constant	24,614.755***	15,145.050***	28,617.988***	17,592.921***	32,968.476***	28,064.218***	39,147.444***	31,818.944***
	(389.219)	(3,058.807)	(704.529)	(3,091.396)	(781.755)	(5,689.810)	(1,437.579)	(5,827.088)
Observations	1,743	1,743	1,743	1,743	1,123	1,123	1,123	1,123
R-squared	0.002	0.064	0.028	0.069	0.001	0.054	0.025	0.060

Notes: OLS regression on CR and IQ scores respectively on the time spent on the public good (1-4) and dictator games (5-8). Equivalent to table 14 in section 5. Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Appendix 2

This section documents the sensitivity analysis of the cut point in the time variables. Every regression in this section will include three different points in the time variable, where the middle (marked in grey) represents the cut point we chose. The other points will then work as a control, to verify that the cut point we chose, does not affect the results dramatically.

Table 26

Regressions of decision time for risk aversion gamble in iLEE1

VARIABLES	(1) 75,000 CR	(2) 75,000 CR	(3) 75,000 IQ	(4) 75,000 IQ	(5) 100,000 CR	(6) 100,000 CR	(7) 100,000 IQ	(8) 100,000 IQ	(9) 125,000 CR	(10) 125,000 CR	(11) 125,000 IQ	(12) 125,000 IQ
crscore	**1,114.475***	**1,103.564***			**1,902.993***	**1,975.814***			**2,686.797***	**2,919.063***		
	(388.091)	**(391.345)**			**(511.641)**	**(507.047)**			**(607.894)**	**(594.169)**		
big5a		292.140***		298.083***		295.152***		304.009***		317.088***		323.459***
		(76.437)		(76.640)		(98.449)		(99.673)		(112.683)		(114.922)
big5c		140.223		142.562		149.363		160.616		112.176		124.167
		(87.735)		(88.542)		(111.743)		(112.516)		(128.041)		(129.010)
big5e		-53.821		-70.406		-201.687**		-233.402**		-240.373**		-275.863**
		(76.762)		(77.195)		(100.803)		(100.763)		(118.950)		(119.208)
big5n		89.029		70.558		-74.455		-108.567		-67.949		-106.602
		(78.589)		(78.257)		(98.367)		(98.258)		(113.445)		(112.422)
big5o		227.833***		247.154***		276.921***		307.591***		168.075		200.075*
		(74.097)		(74.659)		(93.277)		(93.975)		(113.935)		(114.223)
young		-5,060.721***		-4,720.436***		-9,012.108***		-7,982.205***		-12,310.554***		-11,047.501***
		(1,298.648)		(1,363.877)		(1,678.986)		(1,779.012)		(1,885.544)		(1,998.444)
youngmiddle		-2,681.345**		-2,431.601**		-6,910.657***		-6,352.171***		-8,659.947***		-8,116.008***
		(1,064.282)		(1,089.169)		(1,381.032)		(1,402.911)		(1,640.475)		(1,667.391)
old		5,514.768***		5,361.599***		5,436.038***		4,730.835**		7,181.101***		6,439.241***
		(1,496.263)		(1,500.670)		(1,889.010)		(1,868.949)		(2,238.124)		(2,254.764)
sex		-650.781		-1,195.058		400.566		-446.753		2,636.423*		1,490.243
		(984.182)		(960.224)		(1,230.874)		(1,209.723)		(1,437.188)		(1,429.777)
highschool		35.747		74.680		77.567		202.566		-38.602		548.512
		(1,686.119)		(1,730.807)		(2,139.704)		(2,169.100)		(2,462.482)		(2,463.426)
shortuni		-1,242.099		-1,230.962		529.019		700.669		1,282.597		1,991.336
		(1,648.462)		(1,694.136)		(2,147.781)		(2,176.661)		(2,475.438)		(2,473.047)
longuni		-2,258.941		-1,752.984		-2,010.363		-938.310		-612.549		1,216.523
		(1,848.152)		(1,880.910)		(2,386.125)		(2,402.794)		(2,741.656)		(2,728.836)
iqscore			**-336.210***	**-152.486**			**-838.762***	**-397.470***			**-1,107.927***	**-437.599***
			(144.826)	**(145.350)**			**(189.855)**	**(192.835)**			**(219.763)**	**(224.566)**
Constant	49,411.468***	32,496.506***	54,330.698***	35,698.361***	55,960.947***	45,635.246***	66,809.166***	52,330.875***	59,399.887***	52,560.985***	73,987.563***	60,986.267***
	(746.022)	(5,190.696)	(1,457.741)	(5,335.271)	(974.805)	(6,803.715)	(1,902.287)	(7,057.213)	(1,144.844)	(7,869.056)	(2,199.681)	(8,120.202)
Observations	831	831	831	831	1,072	1,072	1,072	1,072	1,181	1,181	1,181	1,181
R-squared	0.010	0.101	0.007	0.094	0.013	0.117	0.019	0.108	0.016	0.125	0.021	0.111

Notes: OLS regression on CR and IQ scores respectively on the time spent on the decision making gamble covering risk aversion (no losses possible). This corresponds to the cut point (100,000) made for the risk aversion gamble for iLEE1, and thus the results from table 12 (regression 1-4). The grey area represents the regressions presented in section 5 of this paper, and thus, corresponds to the results we have reported. 515 observations were cut. Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Table 27

Regressions of decision time for risk aversion gamble in iLEE2

VARIABLES	(1) 75,000 CR	(2) 75,000 CR	(3) 75,000 IQ	(4) 75,000 IQ	(5) 100,000 CR	(6) 100,000 CR	(7) 100,000 IQ	(8) 100,000 IQ	(9) 125,000 CR	(10) 125,000 CR	(11) 125,000 IQ	(12) 125,000 IQ
crscore	**662.364**	**864.404***			**541.730**	**637.644**			**256.690**	**64.498**		
	(486.064)	**(471.263)**			**(621.805)**	**(604.525)**			**(738.401)**	**(704.892)**		
big5a		178.193*		163.315*		217.138*		208.229*		143.814		129.481
		(92.564)		(91.968)		(117.198)		(116.052)		(148.048)		(146.772)
big5c		67.661		78.506		28.677		38.977		47.824		67.588
		(103.475)		(103.432)		(132.449)		(131.490)		(158.629)		(155.476)
big5e		67.118		80.132		-79.724		-61.022		-148.124		-114.678
		(95.832)		(94.605)		(127.766)		(127.478)		(149.994)		(148.843)
big5n		88.366		95.089		125.411		139.818		114.166		141.481
		(81.752)		(82.028)		(102.019)		(101.562)		(122.559)		(121.106)
big5o		-103.100		-100.148		20.616		27.108		193.352		196.496
		(90.458)		(91.295)		(109.452)		(110.184)		(124.517)		(124.834)
young		-7,851.945***		-7,093.481***		-12,364.847***		-11,297.053***		-14,089.769***		-12,566.845***
		(1,376.819)		(1,402.977)		(1,755.823)		(1,785.017)		(2,047.269)		(2,062.935)
youngmiddle		-4,711.810***		-4,137.270***		-7,807.441***		-7,005.954***		-8,900.441***		-7,808.043***
		(1,282.774)		(1,304.807)		(1,604.888)		(1,605.835)		(1,937.649)		(1,940.565)
old		6,016.328***		5,897.714***		12,040.209***		11,802.227***		13,024.383***		12,539.284***
		(1,840.834)		(1,825.315)		(2,331.913)		(2,331.020)		(2,661.454)		(2,649.618)
sex		579.548		100.705		-123.303		-621.630		-1,074.598		-1,430.698
		(1,098.411)		(1,087.442)		(1,397.776)		(1,368.866)		(1,644.250)		(1,627.892)
highschool		2,429.381		2,175.173		1,750.789		1,510.618		2,251.272		1,956.736
		(1,857.428)		(1,881.413)		(2,430.056)		(2,441.693)		(2,838.650)		(2,819.097)
shortuni		3,045.090*		3,043.495*		2,500.110		2,444.551		4,118.834		4,070.721
		(1,799.172)		(1,819.494)		(2,367.473)		(2,374.459)		(2,745.310)		(2,729.979)
longuni		2,015.487		2,243.868		1,481.913		1,619.568		2,929.280		2,874.931
		(2,033.823)		(2,028.467)		(2,665.705)		(2,641.476)		(3,108.579)		(3,071.558)
iqscore			**-716.820*****	**-378.755****			**-1,236.110*****	**-539.247****			**-1,574.467*****	**-782.084*****
			(177.252)	**(181.772)**			**(224.333)**	**(221.059)**			**(268.377)**	**(263.360)**
Constant	47,392.256***	38,795.019***	55,509.324***	43,295.295***	53,689.597***	47,549.543***	66,478.516***	52,518.145***	57,697.319***	51,035.860***	73,158.443***	56,409.734***
	(942.164)	(6,718.221)	(1,801.067)	(6,830.242)	(1,235.243)	(8,299.851)	(2,313.571)	(8,300.085)	(1,491.408)	(9,855.536)	(2,777.803)	(9,953.725)
Observations	618	618	618	618	738	738	738	738	787	787	787	787
R-squared	0.003	0.115	0.028	0.118	0.001	0.175	0.041	0.180	0.000	0.154	0.044	0.163

Notes: OLS regression on CR and IQ scores respectively on the time spent on the decision making gamble covering risk aversion (no losses possible). This corresponds to the cut point (100,000) made for the risk aversion gamble for iLEE2, and thus the results from table 12 (regression 5-8). The grey area represents the regressions presented in section 5 of this paper, and thus, corresponds to the results we have reported. 193 observations were cut. Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Table 28

Regressions of decision time for loss aversion gamble in iLEE1

VARIABLES	(1) 100,000CR	(2) 100,000CR	(3) 100,000 IQ	(4) 100,000 IQ	(5) 120,000 CR	(6) 120,000 CR	(7) 120,000 IQ	(8) 120,000 IQ	(9) 140,000 CR	(10) 140,000 CR	(11) 140,000 IQ	(12) 140,000 IQ
crscore	**2,449.980*****	**2,191.684*****			**3,083.595*****	**2,918.842*****			**3,350.490*****	**3,103.460*****		
	(446.233)	**(452.076)**			**(506.836)**	**(518.791)**			**(572.192)**	**(581.345)**		
big5a		145.509		140.256		200.752**		195.587*		189.489		177.965
		(90.709)		(91.974)		(100.950)		(102.799)		(115.585)		(117.648)
big5c		85.287		76.181		232.667**		221.532*		225.908*		225.627*
		(99.135)		(99.037)		(113.640)		(114.010)		(129.712)		(130.223)
big5e		-102.701		-124.971		-203.074**		-237.303**		-282.516**		-323.730***
		(90.473)		(90.990)		(102.995)		(103.587)		(114.620)		(115.730)
big5n		-30.465		-57.263		-20.530		-59.262		-10.519		-46.611
		(86.473)		(86.924)		(99.267)		(100.206)		(114.037)		(115.086)
big5o		138.861		170.298**		271.012***		316.617***		370.942***		425.081***
		(85.251)		(85.663)		(97.238)		(98.180)		(107.789)		(108.682)
young		-3,898.351***		-3,659.386**		-5,007.527***		-4,581.210**		-6,041.654***		-5,111.876**
		(1,489.013)		(1,554.124)		(1,713.591)		(1,795.512)		(1,914.289)		(1,995.351)
youngmiddle		-4,046.667***		-4,081.038***		-4,396.224***		-4,375.232***		-5,500.070***		-5,237.014***
		(1,219.503)		(1,246.247)		(1,391.895)		(1,427.600)		(1,548.392)		(1,580.490)
old		3,991.053**		3,479.410**		4,720.277***		4,032.086**		6,237.299***		5,447.328***
		(1,570.760)		(1,571.466)		(1,787.300)		(1,800.096)		(2,024.247)		(2,050.971)
sex		-1,555.943		-2,352.282**		-1,257.634		-2,283.196*		-1,272.274		-2,408.203*
		(1,079.618)		(1,073.489)		(1,238.609)		(1,239.846)		(1,376.237)		(1,382.457)
highschool		2,167.246		2,442.689		603.479		814.017		2,223.392		2,462.838
		(1,962.942)		(1,990.996)		(2,251.839)		(2,307.306)		(2,469.086)		(2,531.623)
shortuni		4,653.510**		5,198.057***		2,346.588		2,914.256		3,093.621		3,747.520
		(1,869.739)		(1,889.610)		(2,141.206)		(2,188.461)		(2,326.021)		(2,380.756)
longuni		4,484.259**		5,962.872***		1,768.573		3,463.729		2,943.458		4,832.487*
		(2,201.292)		(2,203.928)		(2,493.944)		(2,505.698)		(2,742.398)		(2,758.518)
iqscore			**-339.319****	**-47.912**			**-444.369****	**-100.169**			**-717.151*****	**-286.130**
			(158.464)	**(165.636)**			**(184.970)**	**(196.543)**			**(206.821)**	**(217.078)**
Constant	56,742.628***	48,420.759***	63,606.088***	52,868.114***	60,054.645***	46,223.673***	68,908.885***	52,655.113***	62,637.533***	48,312.589***	74,390.788***	56,331.315***
	(865.151)	(6,317.710)	(1,564.561)	(6,439.690)	(973.476)	(7,140.969)	(1,812.045)	(7,320.002)	(1,097.908)	(8,011.669)	(2,045.125)	(8,237.073)
Observations	1,405	1,405	1,405	1,405	1,547	1,547	1,547	1,547	1,624	1,624	1,624	1,624
R-squared	0.021	0.064	0.003	0.048	0.023	0.066	0.004	0.047	0.020	0.068	0.007	0.053

Notes: OLS regression on CR and IQ scores respectively on the time spent on the decision making gamble covering loss aversion (losses possible). This corresponds to the cut point (120,000) made for the loss aversion gamble for iLEE1, and thus the results from table 13 (regression 1-4). The grey area represents the regressions presented in section 5 of this paper, and thus, corresponds to the results we have reported. 270 observations were cut. Robust standard errors in parentheses

**** p<0.01, ** p<0.05, * p<0.1*

Table 29

Regressions of decision time for loss aversion gamble in iLEE2

VARIABLES	(1) 75,000 CR	(2) 75,000 CR	(3) 75,000 IQ	(4) 75,000 IQ	(5) 100,000 CR	(6) 100,000 CR	(7) 100,000 IQ	(8) 100,000 IQ	(9) 125,000 CR	(10) 125,000 CR	(11) 125,000 IQ	(12) 125,000 IQ
crscore	**1,532.605*****	**1,505.596*****			**1,642.158*****	**1,618.350*****			**2,624.796*****	**2,488.187*****		
	(448.770)	**(453.713)**			**(575.070)**	**(573.233)**			**(699.430)**	**(693.650)**		
big5a		-46.345		-62.850		-94.068		-114.395		-36.302		-74.225
		(92.939)		(93.811)		(118.952)		(119.294)		(141.493)		(142.296)
big5c		48.804		52.093		134.092		145.829		18.676		39.469
		(96.143)		(96.814)		(114.595)		(114.838)		(137.525)		(138.180)
big5e		-37.265		-62.743		-61.341		-74.192		12.901		-11.015
		(90.984)		(91.426)		(107.769)		(107.403)		(128.092)		(128.904)
big5n		-73.262		-90.264		-202.356*		-216.845**		-286.646**		-303.869**
		(88.463)		(88.520)		(104.576)		(105.396)		(121.649)		(122.504)
big5o		51.447		74.542		62.341		97.190		105.355		160.752
		(79.988)		(80.611)		(99.550)		(100.335)		(122.270)		(123.877)
young		-6,931.371***		-6,770.457***		-10,848.703***		-10,059.452***		-13,498.653***		-11,975.205***
		(1,437.107)		(1,473.349)		(1,715.424)		(1,761.718)		(2,043.428)		(2,082.261)
youngmiddle		-3,533.644***		-3,517.678***		-5,609.881***		-5,155.708***		-8,274.550***		-7,330.304***
		(1,207.476)		(1,228.607)		(1,531.121)		(1,578.632)		(1,802.388)		(1,865.487)
old		5,418.486***		5,307.947***		8,496.478***		8,088.809***		10,869.830***		10,032.418***
		(1,663.871)		(1,686.962)		(1,945.498)		(1,964.062)		(2,316.882)		(2,342.690)
sex		1,184.893		614.856		1,285.491		543.046		911.738		-206.364
		(1,100.708)		(1,093.294)		(1,356.666)		(1,337.609)		(1,602.540)		(1,570.563)
highschool		2,741.255		2,947.745		4,324.535*		4,482.771*		3,819.966		3,987.657
		(1,855.518)		(1,858.831)		(2,300.814)		(2,321.957)		(2,675.119)		(2,709.004)
shortuni		2,525.517		2,912.499		4,330.248**		4,714.986**		6,241.123**		6,855.091**
		(1,783.300)		(1,787.783)		(2,201.297)		(2,220.441)		(2,634.875)		(2,671.677)
longuni		3,531.237*		4,136.700**		2,702.848		3,345.879		3,924.718		5,050.762*
		(1,984.525)		(1,991.034)		(2,453.822)		(2,470.240)		(2,956.702)		(3,002.865)
iqscore			**-355.051****	**8.416**			**-901.119*****	**-278.068**			**-1,416.480*****	**-575.233****
			(164.289)	**(168.267)**			**(194.669)**	**(200.942)**			**(230.140)**	**(237.515)**
Constant	43,337.069***	43,314.492***	49,034.055***	46,373.936***	49,649.256***	50,637.910***	60,485.627***	55,489.627***	52,489.600***	53,593.350***	69,495.398***	62,402.831***
	(861.586)	(6,352.481)	(1,639.353)	(6,434.676)	(1,093.606)	(7,713.083)	(1,962.375)	(7,719.936)	(1,284.523)	(9,441.081)	(2,343.751)	(9,453.634)
Observations	817	817	817	817	981	981	981	981	1,061	1,061	1,061	1,061
R-squared	0.013	0.086	0.006	0.075	0.008	0.116	0.021	0.111	0.013	0.136	0.033	0.129

Notes: OLS regression on CR and IQ scores respectively on the time spent on the decision making gamble covering loss aversion (losses possible). This corresponds to the cut point (100,000) made for the loss aversion gamble for iLEE2, and thus the results from table 13 (regression 5-8). The grey area represents the regressions presented in section 5 of this paper, and thus, corresponds to the results we have reported. 169 observations were cut. Robust standard errors in parentheses

**** p<0.01, ** p<0.05, * p<0.1*

Table 30

Regressions of decision time for public good game

VARIABLES	(1) 40,000 CR	(2) 40,000 CR	(3) 40,000 IQ	(4) 40,000 IQ	(5) 50,000 CR	(6) 50,000 CR	(7) 50,000 IQ	(8) 50,000 IQ	(9) 60,000 CR	(10) 60,000 CR	(11) 60,000 IQ	(12) 60,000 IQ
crscore	**-370.982****	**-135.180**			**-412.874***	**-180.636**			**-610.362****	**-333.284**		
	(176.830)	**(176.992)**			**(214.852)**	**(213.302)**			**(253.254)**	**(250.560)**		
big5a		110.632***		113.575***		95.528**		96.756**		134.752***		137.044***
		(35.553)		(35.356)		(44.433)		(44.391)		(50.972)		(51.091)
big5c		46.894		51.160		70.718		75.327		55.212		59.164
		(36.707)		(36.851)		(45.888)		(46.107)		(52.892)		(53.046)
big5e		49.337		51.513		-12.048		-8.624		-56.768		-49.552
		(35.115)		(34.697)		(43.607)		(43.047)		(51.907)		(51.568)
big5n		20.359		22.307		37.004		38.791		35.623		39.256
		(33.696)		(33.619)		(40.884)		(40.836)		(48.933)		(48.919)
big5o		-61.566*		-57.513*		-30.912		-26.902		-22.813		-20.916
		(31.990)		(32.090)		(39.465)		(39.512)		(46.230)		(46.305)
young		-2,217.852***		-1,835.047***		-1,685.769**		-1,110.620		-2,277.222***		-1,669.870*
		(580.615)		(598.290)		(710.965)		(725.744)		(860.417)		(879.693)
youngmiddle		-1,701.929***		-1,465.456***		-1,863.786***		-1,485.010***		-2,540.262***		-2,121.245***
		(453.869)		(460.942)		(536.921)		(541.066)		(646.826)		(655.100)
old		3,819.255***		3,588.112***		5,502.063***		5,145.037***		6,552.000***		6,236.743***
		(607.141)		(607.143)		(731.344)		(732.043)		(858.758)		(867.448)
sex		382.834		396.580		216.807		258.221		454.471		565.445
		(416.965)		(408.486)		(500.974)		(489.609)		(600.630)		(592.997)
highschool		-1,693.403**		-1,720.766**		-1,366.577*		-1,374.897*		-984.051		-994.299
		(698.443)		(695.218)		(819.806)		(816.649)		(981.699)		(982.179)
shortuni		-2,014.391***		-1,983.839***		-1,930.742**		-1,869.930**		-2,243.963**		-2,240.172**
		(649.596)		(647.501)		(762.616)		(757.210)		(913.798)		(911.864)
longuni		-2,480.216***		-2,446.892***		-1,979.460**		-1,901.913**		-2,291.792**		-2,303.198**
		(780.192)		(775.141)		(927.513)		(916.753)		(1,070.282)		(1,059.158)
hypo		493.707		577.979		331.985		449.628		-865.158		-743.918
		(739.775)		(738.290)		(935.633)		(930.840)		(1,050.125)		(1,043.929)
take		-349.344		-354.524		-345.107		-345.211		-1,184.983**		-1,192.335**
		(413.440)		(412.006)		(501.672)		(499.814)		(580.755)		(579.189)
iqscore			**-376.979*****	**-174.896*****			**-520.046*****	**-260.918*****			**-619.448*****	**-276.345*****
			(61.689)	**(63.222)**			**(74.123)**	**(75.949)**			**(87.054)**	**(90.709)**
Constant	22,547.318***	19,008.551***	25,374.896***	19,788.657***	24,614.755***	21,045.824***	28,617.988***	22,418.426***	26,745.388***	23,884.152***	31,315.448***	25,046.562***
	(318.406)	(2,408.079)	(582.071)	(2,397.803)	(389.219)	(2,944.747)	(704.529)	(2,929.089)	(468.198)	(3,451.939)	(829.664)	(3,446.772)
Observations	1,583	1,583	1,583	1,583	1,743	1,743	1,743	1,743	1,854	1,854	1,854	1,854
R-squared	0.003	0.085	0.023	0.089	0.002	0.080	0.028	0.086	0.003	0.089	0.026	0.093

Notes: OLS regression on CR and IQ scores respectively on the time spent on the public good game. This corresponds to the cut point (50,000) made for the public good game, and thus the results from table 14 (regression 1-4). The grey area represents the regressions presented in section 5 of this paper, and thus, corresponds to the results we have reported. 540 observations were cut. Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Table 31

Regressions of decision time for dictator game

VARIABLES	(1) 50,000 CR	(2) 50,000 CR	(3) 50,000 IQ	(4) 50,000 IQ	(5) 75,000 CR	(6) 75,000 CR	(7) 75,000 IQ	(8) 75,000 IQ	(9) 100,000 CR	(10) 100,000 CR	(11) 100,000 IQ	(12) 100,000 IQ
crscore	**-878.040*****	**-615.535***			**-550.237**	**-220.054**			**-529.207**	**-324.088**		
	(316.032)	**(315.777)**			**(438.165)**	**(451.475)**			**(538.569)**	**(540.263)**		
big5a		-25.197		-24.841		108.884		106.119		204.410**		200.560**
		(61.157)		(60.960)		(85.122)		(84.784)		(102.220)		(101.477)
big5c		131.182**		132.960**		8.535		17.334		115.177		131.438
		(65.852)		(65.583)		(88.959)		(88.300)		(103.758)		(102.506)
big5e		23.363		40.532		-8.498		9.673		-37.703		-13.087
		(58.459)		(58.258)		(79.274)		(78.524)		(100.717)		(100.553)
big5n		72.259		78.710		-41.666		-28.854		40.819		61.681
		(57.361)		(57.606)		(79.446)		(78.989)		(105.223)		(104.057)
big5o		-103.564*		-110.592*		-126.726*		-124.210*		-106.258		-99.549
		(56.748)		(56.569)		(75.145)		(74.994)		(94.879)		(95.126)
young		-3,572.997***		-3,125.105***		-2,774.074**		-1,884.929		-2,678.681		-1,322.836
		(957.737)		(985.578)		(1,405.634)		(1,419.810)		(1,806.102)		(1,867.710)
youngmiddle		-2,334.542***		-1,978.815**		-3,091.653***		-2,455.643**		-3,615.074**		-2,588.106*
		(850.978)		(872.856)		(1,146.047)		(1,155.040)		(1,404.177)		(1,425.439)
old		3,847.031***		3,548.250***		5,820.852***		5,242.574***		7,565.183***		6,588.942***
		(965.183)		(971.926)		(1,309.268)		(1,325.616)		(1,640.591)		(1,655.516)
sex		923.922		1,115.564		1,133.160		1,113.236		-1,067.481		-1,128.510
		(733.372)		(718.421)		(1,013.867)		(979.922)		(1,278.172)		(1,253.173)
highschool		-2,944.511**		-2,950.207**		-1,612.409		-1,566.091		263.377		291.046
		(1,235.484)		(1,230.869)		(1,674.783)		(1,677.726)		(2,019.483)		(2,025.430)
shortuni		-3,983.326***		-3,946.658***		-4,434.066***		-4,244.447***		-3,344.513*		-3,144.790
		(1,176.888)		(1,177.197)		(1,535.349)		(1,541.321)		(1,905.199)		(1,911.750)
longuni		-3,344.410**		-3,481.469**		-3,705.367**		-3,574.743*		-1,736.278		-1,544.460
		(1,376.432)		(1,365.951)		(1,835.076)		(1,826.827)		(2,288.145)		(2,271.728)
iqscore			**-521.553*****	**-278.716****			**-780.625*****	**-424.051*****			**-1,072.729*****	**-684.242*****
			(106.711)	**(111.761)**			**(148.271)**	**(150.375)**			**(184.075)**	**(198.735)**
Constant	28,392.280***	28,576.302***	31,824.759***	29,444.560***	32,968.476***	35,970.189***	39,147.444***	38,040.185***	36,439.551***	31,188.862***	45,192.932***	34,624.982***
	(581.890)	(4,216.977)	(1,053.792)	(4,246.827)	(781.755)	(5,748.274)	(1,437.579)	(5,769.486)	(972.147)	(6,980.813)	(1,793.591)	(6,953.948)
Observations	952	952	952	952	1,123	1,123	1,123	1,123	1,204	1,204	1,204	1,204
R-squared	0.008	0.079	0.025	0.082	0.001	0.059	0.025	0.065	0.001	0.054	0.029	0.064

Notes: OLS regression on CR and IQ scores respectively on the time spent on the dictator game. This corresponds to the cut point (75,000) made for the dictator game, and thus the results from table 14 (regression 5-8). The grey area represents the regressions presented in section 5 of this paper, and thus, corresponds to the results we have reported. 211 observations were cut. Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Appendix 3

This section holds the corresponding OLS regressions from the probit analysis conducted in section 5.2.2.

Table 32

Regressions of public good game money distribution

VARIABLES	(1) CR	(2) CR	(3) IQ	(4) IQ
crscore	**0.708****	**0.412**		
	(0.302)	**(0.308)**		
big5a		0.269***		0.269***
		(0.065)		(0.065)
big5c		-0.146**		-0.149**
		(0.067)		(0.067)
big5e		0.106*		0.100
		(0.061)		(0.061)
big5n		-0.088		-0.093
		(0.059)		(0.059)
big5o		0.113*		0.119**
		(0.058)		(0.058)
young		-3.222***		-3.279***
		(1.065)		(1.096)
youngmiddle		0.941		0.880
		(0.791)		(0.805)
old		-0.881		-0.912
		(0.945)		(0.963)
sex		-1.351*		-1.500**
		(0.715)		(0.706)
highschool		2.208*		2.235*
		(1.228)		(1.230)
shortuni		2.006*		2.080*
		(1.144)		(1.146)
longuni		3.362**		3.580***
		(1.355)		(1.352)
hypo		-6.721***		-6.760***
		(1.408)		(1.412)
take		0.456		0.467
		(0.757)		(0.757)
iqscore			**0.045**	**0.036**
			(0.102)	**(0.111)**
Constant	33.685***	24.801***	34.338***	25.350***
	(0.543)	(4.166)	(0.945)	(4.209)
Observations	2,291	2,291	2,291	2,291
R-squared	0.002	0.040	0.000	0.040

Notes: OLS regression with CR and IQ score respectively on the share of money (DKK) given (or taken) to (from) the common pot in the public good game. Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Table 33

Regressions of dictator game money distribution

VARIABLES	(1) CR	(2) CR	(3) IQ	(4) IQ
crscore	**4.193*****	**3.717*****		
	(0.819)	**(0.824)**		
big5a		-0.566***		-0.562***
		(0.173)		(0.174)
big5c		0.091		0.068
		(0.177)		(0.178)
big5e		0.286*		0.202
		(0.167)		(0.165)
big5n		-0.045		-0.091
		(0.157)		(0.155)
big5o		-0.521***		-0.479***
		(0.149)		(0.148)
young		10.893***		8.962***
		(2.878)		(2.936)
youngmiddle		4.795**		3.253
		(2.300)		(2.345)
old		-3.499		-2.528
		(2.226)		(2.249)
sex		-0.543		-1.967
		(1.982)		(1.976)
highschool		2.576		2.856
		(3.320)		(3.314)
shortuni		3.171		3.555
		(3.104)		(3.092)
longuni		9.195**		10.608***
		(3.703)		(3.677)
iqscore			**1.582*****	**1.051*****
			(0.266)	**(0.283)**
Constant	92.856***	109.302***	85.256***	109.263***
	(1.398)	(11.508)	(2.308)	(11.515)
Observations	1,34	1,34	1,34	1,34
R-squared	0.020	0.071	0.024	0.065

Notes: OLS regression with CR and IQ score respectively on the share of money (DKK) taken to keep in the dictator game. Robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*