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Cognitive ability and risk aversion: A systematic review and meta analysis

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Abstract

Are highly intelligent people less risk averse? Over the last two decades scholars have argued the existence of a negative relationship between cognitive ability and risk aversion. Although numerous studies support this, the link between cognitive ability and risk aversion has not been found consistently. To shed new light on this topic, a systematic review and meta-analysis was conducted. A total of 97 studies were identified and included for meta-analysis in the domain of gains (N=90,723), 41 in the mixed domain (N=50,936), and 12 in the domain of losses (N=4,544). Results indicate that there exists a weak, but significant negative relationship between cognitive ability and risk aversion in the domain of gains. However, no relationship was observed in the mixed domain or in the domain of losses. Several meta-regressions were performed to investigate the influence of moderator variables. None of the moderator variables were found to consistently influence the relationship between cognitive ability and risk aversion across the domain of gains, mixed and losses. Moreover, no significant difference was observed between males and females across all three domains. In conclusion, this systematic review and meta-analysis provides new evidence that the relationship between cognitive ability and risk aversion is domain specific and not as strong as suggested by some previous studies.

Keywords: risk aversion, cognitive ability, risk preferences, intelligence, meta-analysis

1 Introduction

In economic theory, risk aversion is assumed to be a key determinant of human decision making. Naturally, the study of risk aversion has gained a lot of attention, attracting researchers from all over the world. For the past two decades, a number of scholars have argued that highly intelligent individuals tend to be less risk averse (Benjamin, Brown & Shapiro, 2013; Dohmen, Falk, Huffman & Sunde, 2010, 2018; Frederick, 2005), and thus more likely to optimize their choices in line with the normative benchmark of Expected Utility Theory (Rabin, 2000; Rabin & Thaler, 2001). Although a substantial amount of empirical evidence supports this conclusion (Dohmen et al., 2018), several studies do not find cognitive ability to be consistently related to risk aversion. For instance, some studies have found cognitive ability to be negatively related to risk aversion in the domain of gains but positively related in the mixed domain (Burks, Carpenter, Goette & Rustichini, 2009; Chapman, Snowberg, Wang, & Camerer, 2018). Similarly, Andersson, Holm, Tyran and Wengström (2016), concluded that the relationship might be spurious and dependent on the choice architecture of the decision task used to elicit risk preferences. Specifically, they reported a negative relationship when the percentage of alternative responses indicating risk aversion was set to 80% and a positive relationship when this was set to 50%. A potential explanation for this result is that people with low cognitive ability tend to make more random errors, leading risk aversion to be overestimated for this group when the percentage of alternatives permitting a choice indicating risk aversion is high, while underestimated when the opposite is the case (Andersson et al., 2016). Finally, several studies suggest that the negative relationship between cognitive ability and risk aversion exists only when the decision task used to elicit risk aversion is unincentivized and purely hypothetical (Sousa & Rangel, 2014; Taylor, 2013, 2016). In summary, it is unclear whether a negative relationship actually exists, and if so, to what extent. The purpose of this study is to investigate the nature of the relationship between cognitive ability and risk aversion, through a systematic literature review and meta-analysis.

The remainder of this article is organized as follows. First, a brief definition of cognitive ability and risk aversion is provided. Next, several theoretical explanations for why cognitive ability and risk aversion might be negatively related are presented, followed by an outline of the present investigation. Then the literature review and meta-analysis are discussed.

1.1 Defining Cognitive Ability and Risk Aversion

When conducting a systematic literature review and meta-analysis it is important to define the key variables of interest

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(Borenstein, Hedges, Higgins & Rothstein, 2009; Cooper, 2010).

Cognitive ability is one of the best researched, yet most controversial constructs within the field of psychology (Eysenck, 1998; Freund & Kasten, 2012; Sternberg, 1985). In general terms, cognitive ability is considered an extensive category, encompassing a wide range of abilities such as reasoning, problem solving and abstract thinking (Gottfredson, 1997). Throughout the history of the field, several influential scholars have attempted to converge on a single definition of the construct (Carroll, 1997; Freund & Kasten, 2012). Although no uniform definition of cognitive ability exists, Murphy and Davidshofer (1998) provides a definition that has proven useful in applied psychology (e.g., Seijts & Crim, 2009; Yeo & Neal, 2004). In line with their definition, cognitive ability will for the purposes of this study be defined as individual differences in the capacity to successfully perform tasks that require the manipulation, retrieval, evaluation or processing of mental information. This definition is closely related to what psychologists refer to as g or general cognitive ability, a factor considered to be the core of, and primary source of variance common to, cognitive abilities and cognitive ability tests (Spearman, 1904a; Yeo & Neal, 2004).

Based on the definition put forward by Fox, Erner and Walters (2016), an individual will for the purposes of this study be considered risk averse if he or she prefers a certain or risky option to a riskier option with equal or higher expected value. Conversely, an individual will be considered risk seeking, if he/she prefers a risky option to a certain or less risky option with higher expected value.

1.2 Theoretical Explanations

Various theoretical explanations have been put forward to explain why cognitive ability and risk aversion might be negatively related. One prominent explanation based on dual process theory (Evans & Stanovich, 2013; Kahneman & Frederick, 2002; Loewenstein & O'Donoghue, 2004) is that people with high cognitive ability are more reflective and, thus, less likely to make judgement and decision errors (Benjamin et al., 2013). According to dual-process theory, judgment and decision-making is the result of an interaction between two distinct cognitive processes; type 1 and type 2 (Evans & Stanovich, 2013). Type 1 are fast, automatic, low-effort and high-capacity processes, usually associated with heuristic and intuitive decision-making (Evans & Stanovich, 2013; Frankish, 2010). Type 2 are conversely, slow, controlled, high-effort and low capacity processes, typically associated with deliberate, reflective and rational decision-making (Evans & Stanovich, 2013; Frankish, 2010). Given that type 2 processes are assumed to tax working memory capacity (Evans & Stanovich, 2013; Stanovich, 2010), which is known to be highly correlated with cognitive ability (Conway, Kane & Engle, 2003; Kyllonen & Christal, 1990; Süß, Oberauer, Wittmann, Wilhelm, & Schulze, 2002), it is likely that people with high cognitive ability are more capable of engaging in reflective and rational decision-making. The dual-process explanation holds that people with high cognitive ability are likely to realize that risk aversion over small stakes is irrational (Rabin, 2000; Rabin & Thaler, 2001), because they have more cognitive capacity to deliberately reflect and think about their choices. In support of this argument, Cokely and Kelley (2009) found that highly intelligent individuals were more likely to engage in expected value maximization, report more elaborate and reflective thought patterns, and spend more time deliberating when choosing between prospects. Moreover, many other studies have shown that people with high cognitive ability display fewer behavioral biases across a wide range of decision tasks that arguably require type 2 processes to derive what is considered to be the normative response (e.g., Bergman, Ellingsen, Johannesson & Svensson, 2010; Hoppe & Kusterer, 2011; Oechssler, Roider & Schmitz, 2009; Stanovich & West, 1998; Toplak, West & Stanovich, 2011).

A similar explanation is that people with high cognitive ability are more likely to bracket their choices broadly; considering the bearing of their experimental decisions in a broader lifetime perspective (Dohmen et al., 2010; Koch & Nafziger, 2016; Read, Loewenstein & Rabin, 1999). Theoretically, this makes sense, as broad bracketing is cognitively taxing compared to narrow bracketing (Read et al., 1999), increasing the likelihood that people with low cognitive ability engages less in broad bracketing due to a lack of cognitive resources. Hence, given that broad bracketing has been linked with lower levels of risk aversion (Gneezy & Potters, 1997; Hilgers & Wibral, 2014; Thaler, Tversky, Kahneman & Schwartz, 1997), it is not unlikely that broad bracketing is one of the driving forces behind the negative relationship between cognitive ability and risk aversion observed in some previous studies.

A third possible explanation is that risk preferences play a role in the development of cognitive ability, and that individual risk preferences influence people's choice of environment, which in turn could affect cognitive development (Dohmen et al., 2018). As an example, risk preferences might play a role in choices about investment in education, which has been shown to foster the development of cognitive abilities (Falch & Sandgren Massih, 2011; Ritchie, Bates & Deary, 2015; Schneeweis, Skirbekk & Winter-Ebmer, 2014). On the other hand, it is of course possible that people with high cognitive ability seek out environments which foster the development of risk tolerance. For instance, several studies have shown that people with high cognitive ability are more active in the stock market (Christelis, Jappelli & Padula, 2010; Grinblatt, Keloharju & Linnainmaa, 2011; Van Rooij, Lusardi & Alessie, 2011), which could lead them to become more risk tolerant over time.

Finally, it could be that the relationship between cognitive ability and risk aversion, is coevolutionary: meaning that certain configurations of cognitive ability and risk aversion have been evolutionary beneficial (Dohmen et al., 2010, 2018). Hence, evolutionary pressures might have created a general tendency for low cognitive ability to be coupled with risk aversion and vice versa.

1.3 The Present Investigation

In light of the mixed findings on the relationship between cognitive ability and risk aversion, the first aim of this study is to systematically investigate the nature of the relationship across the domain of gains, mixed and losses. In line with the existing literature, the second aim is to examine to what extent the choice architecture of the decision task used to elicit risk preferences influence the relationship between cognitive ability and risk aversion. The current study will also ask whether the relationship exists only when the decision task is unincentivized and purely hypothetical, and whether the relationship is influenced by how cognitive ability is measured. Finally, given that age (Defoe, Dubas, Figner & van Aken, 2015; Mata, Josef, Samanez-Larkin & Hertwig, 2011) and gender (Charness & Gneezy, 2012; Croson & Gneezy, 2009) have been found to be related to risk preferences, the last aim of this study is to investigate the influence of these variables on the relationship between cognitive ability and risk aversion.

2 Method

In line with the guidelines provided by Cooper (2010) the systematic literature review and meta-analysis performed in this study comprised three steps: (1) literature search, (2) data extraction and coding, and (3) data analysis.

2.1 Step 1. Literature Search

In order to identify studies examining the relationship between cognitive ability and risk aversion, the following four electronic databases were searched: Econlit, PsycInfo, Business Source Complete, and Academic Search Complete. All databases were searched using the following keywords in the first search field: "risk avers*" OR "loss avers*" OR "prospect theory" OR "expected utility" OR "risk toleran*" OR "risk preference*" OR "risk neutral" OR "risk attitude*"; and the following keywords in the second search field: "cognitive abilit*" OR "intelligence" OR "IQ" OR "cognitive skills" OR "mental abilit*" OR "cognitive function*" OR "cognitive performance" OR "intelligence quotient" OR "general mental abilit*" OR "cognitive capacit*" OR "mental capacit*" OR "intellectual function*". The keywords from the two search fields were combined using the Boolean operator "AND", leading to the final search string presented below: ("risk avers*" OR "loss avers*" OR "prospect theory" OR "expected utility" OR "risk toleran*" OR "risk preference*" OR "risk neutral" OR "risk attitude*") **AND** ("cognitive abilit*" OR "intelligence" OR "IQ" OR "cognitive skills" OR "mental abilit*" OR "cognitive function*" OR "cognitive performance" OR "intelligence quotient" OR "general mental abilit*" OR "cognitive capacit*" OR "mental capacit*" OR "intellectual function*")

The search was limited to studies written in English published from 1900 to 2018 and yielded a total of 692 hits. Next, Scopus was searched using the same combination of keywords in first and second search-field. The Scopus search was also limited to studies written in English, published from 1900 to 2018 and yielded a total of 658 hits. Finally, four independent searches on Google Scholar were conducted using the keywords: (1) "risk aversion" AND "cognitive ability"; (2) "risk aversion" AND "intelligence"; (3) "risk aversion" AND "mental ability"; (4) "risk aversion" AND "cognitive skills". Each independent Google Scholar search resulted in somewhere between 625 and 19,900 hits, of which Google Scholar displayed the first thousand. All searches were conducted from 03.12.2018 to 11.12.2018. To supplement the electronic search, a manual search of reference lists of key empirical and theoretical articles was performed. The manual search yielded no additional studies. For all studies identified as relevant, title and abstract were screened for appropriate content and a total of 633 studies were extracted for full text screening. For an overview of the literature search process see Figure 1.

2.2 Exclusion and Inclusion Criteria

Studies were included for data extraction and coding if they reported either Pearson´s r, Spearman´s rho, means and standard deviations (i.e., descriptive statistics), or beta-coefficients for the relationship between cognitive ability and risk aversion. Studies were excluded if they (a) investigated decision-making under ambiguity, (b) relied on self-report measures of risk aversion, (c) used academic performance, literacy, reading proficiency, financial literacy, or educational attainment as proxies for cognitive ability, or (d) solely relied on participants experiencing any form of mental health problems or cognitive impairment. After carefully reviewing all 633 studies based on the inclusion and exclusion criteria, 287 studies were selected for coding and data extraction. More specifically, 111 studies were excluded because they relied upon self-report measures of risk aversion, while 114 studies were excluded for using either academic performance, literacy, reading proficiency, financial literacy or educational attainment as proxies for cognitive ability. Another 107 studies were excluded because they did not report data on either cognitive ability, risk aversion or both. Three studies were excluded because data were available only for participants with mental health problems or cognitive impairment. Finally, 11 studies were excluded for investigating decision-making under ambiguity.

2.3 Step 2. Data Extraction and Coding

In order to obtain as much data as possible, all corresponding authors were contacted via email and asked to provide the raw data or any relevant information on the relationship between cognitive ability and risk aversion in all three domains. The response rate was approximately 29%. Next, data was extracted from the remaining 205 studies from which the raw data was not obtained. Following, Peterson and Brown (2005), Pearson's r was imputed from beta coefficients using the following formula whenever necessary: $r = \beta + .05\lambda$, where $\lambda = 1$ if $\beta > 0$ and $\lambda = 0$ if $\beta < 0$. In cases where only means and standard deviations were reported, Pearson´s r was computed by using the formulas provided by Borenstein et al. (2009). Whenever data for the same participants was reported across multiple outcomes, effect sizes were combined, in line with guidelines provided by Borenstein and colleagues (2009). In 134 studies out of the 287 studies included for data extraction, the information reported on the relationship between cognitive ability and risk aversion was insufficient. That is, even though these studies appeared to contain data on both cognitive ability and risk aversion neither Pearson´s r, Spearman's rho, nor the data necessary to impute Pearson´s r were reported. Hence, data was available from 153 articles. Among these, several had overlapping data. To avoid using the same data multiple times, only one study per data set was included in the final analysis. In total, 97 studies were included for meta-analysis in the domain of gains, 41 in the mixed domain, and 12 in the domain of losses.

To allow for moderator analysis, studies were coded based on several different features. First, all studies were coded based on sample characteristics, including mean age of the participants, male to female ratio, and sample type (i.e., student, community or children). Second, studies were coded based on the class of decision task used to measure risk aversion. More specifically, each decision task was categorized based on whether it was incentivized, the probabilities and payoffs were varied or kept constant and if there was a certain option or not. The percentage of possible risk averse choices (i.e., the percentage of choices in which the riskier option had equal or higher expected value than the safer option) was also calculated if possible. Third, in order to investigate the extent to which the study purpose influenced results, all studies were coded based on whether or not one of their primary objectives was to investigate the relationship between cognitive ability and risk aversion. Fourth, studies were coded based on the psychometric measure used to assess cognitive ability (as described shortly), and whether or not participants received payment for participating in the experiment.

2.4 Measures of Cognitive Ability

All studies included measured cognitive ability with one of the following psychometric measures: Cognitive Reflection Task (CRT), Raven´s Progressive Matrices (RPM), numeracy tests (NUM), working memory capacity tests (WMC), or cognitive ability test batteries (CATB).

CRT is a three-item instrument designed to measure cognitive ability and reflective thinking (Frederick, 2005). The task is frequently used in experimental research within the field of economics (e.g., Albaity, Rahman, & Shahidul, 2014; Corgnet et al., 2016; Deppe et al., 2015) and has been associated with other measures of cognitive ability such as the Wonderlic Personnel Test (Frederick, 2005).

RPM is a widely recognized nonverbal measure of fluid intelligence which has been used across a wide range of disciplines (Carpenter, Just & Shell, 1990; Raven, 2000). It consists of 3 x 3 matrices, in which the bottom right figure is missing and must be identified among several alternatives. The test-taker is instructed to look across the rows and/or down the columns to find a pattern and determine the missing entry. Importantly, the difficulty of the matrices is gradually increased, so that it requires greater mental capacity to determine the missing entry for each consecutive matrix (Raven, 2000).

NUM refers to a variety of tests designed to measure numerical ability. NUM usually consists of a range of mathematical problems to be solved without using a calculator (e.g., Cokely, Galesic, Schulz, Ghazal & Garcia-Retamero, 2012; Lipkus, Samsa & Rimer, 2001; Weller et al., 2013). Numerical ability has consistently been linked with numerous cognitive ability measures (e.g., Cokely et al., 2012; Cokely & Kelley, 2009; Del Missier, Mäntylä & De Bruin, 2012; Liberali, Reyna, Furlan, Stein & Pardo, 2012), and can be considered a reasonable measure of cognitive ability.

WMC typically consist of a set of tasks where the participant is asked to recall a number of items while performing an attention-demanding assignment (Engle, 2002). Working memory capacity has consistently been found to be highly correlated with general intelligence (Conway et al., 2003; Kyllonen & Christal, 1990), and is believed to be involved in a wide range of complex cognitive operations, such as comprehension, reasoning and problem solving (Conway et al., 2005; Engle, 2002).

CATB refers to comprehensive measures of intelligence where several instruments are used to assess different aspects of an individual's cognitive ability. Common examples of such measures are the Wechsler Adult Intelligence Scale (WAIS; Wechsler, 2008), and the Stanford-Binet Intelligence Scale (SBIS; Roid, 2003), which both consist of no less than ten subtests (DiStefano & Dombrowski, 2006; Roid, 2003; Wechsler, 2008). Although CATB´s provide a comprehensive measure of cognitive ability, it is often not feasible to use such measures in experimental research, as they are

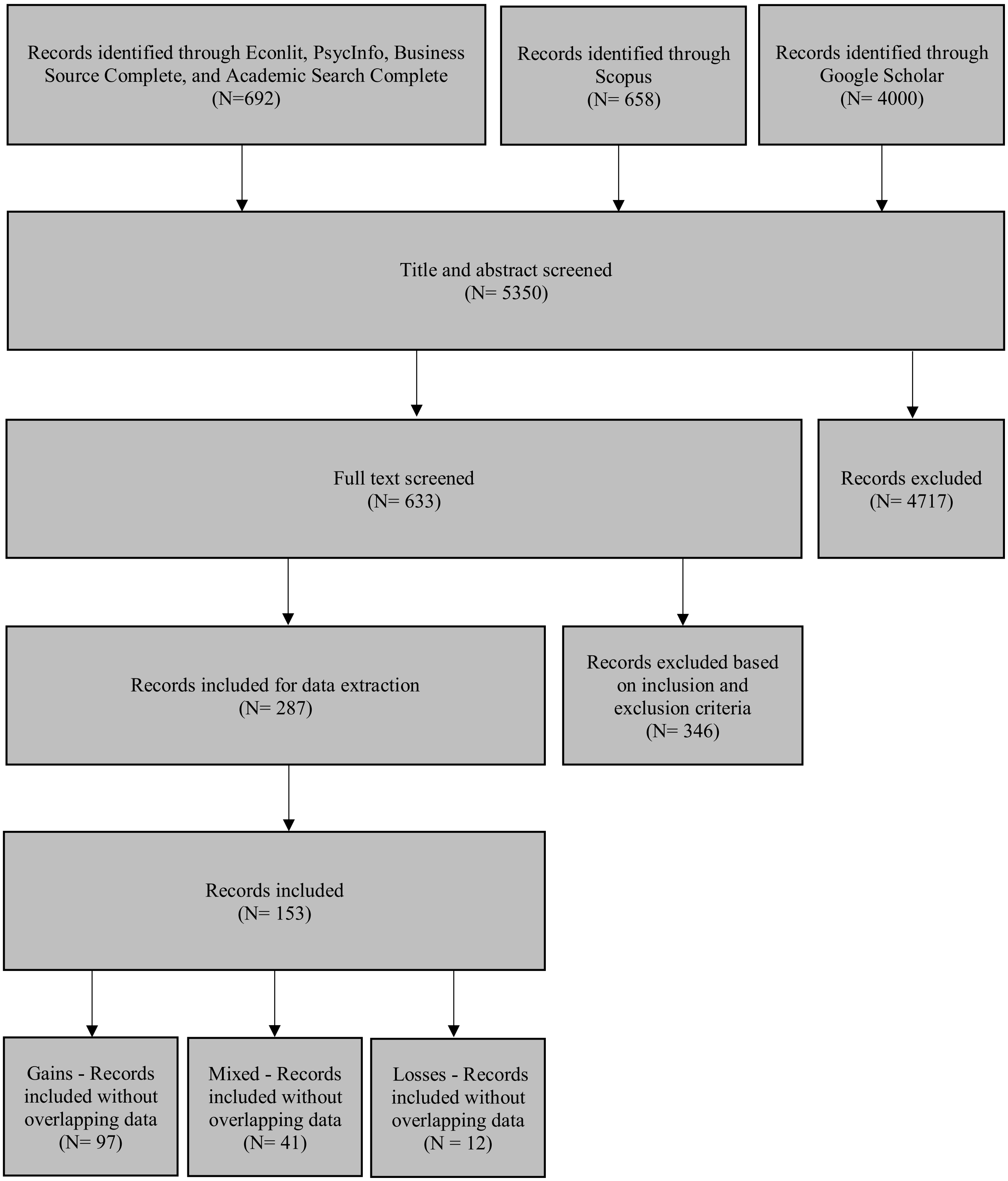


Figure 1: Overview of the literature search.

time consuming and difficult to administer. Instead, most researchers either adopt a small number of subtests from a well-established CATB, or construct a less time consuming CATB by combining a few commonly used cognitive ability measures such as those mentioned above (e.g., RPM, CRT, NUM WMC, etc.). Accordingly, CATB will in this study refer to any measure utilizing more than one instrument to assess cognitive ability.

2.5 Measures of Risk Aversion

Across all three domains risk aversion was measured with one of the following decisions tasks: Bomb Risk Elicitation Task (BRET), Decision Task Battery (DTB), Eckel-Grossman Risk Task (EGRT), Ellsberg Urn Risk Task (EURT), Gift Gambling Task (GGT), Income Gambling Task (IGT), Lottery Task (LT), Multiple Price List (MPL), One-shot Gambling Task (OGT), Sabater-Grande-Georgantzis Lottery Panel (SGG), Wheel of Fortune Task (WFT), Cups Task (CT), Portfolio Choice Task (PCT), Budget Line Allocation Task (BLAT), Cambridge Gambling Task (CGT), Gneezy-Potters Investment Task (GPIT) or Adaptive Lottery Task (ALT). Specifically, risk aversion was measured with 13 different decision tasks in the domain of gains (i.e. ALT, BRET, CT, DTB, EGRT, EURT, GGT, IGT, LT, MPL, OGT, SGG, WTF), 12 in the mixed domain (i.e., ALT, BLAT, CGT, DTB, EGRT, GPIT, IGT, LT, MPL, OGT, PCT, SGG), and 6 in the domain of losses (i.e., ALT, CT, EGRT, GGT, LT, MPL).

BRET is a dynamic real time elicitation task in which the participant is required to decide how many boxes to collect in a matrix containing 100 boxes, one of which hides a bomb (Crosetto & Filippin, 2013). The payoff of each box collected is exactly the same. Hence, the potential earning increases linearly. In case the box with the bomb is collected, the payoff for the whole round is zero. As all outcomes, as well as the probabilities associated with each outcome, is fully specified, BRET allows for a good estimation of individual risk preferences in the domain of gains, simply by counting the number of boxes collected (Crosetto & Filippin, 2013; Holzmeister & Pfurtscheller, 2016).

EGRT is a simple risk elicitation method in which the participant is asked to choose between one of six gambles (Dave, Eckel, Johnson & Rojas, 2010; Eckel & Grossman, 2008). Each gamble typically involves a 50% chance of winning a low payoff and a 50% chance of winning a high payoff. One of the gambles is a sure thing, in which the low and high payoff is exactly equal. The gambles are designed so that the expected payoff increases linearly with risk, as represented by the standard deviation (Charness, Gneezy & Imas, 2013). A risk averse individual should thus choose gambles with lower standard deviations whereas a risk neutral individual should choose the gamble with the highest expected return.

In EURT, participants are presented with an urn containing five blue and five yellow balls. For each round a random ball is drawn from the urn, and participants are asked to guess its color. If the participants guess correctly, they win a specified amount of money. Before the ball is drawn, however, each participant is asked to indicate the price they are willing to sell the bet for. A computer then generates a random offer to buy the bet. If this sum is higher than the minimum selling price set by the participant, the bet is sold and no ball is drawn from the urn. If the offer is lower than the minimum selling price, a ball is drawn and the bet is carried out. Risk aversion is inferred based on the minimum selling price set by the participant. A high selling price indicates risk tolerance while a low selling price suggests risk aversion (Borghans, Heckman, Golsteyn & Meijers, 2009).

The GGT is a simple decision task often used to elicit risk preferences among children (Levin & Hart, 2003). The participant is presented with four identical boxes, two of which are placed to the left of the participant and two of which are placed to the right. Under each box on the left side, a small gift is hidden, whereas two small gifts are hidden under one of the boxes on the right. Risk aversion is measured by asking the participant to indicate from which side he or she would like to draw a box. As the expected value of the two sides are equal, participants are considered risk averse if they prefer to draw a box from the left side.

MPL refers to a class of decision tasks in which participants are asked to choose between two different lotteries (Dohmen et al., 2018). MPL generally comes in two formats: The first format involves two lotteries in which the potential outcome of each lottery are kept constant, while the probabilities of the outcomes vary from row to row (e.g., Holt & Laury, 2002); the second format involves a safe and a risky lottery, in which the probabilities of outcomes are kept constant, while the potential outcomes of either the safe or risky lottery are gradually increased (e.g. Andersson et al., 2016). Risk preferences are inferred either based on the number of risky choices made, or on the participant's unique switching point (i.e., the point where the participant switched from the risky to the safe lottery).

OGT refers to a simple type of decision tasks in which the participant is presented with only one choice between a safe/risky option and a riskier option with equal or higher expected value. In this task, risk aversion is inferred based on whether the participant chose the riskiest option or not.

In IGT participants are asked to consider several hypothetical income gambles. More specifically, the participants are asked to choose between a certain income for some specified amount of time or a gamble in which this income is either increased or decreased by some amount with probability p and 1–p (e.g., Barsky, Juster, Kimball & Shapiro, 1997; Beauchamp et al., 2017). Based on the number of rejected gambles, individual risk preferences can be determined.

LT refers to any decision task in which the participants are asked to choose between a number of gambles sequentially. Each set of gambles can be constructed in a number of different ways so that the probabilities and payoffs associated with each gamble changes or are kept constant. Moreover, each gamble may differ with regard to whether the participants has to choose between two different gambles, or a certain option and a gamble. As with most decision tasks, risk aversion is inferred based on the number of risky and safe option chosen by the participant.

SGG is a standard risk elicitation task in which participants are asked to choose one gamble from four different lottery panels (Sabater-Grande & Georgantzis, 2002). Each panel consists of ten gambles with decreasing probabilities and increasing expected value. Consequently, if the participant chooses the first gamble in each lottery panel, he or she can be considered highly risk averse. If the participant, on the other hand, chooses the last gamble in each lottery panel he or she can be considered risk tolerant.

WFT is a visual gambling task in which the participants are asked to make a series of choices between pairs of fortune wheels (Blankenstein, Crone, van den Bos & van Duijvenvoorde, 2016). The first fortune wheel is always presented as a certain option that pays some specified amount of money. The second fortune wheel, on other hand, is presented as a risky option in which the magnitude of the monetary outcome and the probability of obtaining this outcome varies. Accordingly, risk aversion is inferred based on the number of times each participant prefers the first over the second fortune wheel.

CT is another visual gambling task in which participants are asked to choose between 54 gambles presented as two arrays of cups containing monetary payoffs (Levin, Weller, Pederson & Harshman, 2007). In each trial, participants are asked to decide from which of two arrays of two, three or five cups containing monetary payoffs they would like to draw a cup. One of the two arrays is a certain option in which all of the cups contain the same payoff whereas the second array is a risky option in which only one of the cups contains a monetary payoff. In some of the gambles, the risky option has the same expected value as the certain option while in others the expected value is either higher or lower for the risky option. Risk aversion is estimated based on the number of times the participant decides to draw a cup from the certain array.

PCT is a decision task in which the participants are asked to rank their most and least preferred investment options from a menu of three investment portfolios: safe, risky and intermediate (e.g., Bateman, Stevens & Lai, 2015). The safe option guarantees an annual return of x% while the risky option provides a mean annual return of x% + y% with a standard deviation of z%. The intermediate option is dynamically rebalanced so that 50% is invested in the safe and the risky option. The mean annual return of the intermediate option is, thus, the average of the safe and risky option with a standard deviation of z%/2. A highly risk averse investor would, in this setup, always prefer the safe option to the intermediate and risky option, as well as the intermediate option to the risky option. Consequently, risk aversion is estimated based on how each participant ranks the attractiveness of the three portfolios described above.

In BLAT participants are asked to allocate points between accounts x and y, which are represented visually on a two-dimensional budget line (Choi, Fisman, Gale & Kariv, 2007; Choi, Kariv, Müller & Silverman, 2014). After allocating points, either x or y is randomly chosen, and the participant receives the points he or she allocated to the chosen account, while all points in the other account is lost. On each budget line, there are three points: A, B and C. Point A is where the budget line hits the y-axis and represents allocating all points to the y account. Conversely, B is where the budget line hits the x-axis and represents allocating all points to the x account. Finally, point C, which lies on the 45-degree line, ensures a certain payoff and corresponds to an equal allocation between x and y. Importantly, the slope of the budget line AB is always chosen so that the payoff of choosing an allocation between A and C has a higher expected return than point C, whereas choosing an allocation between B and C has a lower expected return than C. Hence, an individual who is infinitely risk averse will always choose an allocation equal to C, whereas an individual who is less risk averse or risk seeking will choose an allocation between A and C or B and C, respectively. This makes it possible to estimate individual risk preferences based on the amount of points allocated between A and C, and B and C on the budget line.

GPIT is a classic investment task in which the participant have to decide how much to invest ($x), out of an initial endowment ($y), in a risky asset (e.g., Charness, Gneezy & Imas, 2013; Gneezy & Potters, 1997). The amount invested yields a dividend of $kx ($k > 1$) with probability p and is lost with probability 1–p. The money not invested ($y–x) is kept by the participant. The payoff of each choice is therefore $y–x+kx, with probability p, and $y–x with probability 1–p. In all cases k and p is chosen so that the expected value of investing is either higher or equal to the expected value of not investing. Risk aversion is estimated based on the amount invested, with lower amounts indicating higher levels of risk aversion.

In CGT a yellow token is hidden under one of ten blue or red boxes (e.g., Clark et al., 2008). The amount of red and blue boxes varies from trial to trial, so that the probability that the token is hidden under a blue or red box, changes. On each trial, participants have to decide how much to wager out of their current endowment, that the yellow token is hidden under either a red or a blue box. If the participant chooses the right color, the amount wagered is added to his or her current endowment. Conversely, if the participant chooses the wrong color the amount is lost. Just like in the GPIT, risk aversion is inferred based on the amount wagered on each trial.

ALT is similar to the standard LT, in which participants are asked to choose between a number of gambles sequentially. However, as opposed to the standard LT, the gambles in ALT is iteratively adapted based on the participant's choices, allowing for a more efficient and precise estimation of individual risk preferences (e.g., Chapman, Snowberg, et al., 2018; Frey, Pedroni, Mata, Rieskamp & Hertwig, 2017).

Finally, DTB refers to measures of risk aversion relying on more than one single elicitation task. That is any measure in which two or more of the decision tasks described above were used to construct a composite score of risk aversion within the domain of gains, mixed or losses.

2.6 Step 3. Data Analysis

First, all effect sizes were converted into a common metric (i.e., correlation coefficients), as previously described. Correlations were defined as negative when people with higher cognitive ability were to be less risk averse. In line with the guidelines provided by Borenstein et al. (2009), all correlation coefficients were converted into Fisher's z. Next, a random-effects model meta-analysis using the restricted maximum likelihood estimator (REML; Viechtbauer, 2005, 2010) was performed in order to investigate the relationship between cognitive ability and risk aversion for the domains of gains, mixed and losses. Moreover, two additional meta-analyses were conducted in each of these three domains, one using only males and one using only females. A random-effects model was chosen, as opposed to a fixed-effect model, because the assumptions behind the random-effects model tend to be more realistic (Borenstein et al., 2009; Cooper, 2010). Results from the meta-analyses is presented as a correlation, ρ, equivalent to Pearson's r. Correlations ranging from .10 to .29, .30 to .49 and .50 to 1.00 are interpreted as weak, moderate and strong, respectively (Cohen, 1988).

In order to test for heterogeneity, Q and I^2 statistics were calculated. The Q statistic was computed by summing the squared deviations of each study's effect from the combined effect size, weighting each study by its inverse variance (Huedo-Medina, Sánchez-Meca, Marín-Martínez & Botella, 2006). The Q statistic tests for heterogeneity by testing the null hypothesis that all studies share a common effect size (Borenstein et al., 2009). Under the null hypothesis, the Q statistic follows a chi-square distribution with k–1 degrees of freedom, k being the number of studies included in the meta-analysis (Huedo-Medina et al., 2006). A significant Q indicates that true heterogeneity exists (Borenstein et al., 2009). The I^2 statistic investigates the amount of true heterogeneity by dividing the result of the Q statistic and its degrees of freedom (k–1) by the Q value, and multiplying it by 100 (Huedo-Medina et al., 2006). Consequently, the I^2 statistic can be interpreted as the percentage of total variance in a set of observed effect sizes due to true heterogeneity. Higgins, Thompson, Deeks and Altman (2003) suggest that I^2 approximating 25%, 50%, and 75% can be considered as low, moderate, and high, respectively.

To investigate the impact of moderator variables, several meta-regressions were performed. Meta-regressions are analogous to standard regression analysis, and can, with appropriate coding, be used to examine the influence of both categorical and continuous moderator variables (Hedges & Pigott, 2004; Viechtbauer, 2010). All moderator analyses were performed independently, as testing multiple moderators simultaneously may lead to a mis-estimation of moderator effects, especially when the number of studies included is small (Steel & Kammeyer-Mueller, 2002).

Publication bias, the tendency to leave out non-significant results and publish only positive results, was examined in two steps. First, it was visually assessed using a funnel plot of all studies included in the random-effects model meta-analysis. If no publication bias exists, the two sides of the funnel plot should be symmetrical (Borenstein et al., 2009; Rothstein, Sutton & Borenstein, 2006). That is, if no publication bias exists, the observed effect sizes should not be asymmetrically distributed around the combined effect size. Second, a rank correlation test (Begg & Mazumdar, 1994) and a regression test (Egger, Smith, Schneider & Minder, 1997) was performed to test for funnel plot asymmetry.

Finally, case deletion diagnostics were performed in order to identify any influential studies and/or possible outliers (Viechtbauer, 2010; Viechtbauer & Cheung, 2010). According to Viechtbauer (2010), studies might be considered either as influential or as outliers if one or more of the following statements are true: (a) the absolute DFFITS value is larger than $3\sqrt{p/(k–p)}$ where p is the number of model coefficients and k the number of studies; (b) the lower tail area of a chi-square distribution with p degrees of freedom cutoff by the Cook's distance is larger than .50; (c) the hat value is larger than 3(p/k) or (d) the DFBETAS value is larger than 1. The DFFITS value is an estimate of how many standard deviations the predicted effect for the i_{th} study changes after excluding the i_{th} study from the model fitting. Cook´s distance is essentially the Mahalanobis distance between the full set of predicted values with or without the i_{th} study included in the model fitting. The hat value is simply the i_{th} diagonal element of the hat matrix, also known as the so-called leverage of the i_{th} study. Finally, the DFBETAS value indicates how many standard deviations the estimated correlations coefficient changes after removing the i_{th} study from the model fitting.

All statistical analyses were performed in R (R Core Team, 2017) with the following packages installed: metafor (Viechtbauer, 2010) and dplyr (Wickham, François, Henry & Müller, 2018).

3 Results

3.1 Descriptive Results for the Domain of Gains

As previously described, a total of 97 studies published between 2003 and 2018 were included for meta-analysis in the domain of gains (N = 90,723). The mean age of participants was available for 66 studies and ranged from 6.0 to 81.2 years with a mean of 29.5. Participants were either university, college or high school students in 56 of the 97 studies included. Out of the remaining 41 studies, 35 were based on various community samples, while 5 relied on samples of children. For the last study the specifics of the sample used was not available. In 35 studies there were more males than females, while the opposite was true in 42 studies. The male to female ratio was exactly 1.00 in one study while the proportion of males and females was unavailable for 19 studies. Risk aversion was measured using MPL in 45 studies, LT in 26, OGT in 7, DTB in 5, EGRT in 4 and BRET in 3. In the remaining 7 studies risk aversion was assessed with one of the following decision tasks: ALT, CT, EURT, GGT, IGT, SGG, and WFT. The decision task was fully incentivized in 23 studies, randomly incentivized in 47, and purely hypothetical in 14. Moreover, participants were paid for participation in 81 out of 97 studies. Information about whether the participants were paid and the extent to which the decision task was incentivized were unavailable in 16 and 13 studies, respectively. The average payment for the whole experiment ranged from \$5 to \$125 with a mean of \$30. The average payment was, however, only available for 34 studies. Cognitive ability was measured using CATB in 36 studies, CRT in 30, RPM in 18, NUM in 12 and WMC in 1. Finally, in 24 of the 97 studies included, one of the primary purposes of the study was to investigate the relationship between cognitive ability and risk aversion. For an overview of the studies included for meta-analysis in the domain of gains see Table 1.

3.2 Random-Effects Model Meta-Analysis for the Domain of Gains

Results from the random-effects model meta-analysis suggest that there exist a weak but significant negative relationship between cognitive ability and risk aversion in the domain of gains (k = 97, $\rho = -.07$, Z = −6.11, p < .001, 95% CI [−.10, −.05]). Looking at the results for males (k = 51, $\rho = -.09$, Z = − 4.81, p < .001, 95% CI [−.12, −.05]) and females only (k = 48, $\rho = -.05$, Z = −4.39, p < .001, 95% CI [−.08, −.03]) a similar pattern emerges. The forest plots depicted in Figure 2 provides an overview of the studies included, their individual correlation coefficients with 95% confidence intervals, and the overall results from the random-effects model meta-analyses.

3.3 Test for Heterogeneity in the Domain of Gains

The results from the Q statistics were highly significant for the full sample (Q = 612.83, df = 96, p <.001) as well as for males only (Q = 210.79, df = 50, p < .001), indicating the presence of true heterogeneity. The Q statistic for females only, however, was not significant (Q = 60.38, df = 47, p >.05), suggesting that only a small amount of true heterogeneity exist between the studies included when looking exclusively at the results for females. These results were further confirmed by the I^2 statistics which indicated that the amount of total variance observed due to true heterogeneity was high for the full sample (I^2 = 88.69%, 95% CI [83.49, 92.09]) and males only (I^2 = 78.48%, 95% CI [60.85, 89.44]), but low for females (I^2 = 33.56%, 95% CI [.00, 72.33]).

3.4 Moderator Analysis for the Domain of Gains

The results from the meta-regressions showed that none of the moderator variables had any influence on the relationship between cognitive ability and risk aversion in the domain of gains for the full sample and males only (see Table 2–3). Looking at the results for females only, the meta-regressions suggest that both the decision task used, and the payoff structure of the riskier choice explained a substantial amount of the observed heterogeneity (Table 4). Specifically, the relationship between cognitive ability and risk aversion is stronger when the payoff of the riskier choice is kept constant compared to when it changes. Even though the overall result of the meta-regressions suggests that the decision task used to measure risk aversion explains a substantial amount of the observed heterogeneity for females only, no single tasks appeared to significantly influence the relationship between cognitive ability and risk aversion.

3.5 Descriptive Results for the Mixed Domain

A total of 41 studies published from 1993 to 2018 were included for meta-analysis in the mixed domain (N = 50,936). The mean age of participants was available for 27 studies and ranged from 8.9 to 75.4 years with a mean of 31.9. Participants were either university, college or high school students in 17 of 41 studies included. Out of the remaining 24 studies 18 were based on various community samples, while 6 relied on samples of children. In 12 studies there were more males than females, while the opposite was true in 18 studies. The male to female ratio was exactly 1.00 in one study while the proportion of males and females was not available for 10 studies. Risk aversion was measured using GPIT in 11 studies, LT in 9, and MPL in 8. ALT, BLAT, OGT and IGT were all used to measure risk aversion in 2 studies, while EGRT, CGT, DTB, PCT and SGG were used in the remaining

FIGURE 2: Forest plots for the domain of gains — full sample, males and females only.

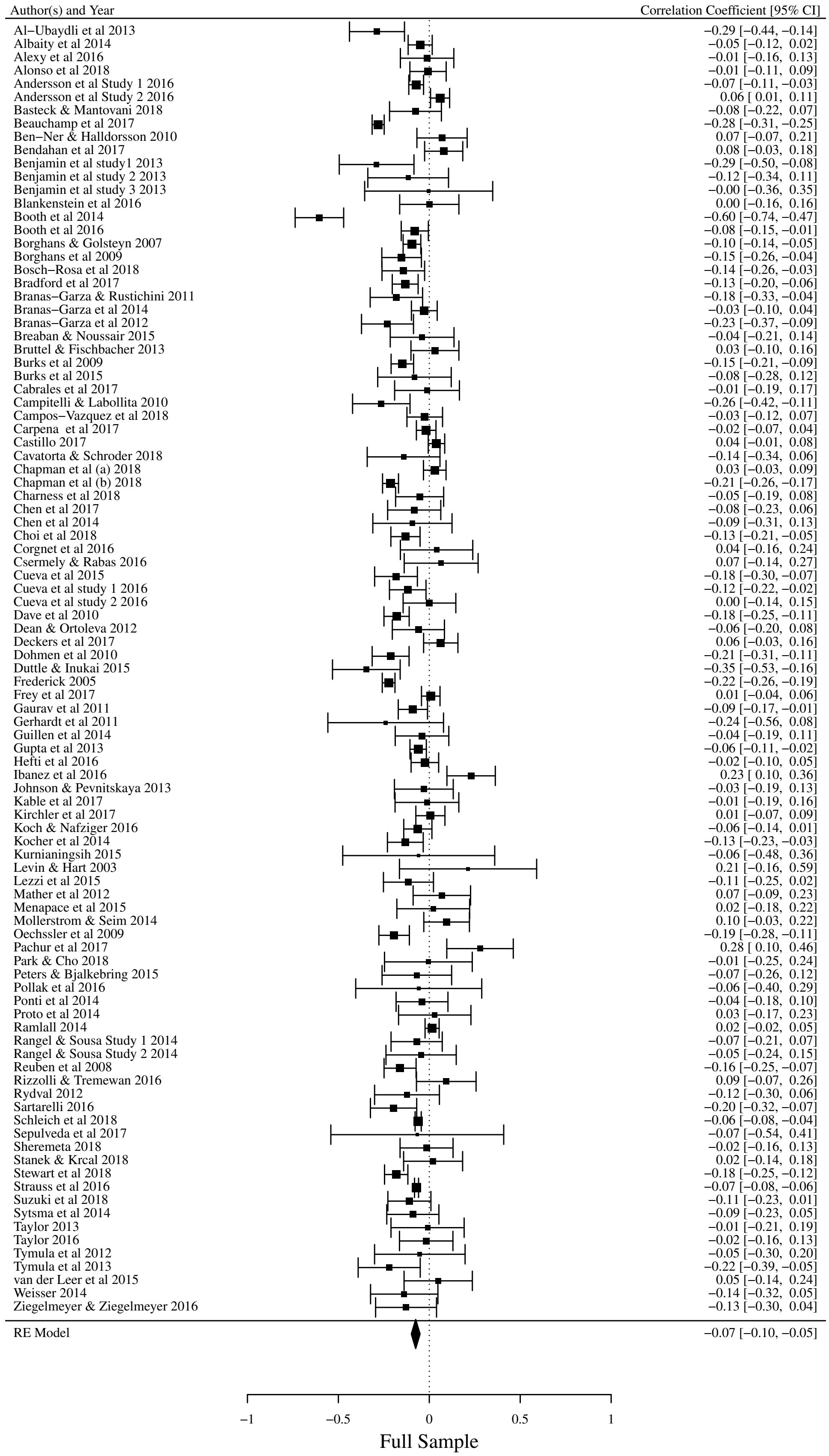
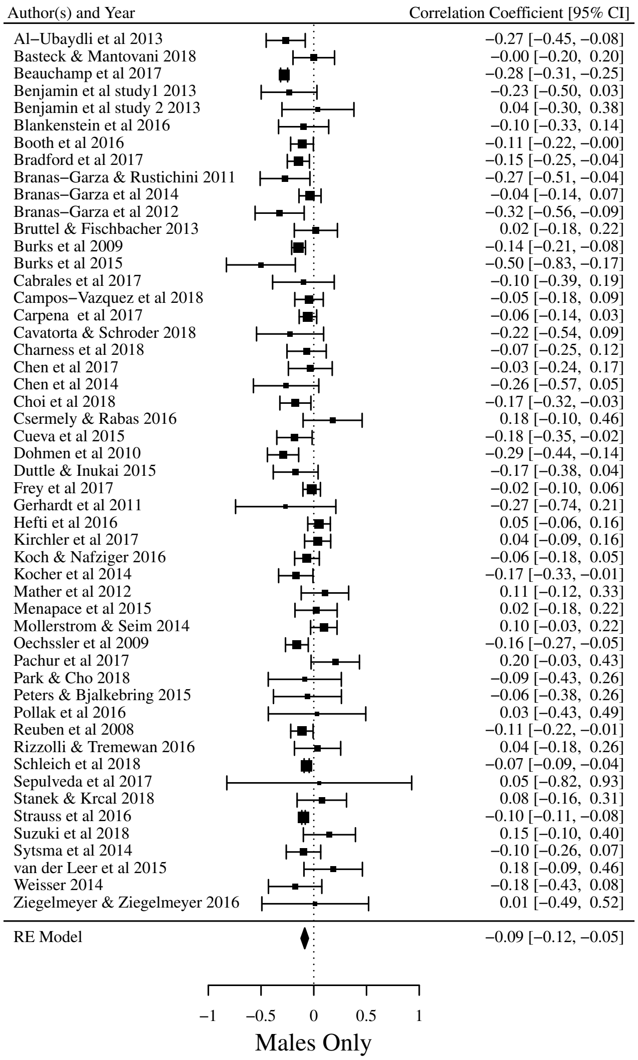
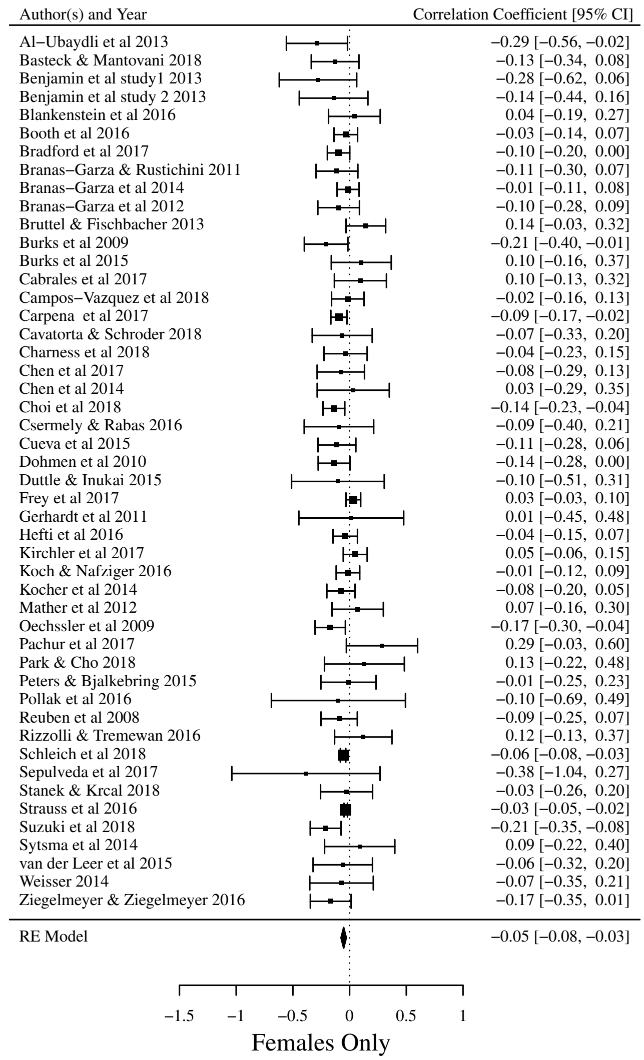


Figure 2 continued.





5 studies. The decision task was fully incentivized in 11 studies, randomly incentivized in 14, and purely hypothetical in 11. Moreover, participants were paid for participating in the experiment in 31 out 41 studies. Information about whether participants were paid for their participation and the extent to which the decision task was incentivized was unavailable in 10 and 5 studies, respectively. The average payment for the whole experiment ranged from \$2 to \$58 with a mean of \$21. However, information about the average payment was only available for 10 studies. Cognitive ability was measured using CATB in 19 studies, CRT in 9, RPM in 8, and NUM in 5. Finally, in 5 of the 41 studies included, one of the primary purposes of the study was to investigate the relationship between cognitive ability and risk aversion. For an overview of studies included for meta-analysis in the mixed domain see Table 5.

3.6 Random-Effects Model Meta-Analysis for the Mixed Domain

Results from the random-effects model meta-analysis indicate no relationship between cognitive ability and risk aversion in the mixed domain (k = 41, ρ = .01, Z = 0.82, p > .05, 95% CI [−.02, .04]). The same goes for the result for males only (k = 24, ρ = −.01, Z = −0.32, p > .05, 95% CI [−.05, .04]). However, the result for females only suggest a weak but significant positive relationship between cognitive ability and risk aversion in the mixed domain (k = 24, ρ = .03, Z = 2.15, p < .05, 95% CI [.00, .06]). The forest plots depicted in Figure 3 provide an overview of the included studies, their individual correlation coefficients with 95% confidence intervals, and the overall results from the random-effects model meta-analyses described above.

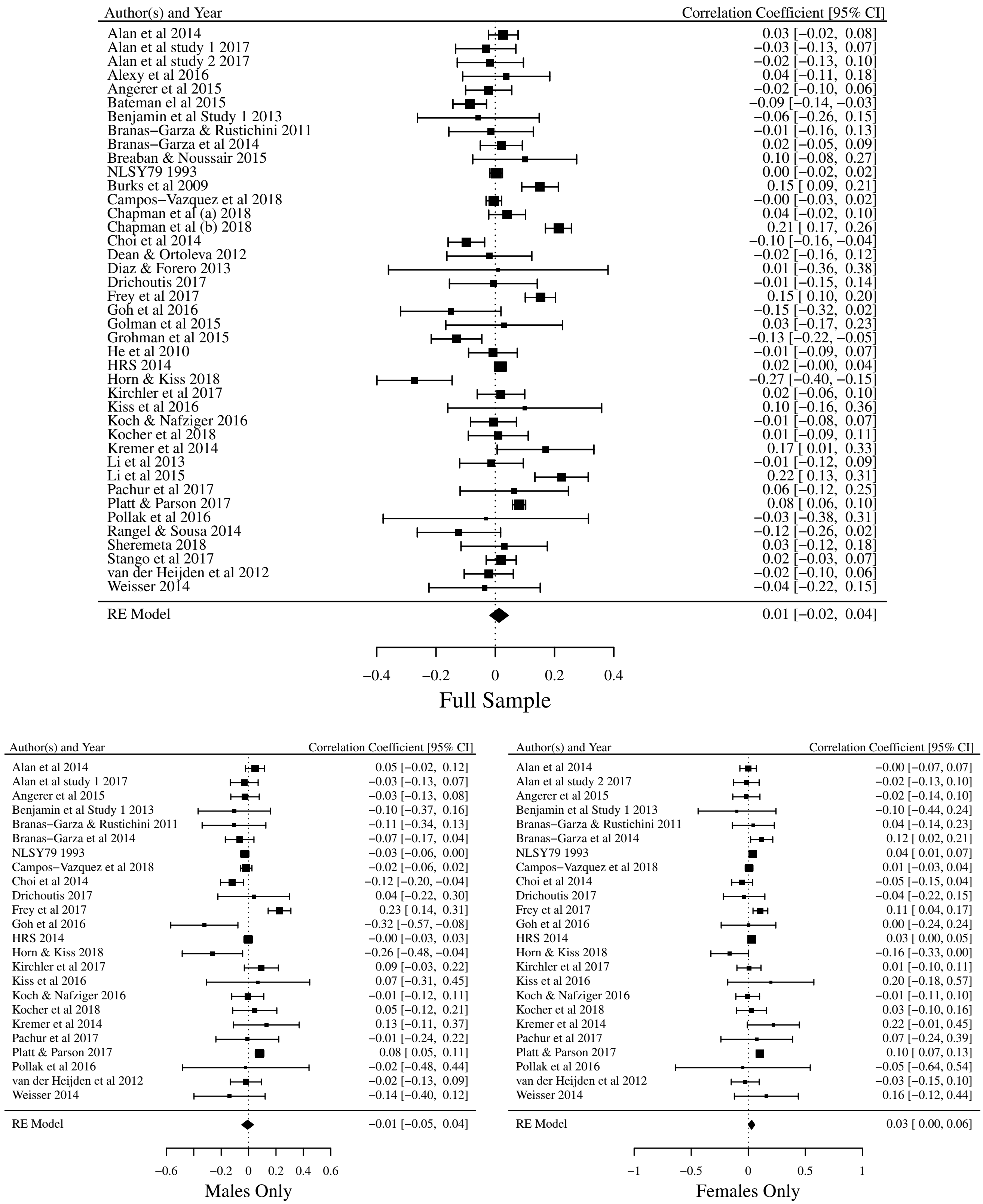


FIGURE 3: Forest plot for the mixed domain — full sample, males and females only.

3.7 Test for Heterogeneity in the Mixed Domain

Results from the Q statistics were highly significant for the full sample (Q = 247.07, df = 40, $p < .001$), males (Q = 86.42, df = 23, $p < .001$), and females only (Q = 45.57, df = 23, $p < .01$), indicating a substantial amount of true heterogeneity among the 41 studies included in the mixed domain. These results were further confirmed by the I^2 statistics which indicated that the amount of total variance observed due to true heterogeneity was high for the full sample (I^2 = 88.49%, 95% CI [79.25, 92.88]) and males (I^2 = 80.74%, 95% CI [58.75, 92.55]), while moderate for females (I^2 = 54.65%, 95% CI [7.97, 82.23).

3.8 Moderator Analysis for the Mixed Domain

The overall results from the meta-regression showed that only the cognitive ability measure and the decision task used had an influence on the relationship between cognitive ability and risk aversion in the mixed domain (Table 6). More specifically, the relationship between cognitive ability and risk aversion is positive when cognitive ability was measured with CATB, while increasingly negative when assessed by RPM, CRT and NUM. Similarly, the meta-regressions suggest that the relationship between cognitive ability and risk aversion is positive when risk aversion was measured using ALT, while less positive and even negative when one of the following decision tasks were utilized: CGT, MPL, IGT, OGT, LT, GPIT, BLAT, PCT or EGRT.

For males only, the decision task used, probabilities and whether or not there was a certain option were found to be significant predictors (Table 7). Specifically, the relationship between cognitive ability and risk aversion is positive when the probabilities of the decision task was changing as well as when there was no certain option, while negative when the opposite was true. Moreover, the relationship was found to be increasingly positive when risk aversion was measured using CGT and DTB.

For females only, cognitive ability measure, the decision task used, probabilities, and whether or not there was a certain option were significant predictors for the relationship of interest (Table 8.). More specifically, the relationship between cognitive ability and risk aversion is positive when cognitive ability was measured using CATB while increasingly negative when assessed by RPM and CRT. Similarly, the relationship is positive when risk aversion was measured using ALT, while moving toward negative when using GPIT and BLAT. Finally, the relationship between cognitive ability and risk aversion is stronger when there was no certain option and the probabilities were changing.

3.9 Descriptive Results for the Domain of Losses

A total of 12 studies published from 2003 to 2018 were included for meta-analysis in the domain of losses (N = 4,544). The mean age of participants was available for 11 studies and ranged from 6.0 to 68.7 years with a mean of 32.1. Participants were either university, college or high school students in 4 of 12 studies. Out of the remaining 8 studies, 7 were based on various community samples, while one relied on samples of children. In 6 studies there were more males than females, while the opposite was true in 5 studies. For one study, the proportion of males and females was not available. Risk aversion was measured using LT in 6 studies and MPL in 2. In the remaining 4 studies risk aversion was assessed with one of the following decision tasks: ALT, CT, EGRT and GGT. The decision task was fully incentivized in 2 studies and randomly incentivized in 7. Moreover, participants were paid for participation in 10 out of 12 studies. Information about whether the participants were paid for their participation and the extent to which the decision task was incentivized were unavailable in 2 and 3 studies, respectively. The average payment for the whole experiment ranged from $9 to $25 with a mean of $15. The average payment was however only available for 3 studies. Cognitive ability was measured using CATB in 9 studies, CRT in 2 and RPM in 1. Finally, in 4 of the 12 studies included, one of the primary purposes of the study was to investigate the relationship between cognitive ability and risk aversion. For an overview of the studies included for meta-analysis in the domain of losses see Table 9.

3.10 Random-Effects Model Meta-Analysis for the Domain of Losses

Results from the random-effects model meta-analysis indicate no link between cognitive ability and risk aversion in the domain of losses ($k = 12$, $\rho = -.05$, Z = −1.10, $p > .05$, 95% CI [−.13, .04]). The story is the same for males only ($k = 8$, $\rho = -.05$, Z = −0.68, $p > .05$, 95% CI [−.18, .09]) and females only ($k = 8$, $\rho = -.01$, Z = −0.19, $p > .05$, 95% CI [−.11, .09]). The forest plots in Figure 4 provides an overview of the studies included, their individual correlation coefficients with 95% confidence intervals, and the overall results from the random-effects model meta-analyses described above.

3.11 Test for Heterogeneity in the Domain of Losses

The result from the Q statistics were significant for the full sample (Q = 50.63, df = 11, $p < .001$), males (Q = 29.18, df = 7, $p < .001$), and females only (Q = 19.10, df = 7, $p < .01$), indicating the existence of true heterogeneity. These results were further corroborated by the I^2 statistics which

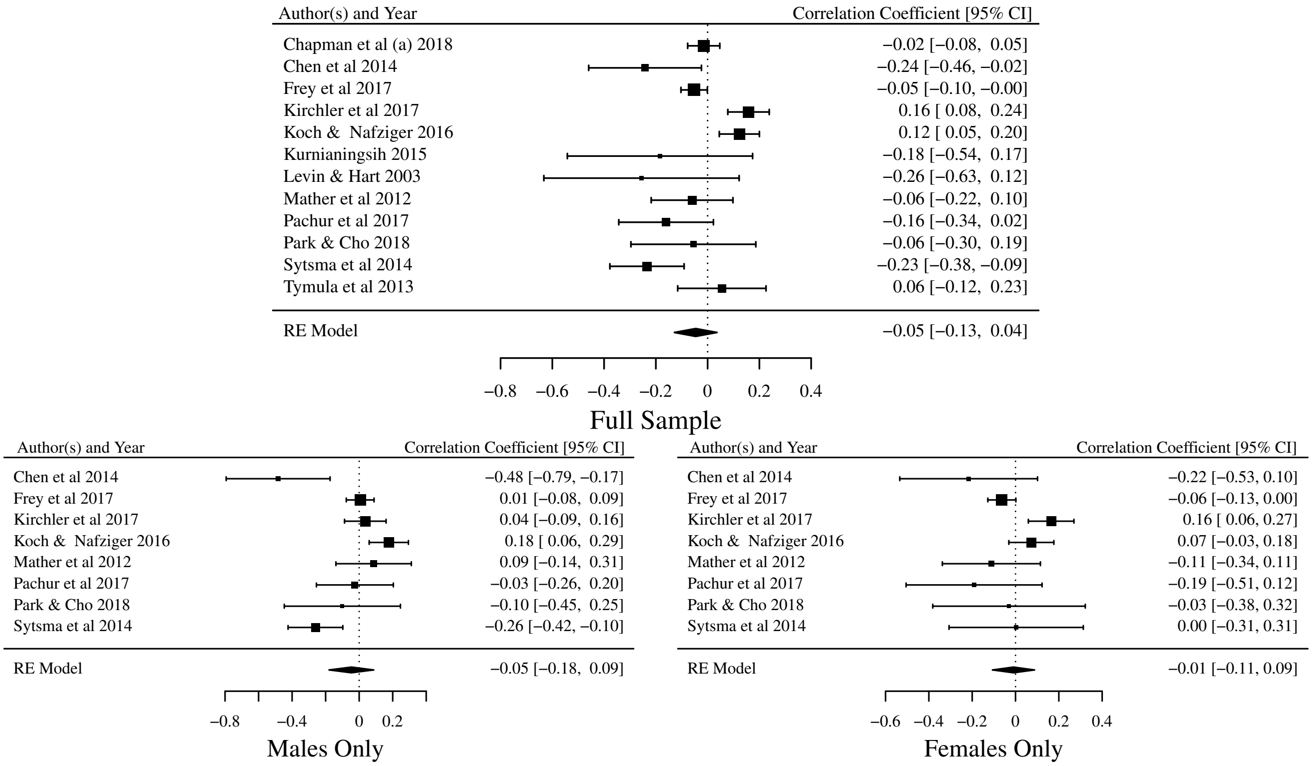


FIGURE 4: Forest plots in the domain of losses — full sample, males and females only

indicated that the amount of total variance observed due to true heterogeneity was high for the full sample (I^2 = 82.13%, 95% CI [56.30, 94.07]) and males (I^2 = 81.15%, 95% CI [51.46, 96.43]) as well as moderate for females (I^2 =63.26%, 95% CI [8.58, 90.88]).

3.12 Moderator Analysis for the Domain of Losses

The meta-regressions indicate that cognitive ability measure, probabilities, and the payoff structure of the riskier choice had a significant influence on the relationship between cognitive ability and risk aversion in the domain of losses (Table 10). More specifically, the relationship is positive when cognitive ability was measured using CRT, while increasingly negative when measured using either CATB or RPM. Furthermore, the relationship between cognitive ability and risk aversion is positive when the probability was kept constant at 50% and the payoff of the riskier option did not change, while negative when this was not the case.

For males only, both the payoff structure of the safer choice and the decision task used to measure risk aversion were significant predictors of the relationship of interest (Table 11). The relationship between cognitive ability and risk aversion is positive when risk aversion was measured using MPL, while increasingly negative when assessed with either EGRT or CT. Moreover, the relationship moved in the negative direction when the payoff of the safer choice was kept constant.

For females only, the percentage of risk averse choices, cognitive ability measure, probabilities, sample type, and the payoff structure of the riskier choice influenced the relationship between cognitive ability and risk aversion for males only (Table 12). The result for percentage of risk averse choices suggest that the relationship of interest moves in a negative direction as the percentage of risk averse choices increases. Moreover, the relationship between cognitive ability and risk aversion is negative when cognitive ability was measured with CATB, while going in the opposite direction when assessed by CRT. Conversely, the relationship is positive when the probability was kept constant at 50%, the sample consisted of students, and the payoff of the riskier choices was kept constant, while negative when this was not the case.

3.13 Comparing Males and Females Across the Domain of Gains, Mixed and Losses

In order to compare the results for males and females across the domain of gains, mixed and losses, three separate meta-regressions were performed. The results indicate no significant differences between males and females in the domain of gains (Q_M (df = 1) = 2.43, p > .05), mixed (Q_M (df = 1) = 2.02, p >.05) or losses (Q_M (df = 1) = 0.19, p >.05). These results corroborate findings from Table 2, 6 and 10 that the male to female ratio has no influence on the relationship between cognitive ability and risk aversion in either of the three domains.

3.14 Publication Bias

Nine funnel plots were created by plotting each effect size against the standard error of the observed effect sizes for the full sample, males and females only across all three domains (Figure 5–7). Visual examination of each funnel plot suggests that the observed effect sizes are not asymmetrically distributed around the combined effect size, implying that no publication bias exist. Furthermore, neither the rank correlation test nor the regression test for funnel plot asymmetry provides any substantial evidence of publication bias for the full sample (Gains: $\tau = -.01$, $p > .05$, Z = 0.91, $p > .05$; Mixed: $\tau = .08$, $p > .05$, Z = −0.97, $p > .05$; Losses: $\tau = -.12$, $p > .05$; Z = −2.10, $p < .05$), males (Gains: $\tau = -.06$, $p > .05$; Z = 0.64, $p > .05$; Mixed: $\tau = .08$, $p > .05$; Z = −1.35, $p > .05$; Losses: τ =-.36, $p > .05$; Z = −1.56, $p > .05$), and females only (Gains: $\tau = .07$, $p > .05$, Z = −0.11, $p > .05$; Mixed: $\tau = .14$, $p > .05$; Z = −0.56, $p > .05$; Losses:τ =-.14, $p > .05$; Z = −1.29, $p > .05$) across the domain of gains, mixed and losses.

3.15 Case Deletion Diagnostics

As shown in Figures 8–10, two studies were found to be influential when looking at the results for the full sample across the three decision domains. Similarly, when looking at the results for males only, two studies were identified as influential across the domain of gains, mixed and losses, while four studies could be regarded as influential for females only. The results did however not change substantially after removing all studies identified as influential from the full sample (Gains: $k = 96$, $\rho = -.07$, Z = −6.31, $p < .001$, 95% CI [−.09, −.05]; Mixed: $k = 40$, $\rho = .02$, Z = 1.35, $p > .05$, 95% CI [−.01, .05]), males (Gains: $k = 50$, $\rho = -.08$, Z = −4.94, $p < .001$, 95% CI [−.11, −.05]; Losses: $k = 7$, $\rho = .00$, Z = −0.00, $p > .05$, 95% CI [−.11, .11]) and females only (Gains: $k = 45$, $\rho = -.06$, Z = −4.39, $p < .001$, 95% CI [−.09, −.03]; Mixed: $k = 23$, $\rho = .02$, Z = 2.28, $p < .05$, 95% CI [.00, .04]).

4 Discussion

In this study a systematic review and meta-analysis was conducted in order to empirically investigate the nature of the relationship between cognitive ability and risk aversion. A total of 97 studies (N=90,723) was included for meta-analysis in the domain of gains, 41 (N=50,936) in the mixed domain and 12 (N=4,544) in the domain of losses. The overall results from the random-effects model meta-analyses suggest that a weak, but significant relation between cognitive ability and risk aversion exist in the domain of gains. Thus, the current meta-analysis provides evidence that highly intelligent individuals tend to be less risk averse in the domain of gains. However, the strength of the relationship between cognitive ability and risk aversion was estimated to be rather weak ($\rho = -.07$), and not as strong as suggested by some previous studies. No evidence was found for a relationship between cognitive ability and risk aversion in the mixed domain or the domain of losses. Taken together, these results suggest that the relationship between cognitive ability and risk aversion is domain specific and present only for the domain of gains. Given the weak nature of this relationship, we should be cautious in drawing conclusions about its practical significance.

Interestingly, the relationship between cognitive ability and risk aversion appear to be quite stable across genders. That is, even though the relationship between cognitive ability and risk aversion appears to differ somewhat between males and females for the domains of gains ($\rho_{male} = -.09$; $\rho_{female} = -.05$), mixed ($\rho_{male} = -.01$; $\rho_{female} = .03$) and losses ($\rho_{male} = -.05$; $\rho_{female} = -.01$), these differences were not found to be significant. This is important, as it suggests that the observation that females tend to be more risk averse than males (e.g., Charness & Gneezy, 2012; Croson & Gneezy, 2009), is probably not driven by gender differences in cognitive ability. Contrary, to the results from the full sample and males only, a significant positive relationship between cognitive ability and risk aversion was observed in the mixed domain for females only. This suggest that highly intelligent females tend to be more risk averse in the mixed domain, compared to females with lower cognitive ability. However, as with the negative correlation observed in the domain of gains, the relationship is very weak ($\rho = .03$), and, thus, potentially not of practical significance. Notably, the amount of true heterogeneity observed, were consistently higher for males as compared to females across all three domains (Gains [I^2_{male} = 78.48%, I^2_{female} =33.56%]; Mixed [I^2_{male} = 80.74%, I^2_{female} = 54.65%], Losses [I^2_{male} =81.15%, I^2_{female} = 63.26%]. This is an interesting result, as it suggests that the relationship between cognitive ability and risk aversion is considerably more stable and varies less across studies for females. A possible explanation is that males show more variability in cognitive ability than females (e.g., Arden & Plomin, 2006; Deary, 2003; Feingold, 1992; Lakin, 2013; Lohman & Lakin, 2009; Strand, Deary & Smith, 2006). This is in line with the greater male variability hypothesis, which states that males generally tend to differ more than females on a number of individual characteristics such as personality (Borkenau, McCrae, & Terracciano, 2013), creativity (He & Wong, 2011), and cognitive ability (Arden & Plomin, 2006; Deary, 2003; Feingold, 1992; Lakin, 2013; Lohman & Lakin, 2009; Strand et al., 2006). Consequently, the relationship between cognitive ability and risk aversion might be less stable across studies for males, because the sample of male participants in each study is more likely to vary in terms of cognitive ability. This is, likely due to the fact that the variation between samples depends partially on the amount of variability in the population from which they are drawn (Swinscow & Campbell, 2002).

The fact that the relationship between cognitive ability and risk aversion is non-existent or rather weak across all three domains suggest that risk preferences may reflect an independent construct which does not substantially overlap with intelligence. This interpretation is line with the conclusion drawn by Frey and colleagues (2017), who used several risk elicitation measures to extract a latent risk preference factor (R) which was not found to be associated with cognitive ability. This is very intriguing as cognitive ability has been found to be strongly related to how proficient people are at understanding and evaluating risk (Cokely et al., 2012). Consequently, in some cases there appear to be a gap between people's ability to understand and evaluate risk, and their willingness to take risk. This gap could potentially have important real-world implications as it might lead some people who have a limited understanding of risk to take on too much of it, while others who do have the capabilities to properly evaluate risk might take on too little.

Compared to other meta-analyses linking cognitive ability to individual preferences, the effect sizes reported here are small. For instance, Shamosh and Gray (2008) found the mean correlation between cognitive ability and delayed discounting across 24 studies to be −.23, suggesting that highly intelligent individuals are more patient and have higher levels of self-control. Similarly, in a more recent meta-analysis Sharma, Bottom and Elfenbein (2013), found a positive mean correlation of .24 between cognitive ability and cooperative tendencies across five studies with a total of 1,123 participants. Hence, even though cognitive ability was not found to be strongly related to risk aversion in the present meta-analysis, it should still be regarded as an important variable that needs to be taken into consideration when investigating the antecedents of human decision making.

Overall, none of the moderator variables consistently influenced the relationship between cognitive ability and risk aversion across the domain of gains, mixed and losses. Although no clear pattern from the meta-regressions emerged, the following five moderators were found to be influential in more than one instance: the decision task used to measure risk aversion, the psychometric instrument used to assess cognitive ability, whether the payoff of the riskier choice and probabilities varied or were kept constant, and if there was a certain option or not. Specifically, the decision task used to measure risk aversion consistently moderate the relationship in the mixed domain, while also moderating the relationship in the domain of gains for females and the domain of losses for males. This result suggest that the relationship between cognitive ability and risk aversion is especially sensitive to how risk aversion is assessed in the mixed domain, while only somewhat sensitive to this in the domain of gains and losses.

Similarly, the psychometric measure used to assess cognitive ability was found to influence the relationship between cognitive ability and risk aversion for the full sample and females only in the mixed domain, and the domain of losses. As with the results for the decision task used to measure risk aversion, these results indicate that it somehow matters more how cognitive ability is assessed in the mixed domain and the domain of losses as compared to the domain of gains.

Whether the probabilities were varied or kept constant was not found to moderate the relationship between cognitive ability and risk aversion in the domain of gains, but to be somewhat influential in the mixed domain and the domain of losses. More precisely, it was found to influence the relationship between cognitive ability and risk aversion in the mixed domain for males and females only, as well as in the domain of losses for the full sample and females only. Likewise, whether or not there was a certain option was found to moderate the relationship in the mixed domain for males and females only. In both cases, the relationship between cognitive ability and risk aversion is positive when there was no certain option and less positive when the opposite was true. Finally, whether the payoff of the riskier option was kept constant or varied was found to moderate the relationship in the domain of gains for females, as well as in the domain of losses for the full sample and females only.

Collectively, these results indicate that the relationship between cognitive ability and risk aversion is more sensitive to the setup of the decision task, as well as how cognitive ability is measured in the mixed domain and the domain of losses.

In contrast to the results from Taylor (2013, 2016) and Sousa and Rangel (2014), no evidence of a hypothetical bias was observed. Hence, neither the existence nor the strength of the relationship between cognitive ability and risk aversion were found to be contingent on whether the decision task was incentivized or not. Furthermore, contrary to the results presented by Andersson et al. (2016), the number of possible risk averse choices was not found to moderate the relationship, except in the domain of losses for females only. These results suggest that the negative relationship observed between cognitive ability and risk aversion in the domain of gains is most likely not just an artefact of people with low cognitive ability making more random choice errors.

Across all three domains there was no substantial evidence of publication bias when looking at the funnel plots as well as the results from the rank correlation tests (Begg & Mazumdar, 1994) and the regression tests (Egger et al., 1997). Furthermore, the moderator analyses indicate that results were not influenced by whether or not one of the primary purposes of the study was to investigate the relationship between cognitive ability and risk aversion. All in all, these results strengthen the conclusions drawn from current meta-analysis, as they suggest that the estimated effect sizes are not considerably skewed in any direction due to publication bias.

4.1 Limitations

This study is the first to systematically review and synthesize data on the relationship between cognitive ability and risk aversion. Furthermore, it is the first study that systematically explores the circumstances under which the relationship between cognitive ability and risk aversion exist, as well as whether specific factors moderate it. Despite these strengths, some limitations should be acknowledged.

First, several scholars have pointed out that many of the decision tasks most commonly used to elicit risk preferences are subject to a considerable amount of measurement error (Crosetto & Filippin, 2016; Frey et al., 2017; Pedroni et al., 2017). Given that the measurement error associated with any two measures naturally impose an upper limit for the correlation that can be expected between them (Muchinsky, 1996; Spearman, 1904b), it is likely that the current meta-analysis underestimates the true strength of the relationship between cognitive ability and risk aversion. In light of this fact, it would have been more appropriate to conduct the meta-analysis using disattenuated correlations (Osborne, 2008). Unfortunately, this was not possible, because the data needed to correct for attenuation (i.e., reliability estimates for both the decision task and cognitive ability measure) was rarely available or impossible to obtain. On the other hand, it is important to note that correcting for attenuation when the reliability estimate drops below .70 can lead to overestimation of the strength of the relationship of interest (Osborne, 2008). Accordingly, given that the measurement error, associated with many of the decision tasks commonly used to elicit risk preferences, is far from zero, correcting for attenuation would have been problematic in the context of the current meta-analysis.

Second, the systematic literature search as well as all the coding and data-extraction procedures was only performed by one individual. This is a limitation as it naturally increases the risk of human errors (Mathes, Klaßen & Pieper, 2017).

Third, recent evidence suggest that the imputation of beta values, proposed by Peterson and Brown (2005), could be somewhat problematic, as it has been found to produced overly small estimates of meta-analytic mean correlations (Roth, Le, Oh, Van Iddekinge & Bobko, 2018). Although this clearly presents a limitation, the meta-regressions suggests that the results were not significantly influenced by whether or not Pearson's r was imputed using the Peterson and Brown (2005) formula. Hence, even though the imputation proposed by Peterson and Brown (2005) generally tend to produce overly small estimates of meta-analytic mean correlations (Roth et al., 2018), this does not appear to be a severe problem in the current meta-analysis.

Finally, only a few studies were identified and included for meta-analysis in the domain of losses, making the meta-analytic results for this domain less convincing compared to the results for the mixed domain and the domain of gains (Borenstein et al., 2009). Moreover, given that the number of studies included in domain of losses was so small ($k = 12$) the conclusions drawn from the meta-regressions should be taken with extreme caution (Steel & Kammeyer-Mueller, 2002; Thompson & Higgins, 2002).

4.2 Future Directions

Although the current meta-analysis sheds light on a number of important aspects concerning the relationship between cognitive ability and risk aversion, there is still much work to be done. Future studies should seek to gain a more comprehensive understanding of the circumstances under which a negative relationship between cognitive ability and risk aversion in the domain of gains exists. Looking at the results from the meta-regressions, it is clear that the moderator variables investigated do not sufficiently explain the high amount of heterogeneity observed in the domain of gains. Furthermore, additional studies are needed before any definite conclusions about the relationship between cognitive ability and risk aversion in the domain of losses can or should be drawn.

Another potentially fruitful line of research is to consider the possibility that the relationship between cognitive ability and risk aversion is nonlinear. In a recent study, Mandal and Roe (2014) used NLSY79 and HRS to investigate this possibility and found a quadratic pattern where respondents with the highest and lowest cognitive ability were most risk tolerant. This is intriguing, as it suggests that the inconsistent findings on the relationship between cognitive ability and risk aversion could be explained by the relationship being nonlinear. Following Mandal and Roe (2014) future studies should, therefore, set out to ask whether the relationship is indeed better described as quadratic and nonlinear.

Finally, as many of the decision tasks most commonly used to elicit risk preferences are subjected to a considerable amount of measurement error (Crosetto & Filippin, 2016; Frey et al., 2017; Pedroni et al., 2017), future studies should strive to develop new and better ways of measuring individual risk preferences. In this regard, a promising line of research is the recent development of adaptive elicitations tasks which have been found to reduce measurement error and outperform standard elicitation procedures on a number of important parameters (Chapman, Snowberg, et al., 2018; Toubia, Johnson, Evgeniou & Delquié, 2013). Another viable solution would be to use different risk elicitation tasks to extract a common risk factor (R), thereby increasing accuracy and reducing measurement error (Frey et al., 2017). Extending this possibility, risk could be measured in a variety of domains, both to study effects in each domain and to extract a cross-domain general factor (e.g., Harris, Jenkins & Glaser, 2006).

4.3 Conclusion

In conclusion, the current meta-analysis provides strong evidence for a significant but weak negative relationship between cognitive ability and risk aversion in the domain of gains. However, no significant relationship was found in the mixed domain or the domain of losses, suggesting that the relationship is domain specific. Importantly, no significant difference was observed between males and females across the domain of gains, mixed and losses. Moreover, none of the moderator variables investigated in this study consistently influenced the relationship between cognitive ability and risk aversion across all three domains. Future research should aim to gain a deeper understanding of the relationship between cognitive ability and risk aversion using more reliable measures to elicit risk preferences.

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Appendix

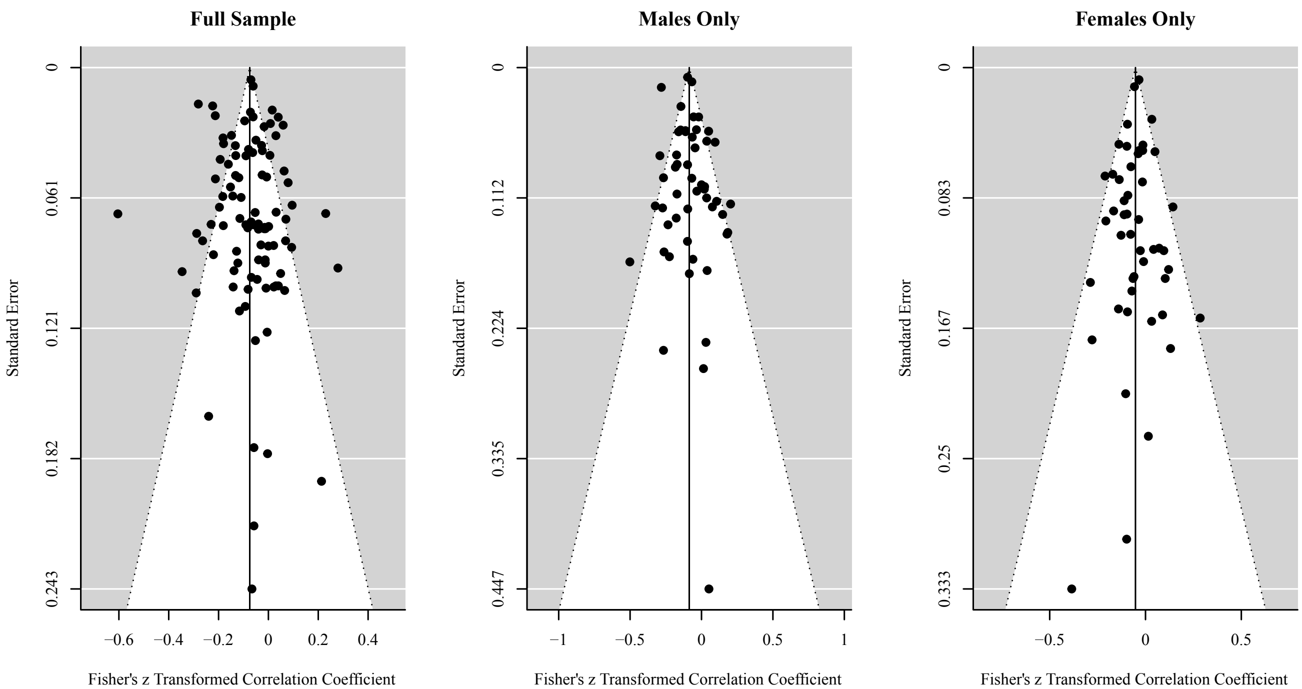

FIGURE 5: Funnel plots for the domain of gains — full sample, males and females only.

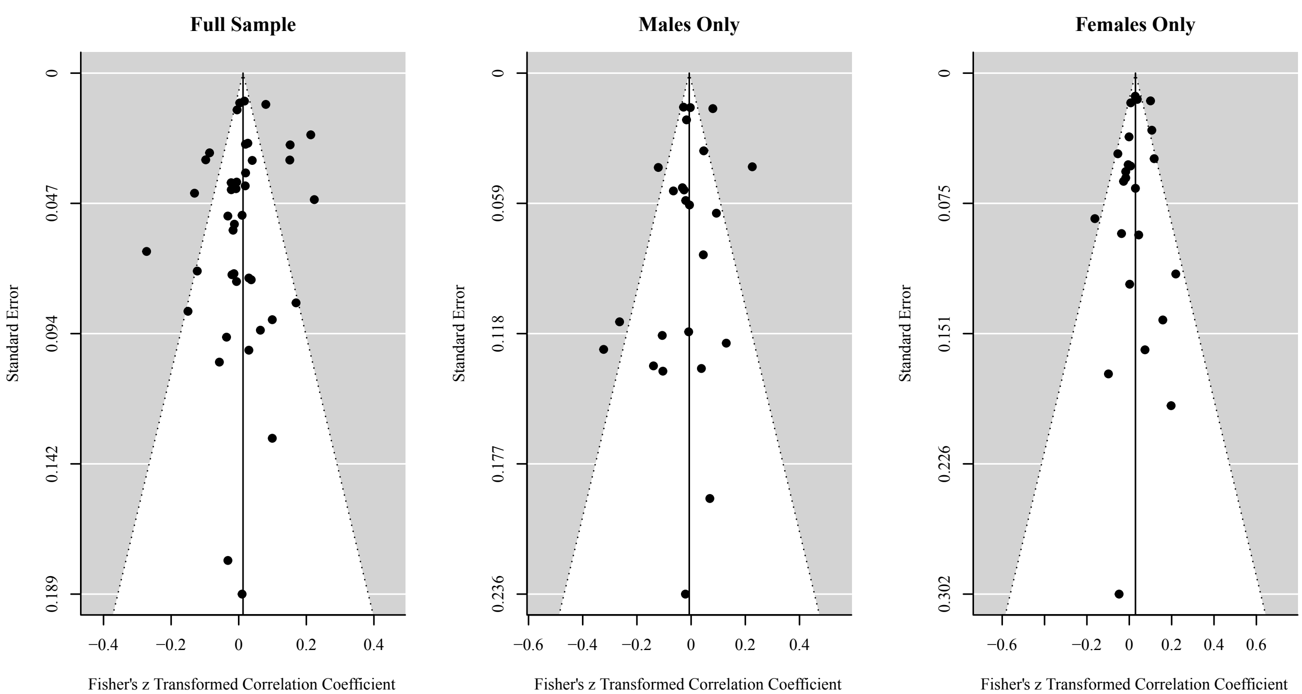

FIGURE 6: Funnel plots for the mixed domain — full sample, males and females only.

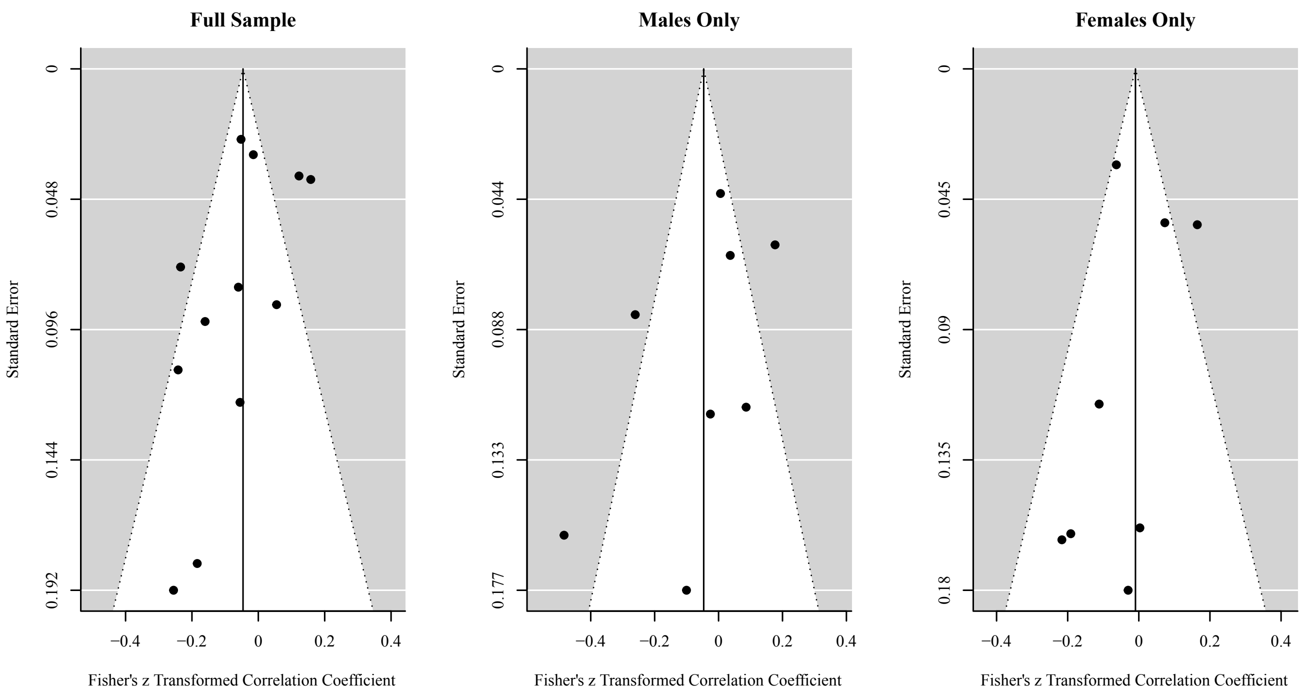

FIGURE 7: Funnel plots for the domain of losses — full sample, males and females only.

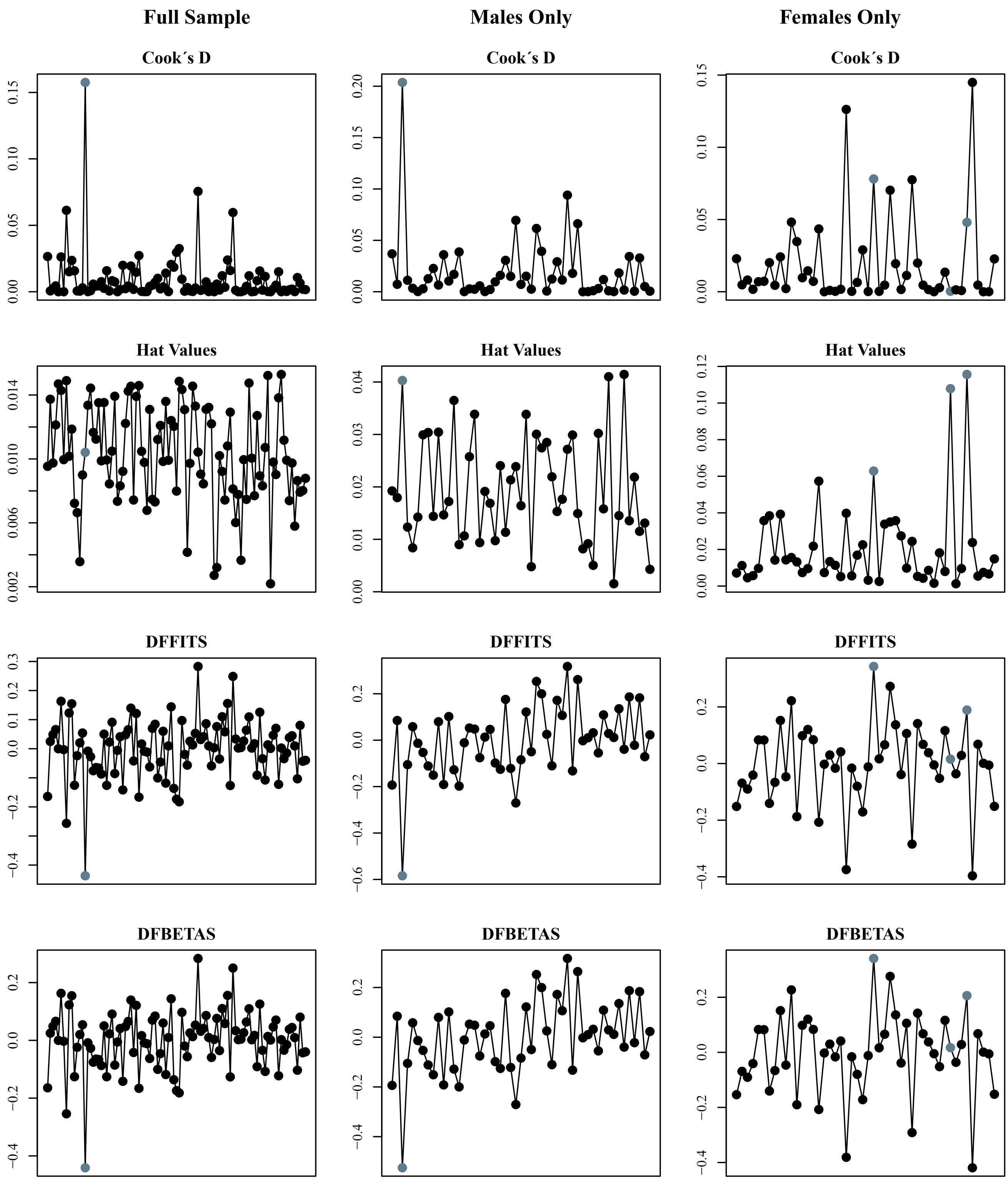

FIGURE 8: Case deletion diagnostics for the domain of gains. (All studies identified as influential are marked with gray)

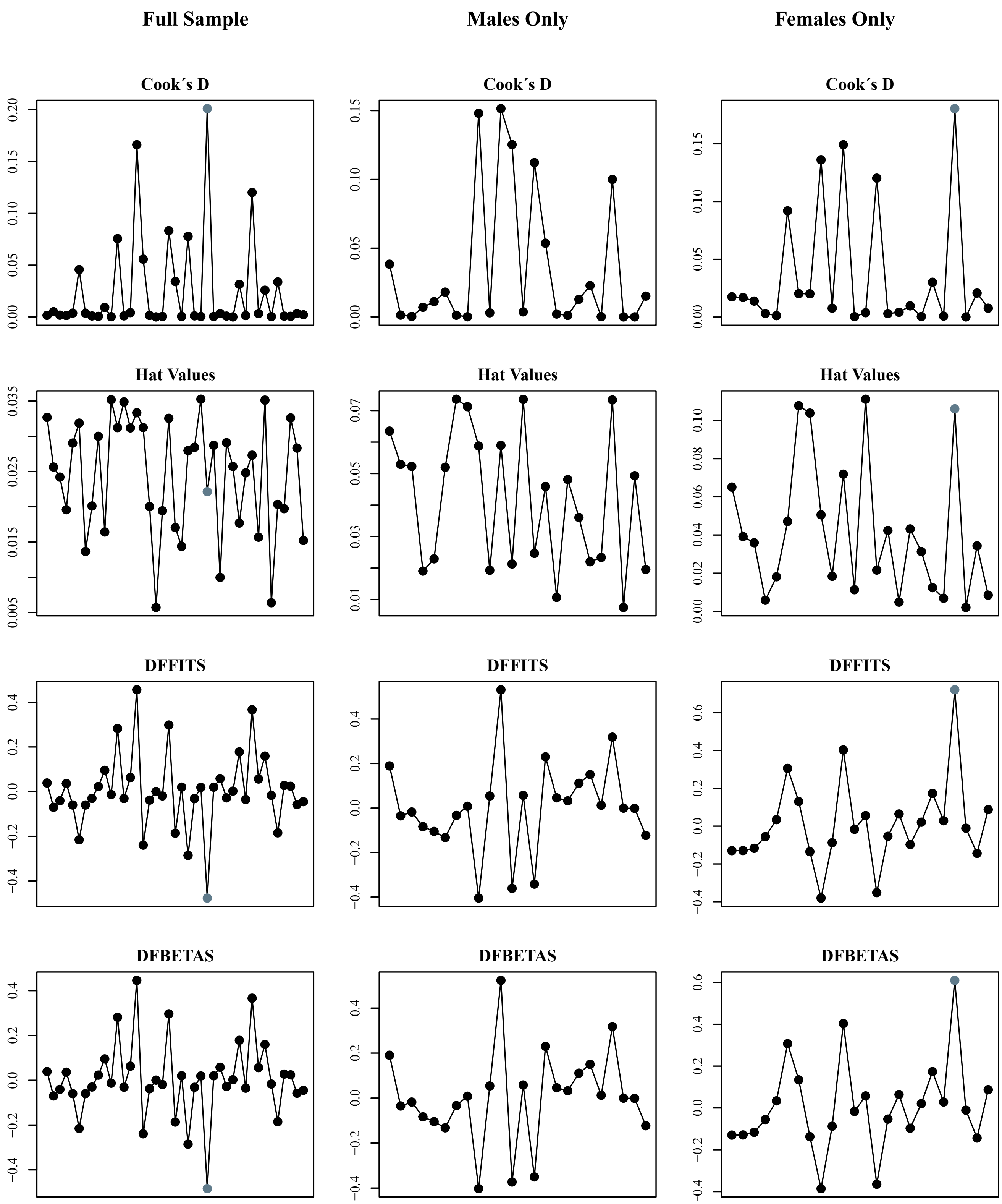

FIGURE 9: Case deletion diagnostics for the mixed domain. (All studies identified as influential are marked with gray)

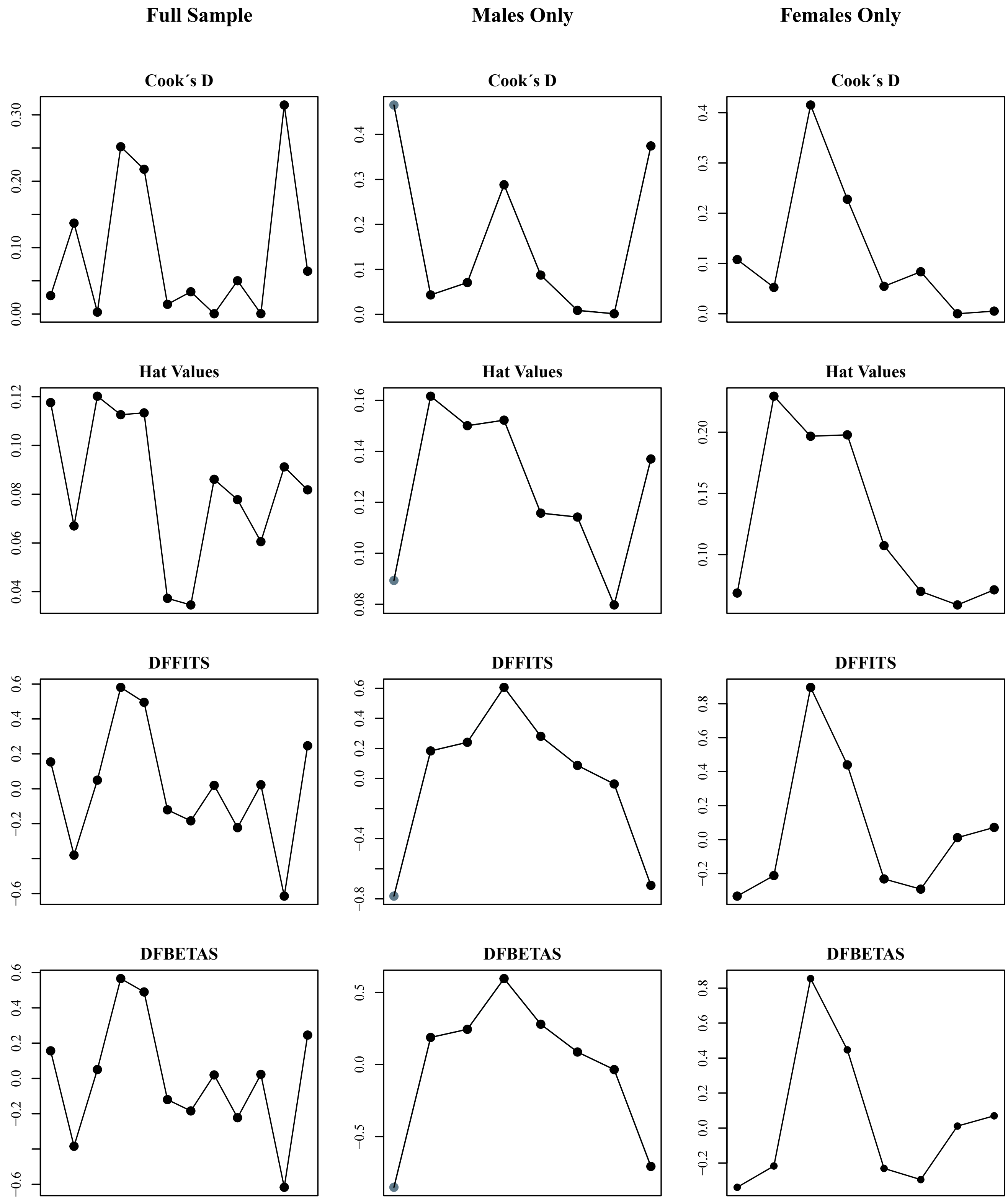

Figure 10: Case deletion diagnostics for the domain of losses. (All studies identified as influential are marked with gray)

Table 1: Overview of studies included in the domain of gains.

Author	Year	N	Male	Female	MF-Ratio	Avrg Age	Sample Type	Payment	Avrg Pay $	CAM	Decision Task	Certain Option	Probabilities
Al-Ubaydli et al	2013	171	115	56	2.054	23.3	S	Yes	30.00	RPM	LT	Yes/No	Changes
Albaity et al	2014	880	367	513	0.715	NA	S	NA	NA	CRT	OGT	Yes	Constant(0.75)
Alexy et al	2016	181	65	116	0.560	NA	S	NA	NA	CRT	DTB	Yes/No	Changes
Alonso et al	2018	389	NA	NA	NA	NA	S	Yes	NA	CRT	MPL	Yes	NA
Andersson et al Study 1	2016	2333	1213	1120	1.083	46.7	CS	Yes	42.00	CATB	MPL	No	Constant(0.50)
Andersson et al Study 2	2016	1396	740	656	1.128	46.7	CS	Yes	31.50	CATB	MPL	No	Constant(0.50)
Basteck & Mantovani	2018	192	102	90	1.133	23.8	S	Yes	17.35	RPM	BRET	No	NA
Beauchamp et al	2017	3482	3482	0	NA	NA	CS	NA	NA	CATB	DTB	Yes	Changes
Ben-Ner & Halldorsson	2010	204	65	139	0.468	20.6	S	Yes	27.00	CATB	LT	Yes	Constant(0.50)
Bendahan et al	2017	352	210	142	1.479	21.1	S	Yes	NA	RPM	OGT	Yes	Changes
Benjamin et al study1	2013	94	58	36	1.611	NA	S	Yes	NA	NUM	LT	Yes	Constant(0.50)
Benjamin et al study 2	2013	81	36	45	0.800	NA	S	Yes	NA	NUM	LT	Yes/No	Constant(0.50)
Benjamin et al study 3	2013	34	NA	NA	NA	NA	S	Yes	NA	NUM	LT	Yes/No	Constant(0.50)
Blankenstein et al	2016	148	71	77	0.922	16.8	S	Yes	NA	RPM	WFT	Yes	Changes
Booth et al	2014	219	144	75	1.920	19.0	S	Yes	NA	RPM	MPL	Yes	Constant(0.50)
Booth et al	2016	693	334	359	0.930	48.0	CS	Yes	NA	RPM	MPL	Yes	Constant(0.50)
Borghans & Golsteyn	2007	1631	NA	NA	NA	NA	CS	NA	NA	CRT	LT	Yes	Constant(0.50)
Borghans et al	2009	327	169	158	1.070	NA	S	Yes	24.28	RPM	EURT	Yes	Constant(0.50)
Bosch-Rosa et al	2018	283	NA	NA	NA	NA	S	Yes	NA	CRT	MPL	No	Changes
Bradford et al	2017	762	352	398	0.884	44.0	CS	Yes	NA	CRT	MPL	No	Changes
Branas-Garza & Rustichini	2011	188	72	116	0.621	22.2	S	NA	NA	RPM	DTB	Yes/No	Changes
Branas-Garza et al	2014	766	355	411	0.864	37.7	CS	Yes	NA	NUM	LT	Yes	Changes
Branas-Garza et al	2012	191	74	117	0.632	22.2	S	Yes	NA	CATB	MPL	No	Changes
Breaban & Noussair	2015	128	NA	NA	NA	NA	S	Yes	25.80	CRT	MPL	No	Changes
Bruttel & Fischbacher	2013	224	95	129	0.736	NA	S	Yes	33.06	CRT	MPL	No	Changes
Burks et al	2009	1009	902	107	8.430	37.3	CS	Yes	53.00	CATB	MPL	Yes	Constant(0.50)
Burks et al	2015	97	39	58	0.672	20.9	S	Yes	NA	CATB	MPL	Yes	Constant(0.50)
Cabrales et al	2017	124	48	76	0.632	NA	S	Yes	21.73	CRT	MPL	No	Changes
Campitelli & Labollita	2010	157	47	110	0.427	24.4	CS	NA	NA	CRT	LT	Yes	Changes
Campos-Vazquez et al	2018	404	214	190	1.126	24.5	CS	Yes	7.90	RPM	MPL	Yes	Constant(0.50)
Carpena et al	2017	1328	562	766	0.734	38.6	CS	Yes	NA	NUM	OGT	Yes	Constant(0.50)
Castillo	2017	1882	NA	NA	NA	8.0	CHS	Yes	NA	CATB	EGRT	Yes	Constant(0.50)
Cavatorta & Schroder	2018	99	41	58	0.707	18.3	S	Yes	24.35	RPM	MPL	No	Changes
Chapman et al (a)	2018	1000	NA	NA	NA	NA	CS	Yes	9.00	CATB	MPL	Yes	Constant(0.50)
Chapman et al (b)	2018	2000	NA	NA	NA	NA	CS	Yes	9.00	CATB	ALT	Yes	Constant(0.50)
Charness et al	2018	223	114	109	1.046	22.1	S	Yes	16.00	RPM	MPL	Yes	Constant(0.66)
Chen et al	2017	183	92	91	1.011	33.0	CS	Yes	28.96	CRT	MPL	No	Changes
Chen et al	2014	84	43	41	1.049	44.0	CS	NA	NA	CATB	CT	Yes	Changes
Choi et al	2018	600	181	419	0.432	38.9	CS	Yes	5.02	RPM	MPL	Yes	Constant
Corgnet et al	2016	100	53	47	1.128	NA	S	Yes	NA	CRT	MPL	No	Changes
Csermely & Rabas	2016	96	52	44	1.182	26.3	S	Yes	23.70	CRT	MPL	No	Constant(0.50)
Cueva et al	2015	281	140	141	0.993	22.5	S	Yes	NA	CATB	MPL	Yes	Constant(0.50)
Cueva et al study 1	2016	384	NA	NA	NA	NA	S	Yes	NA	CRT	LT	No	Changes
Cueva et al study 2	2016	186	NA	NA	NA	NA	S	Yes	NA	CRT	MPL	Yes	Constant(0.50)
Dave et al	2010	801	347	454	0.764	NA	CS	Yes	124.50	NUM	DTB	Yes/No	Changes
Dean & Ortoleva	2012	190	NA	NA	NA	NA	S	Yes	NA	RPM	MPL	Yes	Constant(0.50)
Deckers et al	2017	435	NA	NA	NA	7.8	CHS	Yes	NA	CATB	LT	Yes	Constant(0.50)
Dohmen et al	2010	376	178	198	0.899	46.2	CS	Yes	NA	CATB	MPL	Yes	Constant(0.50)
Duttle & Inukai	2015	114	88	26	3.385	22.6	S	Yes	NA	CRT	LT	Yes	Changes

Note. Not available (NA), cognitive ability measure (CAM), student sample (S), community sample (CS), children sample (CHS), cognitive ability test battery (CATB), ravens progressive matrices (RPM), cognitive reflection task (CRT), numeracy test (NUM), working memory capacity test (WMC), adaptive lottery task (ALT), bomb elicitation risk task (BRET), cups task (CT), decision task battery (DTB), Eckel-Grossman risk task (EGRT), Ellsberg urn risk task (EURT), gift gamble task (GGT), income gamble task (IGT), lottery task (LT), multiple price list (MPL), one-shot gambling task (OGT), Sabater-Grande-Georgantzis lottery panel (SGG), wheel of fortune task (WTF).

Table 1, continued.

Author	Year	N	Male	Female	MF-Ratio	Avrg Age	Sample Type	Payment	Avrg. Pay $	CAM	Decision Task	Certain Option	Probabilities
Frederick	2005	3150	NA	NA	NA	NA	S	Yes	8.00	CRT	LT	Yes	Changes
Frey et al	2017	1480	561	919	0.610	25.0	CS	Yes	NA	CATB	DTB	No	Changes
Gaurav et al	2011	597	525	72	7.292	49.8	CS	Yes	NA	NUM	OGT	Yes	Constant(0.50)
Gerhardt et al	2011	41	20	21	0.952	25.9	S	Yes	NA	CRT	LT	Yes/No	Changes
Guillen et al	2014	180	NA	NA	NA	NA	S	Yes	17.16	CATB	BRET	No	NA
Gupta et al	2013	1904	1010	894	1.130	NA	CHS	NA	NA	NUM	EGRT	Yes	Constant(0.50)
Hefti et al	2016	672	339	333	1.018	23.1	S	Yes	80.00	RPM	MPL	Yes	Constant(0.50)
Ibanez et al	2016	220	82	138	0.594	NA	S	Yes	NA	CATB	SGG	Yes	Changes
Johnson & Pevnitskaya	2013	150	77	73	1.055	20.4	S	Yes	20.40	RPM	MPL	No	Changes
Kable et al	2017	128	71	57	1.246	25.1	CS	NA	NA	CATB	LT	Yes	Changes
Kirchler et al	2017	603	254	349	0.728	23.5	S	Yes	12.16	CRT	LT	Yes	Constant(0.50)
Koch & Nafziger	2016	643	284	359	0.791	21.4	S	Yes	25.00	CRT	MPL	Yes	Constant(0.50)
Kocher et al	2014	400	148	252	0.587	23.6	S	Yes	21.00	CRT	MPL	Yes	Constant(0.50)
Kurnianingsih	2015	25	11	14	0.786	68.7	CS	Yes	NA	CATB	LT	Yes	Changes
Levin & Hart	2003	30	11	19	0.579	6.0	CHS	Yes	NA	CATB	GGT	Yes	Constant(0.50)
Lezzi et al	2015	206	95	111	0.856	NA	S	Yes	12.65	NUM	MPL	No	Changes
Mather et al	2012	157	79	78	1.013	39.0	CS	Yes	NA	CATB	LT	Yes/No	Changes
Menapace et al	2015	99	99	0	NA	43.7	CS	Yes	34.37	NUM	EGRT	Yes	Constant(0.50)
Mollerstrom & Seim	2014	247	247	0	NA	47.2	CS	NA	NA	CATB	LT	Yes	Constant(0.50)
Oechssler et al	2009	551	333	218	1.528	23.9	S	Yes	NA	CRT	OGT	Yes	Constant(0.75)
Pachur et al	2017	118	76	42	1.810	47.4	CS	Yes	NA	CATB	LT	Yes/No	Changes
Park & Cho	2018	69	35	34	1.029	20.2	S	NA	NA	CATB	LT	Yes	Changes
Peters & Bjalkebring	2015	108	40	68	0.588	21.3	S	Yes	NA	CATB	LT	Yes	Constant(0.50)
Pollak et al	2016	35	21	14	1.500	15.9	CHS	NA	NA	CATB	LT	Yes	Changes
Ponti et al	2014	192	NA	NA	NA	NA	S	Yes	NA	CRT	MPL	No	Changes
Proto et al	2014	100	38	62	0.613	21.6	S	Yes	28.00	RPM	MPL	No	Changes
Ramlall	2014	2565	1359	1206	1.127	NA	CS	NA	NA	NUM	OGT	Yes	Constant(0.50)
Rangel & Sousa Study 1	2014	197	118	79	1.494	22.3	S	Yes	18.62	CATB	OGT	Yes	Constant
Rangel & Sousa Study 2	2014	106	50	56	0.893	19.9	S	Yes	13.27	CATB	MPL	Yes	Constant
Reuben et al	2008	498	345	153	2.255	28.3	S	Yes	98.32	CRT	MPL	Yes	Constant(0.50)
Rizzolli & Tremewan	2016	146	83	63	1.317	26.0	NA	Yes	NA	CRT	MPL	No	Constant(0.50)
Rydval	2012	124	58	66	0.879	NA	S	Yes	28.17	WMC	MPL	Yes	NA
Sartarelli	2016	240	129	111	1.162	NA	S	Yes	NA	CRT	MPL	Yes	Constant(0.50)
Schleich et al	2018	13436	6718	6718	1.000	40.9	CS	Yes	NA	CRT	MPL	No	Constant(0.50)
Sepulveda et al	2017	20	8	12	0.667	41.1	CS	Yes	NA	CATB	LT	Yes	Constant(0.50)
Sheremeta	2018	184	NA	NA	NA	NA	S	Yes	NA	CATB	MPL	Yes	Constant(0.50)
Stanek & Krcal	2018	149	73	76	0.961	22.7	S	Yes	NA	CATB	BRET	No	NA
Stewart et al	2018	937	221	716	0.309	81.2	CS	NA	NA	CATB	LT	Yes	Constant(0.50)
Strauss et al	2016	31201	14624	16577	0.882	37.3	CS	NA	NA	CATB	IGT	Yes	Constant(0.50)
Suzuki et al	2018	277	66	211	0.313	26.1	CS	NA	NA	NUM	MPL	Yes	Constant(0.50)
Sytsma et al	2014	190	147	43	3.419	21.0	S	Yes	NA	RPM	EGRT	Yes	Constant
Taylor	2013	98	59	39	1.513	21.8	S	Yes	52.68	CATB	MPL	No	Changes
Taylor	2016	181	89	92	0.967	21.8	S	Yes	NA	CRT	MPL	Yes/No	Changes
Tymula et al	2012	65	31	34	0.912	NA	CS	Yes	NA	CATB	LT	Yes	Changes
Tymula et al	2013	135	70	65	1.077	37.2	CS	Yes	NA	CATB	LT	Yes	Changes
van der Leer et al	2015	112	53	59	0.898	19.9	S	Yes	NA	RPM	MPL	No	Changes
Weisser	2014	115	63	52	1.212	22.8	S	Yes	NA	CRT	MPL	Yes	Constant(0.50)
Ziegelmeyer & Ziegelmeyer	2016	140	18	122	0.148	37.1	CS	Yes	NA	CRT	MPL	No	Changes

Table 1, continued.

Author	Year	Payoff Safer Choice	Payoff Riskier Choice	Incentivized	% Risk Averse Choices	Primary Purpose	R-Recode	R-Male-Recode	R-Female-Recode	Imputed Beta
Al-Ubaydli et al	2013	Changes	Changes	Random	NA	No	−.280	−.260	−.280	No
Albaity et al	2014	Constant	Constant	NA	100	Yes	−.050	NA	NA	No
Alexy et al	2016	Changes	Changes	No	NA	No	−.012	NA	NA	No
Alonso et al	2018	Changes	Constant	Random	NA	No	−.007	NA	NA	Yes
Andersson et al Study 1	2016	Constant	Changes	Random	80	Yes	−.072	NA	NA	No
Andersson et al Study 2	2016	Constant	Changes	Random	50	Yes	.059	NA	NA	No
Basteck & Mantovani	2018	NA	NA	Yes	100	No	−.076	.000	−.127	No
Beauchamp et al	2017	Changes	Changes	No	100	No	−.274	−.274	NA	Yes
Ben-Ner & Halldorsson	2010	Constant	Changes	Random	80	No	.070	NA	NA	Yes
Bendahan et al	2017	Constant	Constant	Yes	100	No	.079	NA	NA	Yes
Benjamin et al study1	2013	Constant	Changes	Yes	80	Yes	−.282	−.230	−.272	No
Benjamin et al study 2	2013	Constant	Changes	Yes	60	Yes	−.116	.039	−.140	No
Benjamin et al study 3	2013	Constant	Changes	Yes	60	Yes	−.003	NA	NA	No
Blankenstein et al	2016	Constant	Changes	Random	100	No	.000	−.096	.042	No
Booth et al	2014	Changes	Constant	Random	80	No	−.540	NA	NA	Yes
Booth et al	2016	Constant	Changes	Random	82	No	−.080	−.111	−.034	No
Borghans & Golsteyn	2007	Constant	Changes	No	NA	No	−.095	NA	NA	No
Borghans et al	2009	Changes	Constant	Yes	100	Yes	−.151	NA	NA	Yes
Bosch-Rosa et al	2018	Constant	Constant	NA	56	No	−.142	NA	NA	No
Bradford et al	2017	Constant	Constant	Random	63	No	−.132	−.145	−.097	No
Branas-Garza & Rustichini	2011	Changes	Changes	No	78	No	−.179	−.266	−.111	No
Branas-Garza et al	2014	Changes	Changes	No	100	No	−.027	−.036	−.013	No
Branas-Garza et al	2012	Constant	Constant	NA	56	No	−.226	−.313	−.096	No
Breaban & Noussair	2015	Constant	Constant	Random	56	No	−.039	NA	NA	No
Bruttel & Fischbacher	2013	Constant	Constant	Random	56	No	.031	.020	.142	No
Burks et al	2009	Changes	Constant	Random	83	No	−.147	−.143	−.204	No
Burks et al	2015	Changes	Constant	Yes	83	Yes	−.081	−.463	.103	No
Cabrales et al	2017	Constant	Constant	Yes	56	No	−.013	−.098	.095	No
Campitelli & Labollita	2010	Changes	Changes	NA	100	Yes	−.258	NA	NA	No
Campos-Vazquez et al	2018	Changes	Constant	Yes	50	Yes	−.025	−.045	−.016	No
Carpena et al	2017	Constant	Constant	NA	100	No	−.017	−.055	−.094	No
Castillo	2017	Constant	Changes	Yes	100	No	.040	NA	NA	No
Cavatorta & Schroder	2018	Constant	Constant	Yes	50	No	−.140	−.221	−.065	No
Chapman et al (a)	2018	Changes	Constant	Yes	NA	No	.030	NA	NA	No
Chapman et al (b)	2018	Constant	Changes	Yes	NA	No	−.210	NA	NA	No
Charness et al	2018	Changes	Constant	Random	83	No	−.053	−.068	−.036	No
Chen et al	2017	Constant	Constant	Random	33	No	−.083	−.033	−.077	No
Chen et al	2014	Constant	Changes	NA	67	Yes	−.093	−.257	.032	No
Choi et al	2018	Changes	Constant	Yes	50	No	−.130	−.173	−0.138	No
Corgnet et al	2016	Constant	Constant	Random	56	No	.040	NA	NA	No
Csermely & Rabas	2016	Constant	Changes	Random	60	No	.065	.177	−.094	No
Cueva et al	2015	Changes	Constant	Random	73	No	−.181	−.181	−.111	No
Cueva et al study 1	2016	Changes	Changes	Random	NA	No	−.118	NA	NA	Yes
Cueva et al study 2	2016	Changes	Constant	Random	52	No	.001	NA	NA	Yes
Dave et al	2010	Changes	Changes	Random	NA	No	−.178	NA	NA	Yes
Dean & Ortoleva	2012	Changes	Constant	Random	NA	No	−.060	NA	NA	No
Deckers et al	2017	Changes	Changes	Yes	50	No	.063	NA	NA	No
Dohmen et al	2010	Changes	Constant	Random	80	Yes	−.210	−.283	−.136	No
Duttle & Inukai	2015	Constant	Changes	Random	100	No	−.333	−.170	−.103	No

Table 1, continued.

Author	Year	Payoff Safer Choice	Payoff Riskier Choice	Incentivized	% Risk Averse Choices	Primary Purpose	R-Recode	R-Male-Recode	R-Female-Recode	Imputed Beta
Frederick	2005	Changes	Changes	No	100	Yes	−.220	NA	NA	No
Frey et al	2017	Changes	Changes	Random	NA	No	.008	−.020	.033	No
Gaurav et al	2011	Constant	Constant	Yes	100	No	−.090	NA	NA	No
Gerhardt et al	2011	Changes	Changes	Random	70	No	−.235	−.260	.015	No
Guillen et al	2014	NA	NA	Yes	100	No	−.040	NA	NA	No
Gupta et al	2013	Constant	Changes	No	100	Yes	−.061	NA	NA	Yes
Hefti et al	2016	Changes	Constant	Random	79	No	−.024	.050	−.038	No
Ibanez et al	2016	Constant	Constant	Random	100	No	.226	NA	NA	No
Johnson & Pevnitskaya	2013	Constant	Constant	Yes	56	Yes	−.030	NA	NA	No
Kable et al	2017	Constant	Changes	NA	NA	No	−.013	NA	NA	No
Kirchler et al	2017	Changes	Constant	Random	80	No	.006	.037	.049	No
Koch & Nafziger	2016	Changes	Constant	Random	52	No	−.063	−.065	−.015	No
Kocher et al	2014	Changes	Constant	Random	50	No	−.131	−.169	−.076	No
Kurnianingsih	2015	Changes	Changes	Random	NA	No	−.058	NA	NA	No
Levin & Hart	2003	Constant	Constant	Yes	100	Yes	.210	NA	NA	No
Lezzi et al	2015	Constant	Constant	Random	56	No	−.114	NA	NA	Yes
Mather et al	2012	Changes	Changes	Random	100	No	.069	.105	.071	No
Menapace et al	2015	Constant	Changes	NA	100	No	.022	.022	NA	No
Mollerstrom & Seim	2014	Changes	Constant	No	NA	No	.095	.095	NA	Yes
Oechssler et al	2009	Constant	Constant	Random	100	Yes	−.191	−.159	−.169	No
Pachur et al	2017	Changes	Changes	Random	63	Yes	.272	.201	.278	No
Park & Cho	2018	Changes	Changes	NA	60	Yes	−.005	−.085	.130	No
Peters & Bjalkebring	2015	Changes	Changes	No	100	No	−.068	−.060	−.010	No
Pollak et al	2016	Changes	Changes	No	NA	No	−.058	.031	−.098	No
Ponti et al	2014	Constant	Constant	Random	56	No	−.040	NA	NA	No
Proto et al	2014	Constant	Constant	Random	56	No	.030	NA	NA	No
Ramlall	2014	Constant	Constant	NA	100	No	.015	NA	NA	No
Rangel & Sousa Study 1	2014	Constant	Constant	Yes	100	Yes	−.069	NA	NA	Yes
Rangel & Sousa Study 2	2014	Changes	Constant	Random	NA	Yes	−.045	NA	NA	Yes
Reuben et al	2008	Changes	Constant	Random	69	No	−.159	−.112	−.092	No
Rizzolli & Tremewan	2016	Constant	Changes	Random	50	No	.093	.036	.120	No
Rydval	2012	Constant	Changes	No	NA	No	−.122	NA	NA	Yes
Sartarelli	2016	Changes	Constant	Random	52	No	−.194	NA	NA	No
Schleich et al	2018	Constant	Changes	Random	50	No	−.061	−.068	−.057	No
Sepulveda et al	2017	Changes	Changes	Yes	NA	No	−.066	.052	−.367	No
Sheremeta	2018	Changes	Constant	Random	60	No	−.015	NA	NA	No
Stanek & Krcal	2018	NA	NA	Yes	100	No	.021	.076	−.027	No
Stewart et al	2018	Constant	Changes	No	90	Yes	−.180	NA	NA	No
Strauss et al	2016	Constant	Changes	No	100	No	−.070	−.097	−.034	No
Suzuki et al	2018	Changes	Constant	NA	63	No	−.109	.147	−.208	No
Sytsma et al	2014	Constant	Changes	NA	NA	No	−.090	−.097	.089	Yes
Taylor	2013	Changes	Changes	Random	56	Yes	−.010	NA	NA	Yes
Taylor	2016	Changes	Constant	Random	NA	Yes	−.017	NA	NA	Yes
Tymula et al	2012	Constant	Changes	Random	NA	No	−.052	NA	NA	Yes
Tymula et al	2013	Constant	Changes	Random	NA	No	−.217	NA	NA	No
van der Leer et al	2015	Constant	Constant	NA	56	No	.049	.182	−.060	No
Weisser	2014	Changes	Constant	No	55	No	−.137	−.175	−.071	No
Ziegelmeyer & Ziegelmeyer	2016	Constant	Constant	Yes	56	No	−.127	.014	−.165	No

Table 2: Moderator analysis for the domain of gains.

Moderator		K	β	SE	95% CI	Test of Moderators	Test of Residual Heterogeneity
MF-Ratio	Intercept	78	−.06**	.02	[−.10, −.02]	Q_M (df = 1) = 1.74	Q_E (df = 76) = 287.08***
	MF-Ratio		−.01	.01	[−.03, .01]		
Age	Intercept	66	−.06	.04	[−.14, .02]	Q_M (df = 1) = 0.12	Q_E (df = 64) = 255.19***
	Avrg. age		−.00	.00	[−.00, .00]		
Sample Type	Intercept (CHS)	96	.02	.06	[−.09, .13]	Q_M (df = 2) = 3.22	Q_E (df = 93) = 570.21***
	CS		−.10	.06	[−.21, .02]		
	S		−.10	.06	[−.22, .01]		
Avrg. Payment	Intercept	34	−.06*	.03	[−.11, −.01]	Q_M (df = 1) = 0.70	Q_E (df = 32) = 177.51***
	Avrg. payment		−.00	.00	[−.00, .00]		
CAM	Intercept (CATB)	97	−.05*	.02	[−.09, −.01]	Q_M (df = 4) = 3.20	Q_E (df = 92) = 599.10***
	CRT		−.04	.03	[−.10, .02]		
	NUM		−.03	.04	[−.11, .05]		
	RPM		−.05	.04	[−.12, .02]		
	WMC		−.08	.14	[−.34, .19]		
Decision Task	Intercept (ALT)	97	−.21*	.10	[−.41, −.02]	Q_M (df = 12) = 14.73	Q_E (df = 84) = 419.39***
	BRET		.18	.12	[−.06, .42]		
	CT		.12	.18	[−.23, .47]		
	DTB		.08	.11	[−.14, .29]		
	EGRT		.19	.11	[−.03, .41]		
	EURT		.06	.15	[−.23, .35]		
	GGT		.43	.24	[−.04, .89]		
	IGT		.14	.14	[−.13, .42]		
	LT		.13	.10	[−.07, .33]		
	MPL		.13	.10	[−.06, .33]		
	OGT		.17	.11	[−.04, .38]		
	SGG		.44**	.15	[.14, .75]		
	WFT		.21	.16	[−.10, .53]		
Certain Option	Intercept (No)	97	−.05	.02	[−09, .00]	Q_M (df = 2) = 2.19	Q_E (df = 94) = 589.20***
	Yes		−.04	.03	[−.10, .01]		
	Yes/No		−.03	.05	[−.12, .07]		
Probabilities	Intercept (Changes)	92	−.08***	.02	[−.12, −.04]	Q_M (df = 4) = 0.42	Q_E (df = 87) = 530.28***
	Constant		−.01	.07	[−.14, .12]		
	Constant (50%)		.00	.03	[−.05, .06]		
	Constant (66%)		.02	.13	[−.22, .27]		
	Constant (75%)		−.04	.08	[−.20, .12]		
Payoff Safer Choice	Intercept (Changes)	94	−.09***	.02	[−.13, −.06]	Q_M (df = 1) = 2.07	Q_E (df = 92) = 539.77***
	Constant		.04	.02	[−.01, .08]		
Payoff Riskier Choice	Intercept (Changes)	94	−.08***	.02	[−.12, −.04]	Q_M (df = 1) = 0.13	Q_E (df = 92) = 603.39***
	Constant		.01	.03	[−.04, .06]		
Incentivized	Intercept (No)	84	−.11***	.03	[−.17, −.05]	Q_M (df = 2) = 1.62	Q_E (df = 81) = 543.61***
	Random		.04	.04	[−.03, .11]		
	Yes		.05	.04	[−.03, .13]		
Risk Averse Choices	Intercept	76	−.04	.06	[−.15, .07]	Q_M (df = 1) = 0.39	Q_E (df = 74) = 512.13***
	Risk Averse Choices %		−.00	.00	[−.00, .00]		
Primary purpose	Intercept (No)	97	−.07***	.01	[−.10, −.04]	Q_M (df = 1) = 0.18	Q_E (df = 95) = 602.08***
	Yes		−.01	.03	[−.07, .04]		
Beta Imputed	Intercept (No)	97	−.07***	.01	[−.10, −.04]	Q_M (df = 1) = 0.68	Q_E (df = 95) = 553.28***
	Yes		−.03	.03	[−.09, .03]		

Note. p < .05 = *, p < .01 = **, p < .001 = ***.

Table 3: Moderator analysis for the domain of gains — males only.

Moderator		K	β	SE	95% CI	Test of Moderators	Test of Residual Heterogeneity
Sample Type	Intercept (CHS)	50	.03	.25	[−.46, .53]	Q_M (df = 2) = 0.54	Q_E (df = 47) = 207.70***
	CS		−.11	.25	[−.61, .39]		
	S		−.13	.25	[−.63, .37]		
Avrg. Payment	Intercept	17	−.07	.04	[−.15, .01]	Q_M (df = 1) = 0.01	Q_E (df = 15) = 26.94*
	Avrg. payment		.00	.00	[−.00, .00]		
CAM	Intercept (CATB)	51	−.11***	.03	[−.17, −.05]	Q_M (df = 3) = 2.00	Q_E (df = 47) = 184.89***
	CRT		.03	.04	[−.05, .12]		
	NUM		.09	.06	[−.04, .21]		
	RPM		.02	.05	[−.07, .12]		
Decision Task	Intercept (ALT)	51	−.10	.15	[−.39, .20]	Q_M (df = 8) = 7.46	Q_E (df = 42) = 107.15***
	BRET		.13	.18	[−.22, .48]		
	CT		−.17	.23	[−.63, .29]		
	DTB		−.08	.16	[−.40, .23]		
	EGRT		.05	.17	[−.29, .39]		
	IGT		−.00	.17	[−.34, .34]		
	LT		.07	.15	[−.23, .37]		
	MPL		.00	.15	[−.30, .30]		
	OGT		−.01	.17	[−.33, .32]		
Certain Option	Intercept (No)	51	−.04	.04	[−.11, .03]	Q_M (df = 2) = 2.40	Q_E (df = 48) = 189.04***
	Yes		−.06	.04	[−.15, .02]		
	Yes/No		−.03	.07	[−.17, .12]		
Probabilities	Intercept (Changes)	49	−.11***	.03	[−.17, −.04]	Q_M (df = 4) = 1.55	Q_E (df = 44) = 144.95***
	Constant		−.03	.09	[−.21, .15]		
	Constant (50%)		.03	.04	[−.04, 0.11]		
	Constant (66%)		.04	.14	[−.23, .30]		
	Constant (75%)		−.05	.11	[−.27, .16]		
Payoff Safer Choice	Intercept (Changes)	49	−.09***	.02	[−.14, −.05]	Q_M (df = 1) = 0.05	Q_E (df = 47) = 174.32***
	Constant		.01	.04	[−.06, .08]		
Payoff Riskier Choice	Intercept (Changes)	49	−.09**	.03	[−.14, −.03]	Q_M (df = 1) = 0.01	Q_E (df = 47) = 205.81***
	Constant		−.00	.04	[−.08, .07]		
Incentivized	Intercept (No)	43	−.11**	.04	[−.20, −.03]	Q_M (df = 2) = 0.57	Q_E (df = 40) = 175.67***
	Random		.03	.05	[−.06, .13]		
	Yes		.01	.06	[−.12, .14]		
Risk Averse Choices %	Intercept	45	−.05	.07	[−.19, .09]	Q_M (df = 1) = 0.35	Q_E (df = 43) = 174.06***
	Risk averse choices %		−.00	.00	[−.00, .00]		
Primary purpose	Intercept (No)	51	−.08***	.02	[−0.11, −.04]	Q_M (df = 1) = 1.66	Q_E (df = 49) = 209.40***
	Yes		−.07	.05	[−.17, .03]		
Beta Imputed	Intercept (No)	51	−.08***	.02	[−.12, −.05]	Q_M (df = 1) = 0.40	Q_E (df = 49) = 119.74***
	Yes		−.04	.06	[−.16, .08]		

Note. $p < .05$ = *, $p < .01$ = **, $p < .001$ = ***.

Table 4: Moderator analysis for the domain of gains — females only.

Moderator		K	β	SE	95% CI	Test of Moderators	Test of Residual Heterogeneity
Sample Type	Intercept (CHS)	47	−.10	.30	[−.69, .50]	Q_M (df = 2) = 0.41	Q_E (df = 44) = 58.72
	CS		.04	.30	[−.56, .63]		
	S		.05	.30	[−.54, .65]		
Avrg. Payment	Intercept	16	−.04	.04	[−.11, .03]	Q_M (df = 1) = 0.14	Q_E (df = 14) = 20.26
	Avrg. payment		−.00	.00	[−.00, .00]		
CAM	Intercept (CATB)	48	−.03	.02	[−.07, .01]	Q_M (df = 3) = 3.80	Q_E (df = 44) = 52.09
	CRT		−.02	.03	[−.08, .04]		
	NUM		−.07	.04	[−.15, .00]		
	RPM		−.04	.03	[−.11, .03]		
Decision Task	Intercept (ALT)	48	.04	.12	[−.19, .27]	Q_M (df = 8) = 17.09*	Q_E (df = 39) = 43.29
	BRET		−.12	.14	[−.40, .15]		
	CT		−.01	.20	[−.40, .38]		
	DTB		−.02	.12	[−.26, .21]		
	EGRT		.05	.20	[−.34, .43]		
	IGT		−.08	.12	[−.30, .15]		
	LT		−.05	.12	[−.28, .19]		
	MPL		−.10	.12	[−.33, .12]		
	OGT		−.15	.12	[−.39, .08]		
Certain Option	Intercept (No)	48	−.04	.02	[−.08, .01]	Q_M (df = 2) = 0.95	Q_E (df = 45) = 60.16
	Yes		−.03	.03	[−.08, .03]		
	Yes/No		−.01	.06	[−.13, .11]		
Probabilities	Intercept (Changes)	46	−.02	.02	[−.06, .02]	Q_M (df = 4) = 7.01	Q_E (df = 41) = 51.20
	Constant		−.10	.06	[−.21, .01]		
	Constant (50%)		−.04	.02	[−.09, .01]		
	Constant (66%)		−.02	.10	[−.22, .18]		
	Constant (75%)		−.15*	.08	[−.30, −.01]		
Payoff Safer Choice	Intercept (Changes)	46	−.05**	.02	[−.08, −.01]	Q_M (df = 1) = 0.07	Q_E (df = 44) = 59.72
	Constant		−.01	.03	[−.06, .04]		
Payoff Riskier Choice	Intercept (Changes	46	−.03	.02	[−.06, .00]	Q_M (df = 1) = 4.35*	Q_E (df = 44) = 53.66
	Constant		−.05*	.02	[−.09, −.00]		
Incentivized	Intercept (No)	41	−.04	.03	[−.09, .01]	Q_M (df = 2) = 1.86	Q_E (df = 38) = 46.26
	Random		−.01	.03	[−.06, .05]		
	Yes		−.05	.04	[−.13, .03]		
Risk Averse Choices %	Intercept	43	−.07*	.04	[−.15, −.00]	Q_M (df = 1) = 0.28	Q_E (df = 41) = 46.96
	Risk averse choices %		.00	.00	[−.00, .00]		
Primary purpose	Intercept (No)	48	−.05***	.01	[−.08, −.03]	Q_M (df = 1) = 0.15	Q_E (df = 46) = 59.72
	Yes		−.02	.04	[−.09, .06]		
Beta Imputed	Intercept (No)	48	−.05***	.01	[−.08, −.03]	Q_M (df = 1) = 0.77	Q_E (df = 46) = 59.68
	Yes		.14	.16	[−.18, .46]		

Note. $p < .05$ = *, $p < .01$ = **, $p < .001$ = ***.

Table 5: Overview of studies included in the mixed domain.

Author	Year	N	Male	Female	MF-Ratio	Avrg Age	Sample Type	Payment	Avrg Pay $	CAM	Decision Task	Certain Option	Probabilities
Alan et al	2014	1550	812	738	1.100	NA	CHS	Yes	NA	RPM	GPIT	Yes	Constant(0.50)
Alan et al study 1	2017	375	375	0	NA	NA	CHS	Yes	NA	CATB	GPIT	Yes	Constant(0.50)
Alan et al study 2	2017	311	0	311	NA	NA	CHS	Yes	NA	CATB	GPIT	Yes	Constant(0.50)
Alexy et al	2016	181	65	116	0.560	NA	S	NA	NA	CRT	SGG	Yes	Changes
Angerer et al	2015	636	361	275	1.313	8.9	CHS	Yes	NA	RPM	GPIT	Yes	Constant(0.50)
Bateman el al	2015	1199	NA	NA	NA	NA	CS	Yes	2.10	NUM	PCT	Yes	Constant
Benjamin et al Study 1	2013	94	58	36	1.611	NA	S	Yes	NA	NUM	LT	Yes	Constant(0.50)
Branas-Garza & Rustichini	2011	192	74	117	0.632	22.2	S	NA	NA	RPM	OGT	Yes	Constant(0.50)
Branas-Garza et al	2014	766	355	411	0.864	37.7	CS	Yes	NA	NUM	OGT	Yes	Constant(0.50)
Breaban & Noussair	2015	128	NA	NA	NA	NA	S	Yes	25.80	CRT	MPL	Yes	Constant(0.50)
NLSY79	1993	8548	4219	4329	0.975	31.9	CS	NA	NA	CATB	IGT	Yes	Constant(0.50)
Burks et al	2009	1009	902	107	8.430	37.3	CS	Yes	58.00	CATB	MPL	Yes	Constant(0.50)
Campos-Vazquez et al	2018	5626	2240	3386	0.662	28.0	CS	NA	NA	RPM	GPIT	Yes	Constant(0.50)
Chapman et al (a)	2018	1000	NA	NA	NA	NA	CS	Yes	9.00	CATB	MPL	Yes	Constant(0.50)
Chapman et al (b)	2018	2000	NA	NA	NA	NA	CS	Yes	9.00	CATB	ALT	Yes	Constant(0.50)
Choi et al	2014	1014	552	462	1.195	53.7	CS	Yes	NA	CRT	BLAT	Yes	Constant(0.50)
Dean & Ortoleva	2012	190	NA	NA	NA	NA	S	Yes	NA	RPM	MPL	Yes	Constant(0.50)
Diaz & Forero	2013	31	31	0	NA	17.0	S	NA	NA	RPM	LT	Yes	Changes
Drichoutis	2017	178	59	119	0.496	21.3	S	Yes	NA	RPM	BLAT	Yes	Constant(0.50)
Frey et al	2017	1479	560	919	0.609	25.0	CS	Yes	NA	CATB	DTB	No	Changes
Goh et al	2016	137	67	70	0.957	75.4	CS	NA	NA	CATB	LT	Yes	Changes
Golman et al	2015	102	48	54	0.889	24.8	S	Yes	NA	NUM	GPIT	Yes	Constant(0.50)
Grohman et al	2015	530	276	254	1.087	34.6	CS	NA	NA	NUM	GPIT	Yes	Constant(0.50)
He et al	2010	572	260	312	0.833	20.5	S	Yes	NA	CATB	LT	Yes	Constant(0.50)
HRS	2014	9720	4116	5604	0.734	58.9	CS	NA	NA	CATB	IGT	Yes	Constant(0.50)
Horn & Kiss	2018	242	82	144	0.569	NA	S	Yes	NA	CRT	GPIT	Yes	Constant(0.50)
Kirchler et al	2017	601	252	349	0.722	23.5	S	Yes	12.16	CRT	LT	Yes	Constant(0.50)
Kiss et al	2016	60	30	30	1.000	NA	S	Yes	NA	CRT	GPIT	Yes	Constant(0.50)
Koch & Nafziger	2016	643	284	359	0.791	21.4	S	Yes	25	CRT	MPL	Yes	Constant(0.50)
Kocher et al	2018	379	151	228	0.662	24.0	S	Yes	21.32	RPM	LT	No	Changes
Kremer et al	2014	147	70	77	0.909	31.4	CS	Yes	NA	CATB	GPIT	Yes	Constant(0.50)
Li et al	2013	336	115	221	0.520	45.6	CS	Yes	NA	CATB	MPL	Yes	Constant(0.50)
Li et al	2015	478	195	283	0.689	46.6	CS	Yes	30	CATB	ALT	NA	Changes
Pachur et al	2017	118	76	42	1.810	47.4	CS	Yes	NA	CATB	LT	No	Changes
Platt & Parson	2017	7769	3885	3884	1.000	14.3	CHS	NA	NA	CATB	CGT	No	Changes
Pollak et al	2016	35	21	14	1.500	15.9	CHS	NA	NA	CATB	LT	Yes	Constant(0.50)
Rangel & Sousa	2014	197	118	79	1.494	22.3	S	Yes	18.62	CATB	EGRT	Yes	Constant(0.50)
Sheremeta	2018	184	NA	NA	NA	NA	S	Yes	NA	CATB	MPL	Yes	Constant(0.50)
Stango et al	2017	1505	NA	NA	NA	NA	CS	Yes	NA	CATB	LT	Yes	Constant(0.50)
van der Heijden et al	2012	562	304	258	1.178	47.8	CS	Yes	NA	CRT	GPIT	Yes	Constant(0.33)
Weisser	2014	112	60	52	1.154	22.8	S	Yes	NA	CRT	MPL	Yes	Constant(0.50)

Note. Not available (NA), cognitive ability measure (CAM), student sample (S), community sample (CS), children sample (CHS), cognitive ability test battery (CATB), ravens progressive matrices (RPM), cognitive reflection task (CRT), numeracy test (NUM), adaptive lottery task (ALT), budget line allocation task (BLAT), Cambridge gamble task (CGT), decision task battery (DTB), Eckel-Grossman risk task (EGRT), Gneezy Potters investment task (GPIT), income gamble task (IGT), lottery task (LT), multiple price list (MPL), one-shot gambling task (OGT), portfolio choice task (PCT), Sabater-Grande-Georgantzis lottery panel (SGG).

Table 5, continued

Author	Year	Payoff Safer Choice	Payoff Riskier Choice	Incentivized	% Risk Averse Choices	Primary Purpose	R-Recode	R-Male-Recode	R-Female-Recode	Imputed-Beta
Alan et al	2014	Changes	Changes	Yes	100	No	.027	.046	−.001	No
Alan et al study 1	2017	Changes	Changes	Yes	100	No	−.032	−.032	NA	Yes
Alan et al study 2	2017	Changes	Changes	Yes	100	No	−.017	NA	−.017	Yes
Alexy et al	2016	Changes	Changes	No	100	No	.037	NA	NA	No
Angerer et al	2015	Changes	Changes	Yes	100	No	−.022	−.026	−.017	No
Bateman el al	2015	Constant	Constant	No	100	No	−.086	NA	NA	Yes
Benjamin et al Study 1	2013	Constant	Changes	Yes	80	Yes	−.057	−.104	−.098	No
Branas-Garza & Rustichini	2011	Constant	Constant	No	100	No	−.014	−.106	.045	No
Branas-Garza et al	2014	Constant	Constant	No	100	No	.020	−.065	.117	No
Breaban & Noussair	2015	Constant	Changes	Random	83	No	.099	NA	NA	No
NLSY79	1993	Constant	Changes	No	100	No	.003	−.028	.038	No
Burks et al	2009	Changes	Constant	Random	58	Yes	.150	NA	NA	Yes
Campos-Vazquez et al	2018	Changes	Changes	NA	100	Yes	−.005	−.017	.007	No
Chapman et al (a)	2018	Changes	Constant	Yes	NA	No	.040	NA	NA	No
Chapman et al (b)	2018	Constant	Changes	Yes	NA	No	.210	NA	NA	No
Choi et al	2014	Changes	Changes	Random	100	No	−.097	−.121	−.054	No
Dean & Ortoleva	2012	Constant	Changes	Random	NA	No	−.020	NA	NA	No
Diaz & Forero	2013	Changes	Changes	Yes	100	No	.010	NA	NA	No
Drichoutis	2017	Changes	Changes	Yes	100	No	−.007	.038	−.037	No
Frey et al	2017	Changes	Changes	Random	NA	No	.151	.222	.106	No
Goh et al	2016	Constant	Changes	NA	NA	No	−.149	−.312	.002	No
Golman et al	2015	Changes	Changes	Random	100	No	.030	NA	NA	No
Grohman et al	2015	Changes	Changes	NA	100	No	−.130	NA	NA	No
He et al	2010	Constant	Changes	Random	88	No	−.008	NA	NA	No
HRS	2014	Constant	Changes	No	100	No	.017	−.003	.028	No
Horn & Kiss	2018	Changes	Changes	Random	100	No	−.266	−.258	−.161	No
Kirchler et al	2017	Constant	Changes	Random	80	No	.019	.093	.006	No
Kiss et al	2016	Changes	Changes	Random	100	No	.099	.069	.195	No
Koch & Nafziger	2016	Changes	Constant	Random	52	No	−.006	−.006	−.005	No
Kocher et al	2018	Changes	Changes	Random	50	No	.010	.045	.029	No
Kremer et al	2014	Changes	Changes	Yes	100	No	.168	.129	.216	No
Li et al	2013	Changes	Changes	No	NA	No	−.013	NA	NA	No
Li et al	2015	Changes	Changes	NA	NA	No	.220	NA	NA	No
Pachur et al	2017	Changes	Changes	Random	69	Yes	.064	−.009	.074	No
Platt & Parson	2017	Changes	Changes	NA	100	No	.080	.080	.100	No
Pollak et al	2016	Constant	Changes	No	100	No	−.032	−.021	−.048	No
Rangel & Sousa	2014	Constant	Changes	No	100	Yes	−.122	NA	NA	Yes
Sheremeta	2018	Constant	Changes	Random	66	No	.030	NA	NA	No
Stango et al	2017	Constant	Constant	No	100	No	.020	NA	NA	Yes
van der Heijden et al	2012	Changes	Changes	Yes	100	No	−.022	−.020	−.027	No
Weisser	2014	Changes	Constant	No	37	No	−.036	−.138	.157	No

Note. Not available (NA), cognitive ability measure (CAM), student sample (S), community sample (CS), children sample (CHS), cognitive ability test battery (CATB), ravens progressive matrices (RPM), cognitive reflection task (CRT), numeracy test (NUM), adaptive lottery task (ALT), budget line allocation task (BLAT), Cambridge gamble task (CGT), decision task battery (DTB), Eckel-Grossman risk task (EGRT), Gneezy Potters investment task (GPIT), income gamble task (IGT), lottery task (LT), multiple price list (MPL), one-shot gambling task (OGT), portfolio choice task (PCT), Sabater-Grande-Georgantzis lottery panel (SGG).

Table 6: Moderator analysis for the mixed domain.

Moderator		K	β	SE	95% CI	Test of Moderators	Test of Residual Heterogeneity
MF-Ratio	Intercept	31	−.01	.02	[−.06, .03]	Q_M (df = 1) = 2.21	Q_E (df = 29) = 144.63***
	MF-Ratio		.02	.01	[−.01, .04]		
Age	Intercept	27	.04	.04	[−.05, .12]	Q_M (df = 1) = 0.30	Q_E (df = 25) = 125.88***
	Avrg. age		−.00	.00	[−.00, .00]		
Sample Type	Intercept (CHS)	41	.01	.04	[−.07, .09]	Q_M (df = 2) = 2.13	Q_E (df = 38) = 228.29***
	CS		.02	.05	[−.07, .11]		
	S		−.03	.05	[−.12, .07]		
AvrgṖayment	Intercept	10	−.00	.06	[−.12, .12]	Q_M (df = 1) = 1.49	Q_E (df = 8) = 92.71***
	Avrg. payment		.00	.00	[−.00, .01]		
CAM	Intercept (CATB)	41	.05**	.02	[.02, .09]	Q_M (df = 3) = 9.33*	Q_E (df = 37) = 186.56***
	CRT		−.09*	.04	[−.16, −.01]		
	NUM		−.11*	.05	[−.20, −.02]		
	RPM		−.06	.04	[−.13, .02]		
Decision Task	Intercept (ALT)	41	.22***	.04	[.14, .29]	Q_M (df = 11) = 53.13 ***	Q_E (df = 29) = 54.88**
	BLAT		−.29***	.06	[−.41, −.17]		
	CGT		−.14*	.06	[−.25, −.02]		
	DTB		−.06	.06	[−.19, .06]		
	EGRT		−.34***	.09	[−.52, −.16]		
	GPIT		−.24***	.04	[−.33, −.16]		
	IGT		−.21***	.05	[−.30, −.11]		
	LT		−.22***	.05	[−.31, −.13]		
	MPL		−.17***	.05	[−.26, −.09]		
	OGT		−.21***	.06	[−.33, −.09]		
	PCT		−.30***	.06	[−.43, −.18]		
	SGG		−.18	.09	[−.37, .01]		
Certain Option	Intercept (No)	40	.08*	.04	[.00, .17]	Q_M (df = 1) = 3.63	Q_E (df = 38) = 183.15***
	Yes		−.09	.05	[−.17, .00]		
Probabilities	Intercept (Changes)	41	.08*	.04	[.01, .15]	Q_M (df = 3) = 5.03	Q_E (df = 37) = 183.67***
	Constant		−.16	.09	[−.34, .01]		
	Constant (33%)		−.10	.10	[−.29, .09]		
	Constant (50%)		−.07	.04	[−.15, .00]		
Payoff Safer Choice	Intercept (Changes)	41	.02	.02	[−.02, .06]	Q_M (df = 1) = 0.14	Q_E (df = 39) = 243.44***
	Constant		−.01	.03	[−.08, .05]		
Payoff Riskier Choice	Intercept (Changes)	41	.01	.02	[−.02, .05]	Q_M (df = 1) = 0.01	Q_E (df = 39) = 246.45***
	Constant		.00	.04	[−.07, .08]		
Incentivized	Intercept (No)	36	−.01	.03	[−.07, .04]	Q_M (df = 2) = 1.52	Q_E (df = 33) = 158.79***
	Random		.03	.04	[−.04, .10]		
	Yes		.05	.04	[−.03, .13]		
Risk Averse Choices %	Intercept		.11	.07	[−.04, .25]	Q_M (df = 1) = 2.36	Q_E (df = 32) = 119.93***
	Risk averse choices %	34	−.00	.00	[−.00, .00]		
Primary purpose	Intercept (No)	41	.01	.02	[−.02, .04]	Q_M (df = 1) = 0.02	Q_E (df = 39) = 245.51***
	Yes		.01	.05	[−.09, .10]		
Beta Imputed	Intercept (No)	41	.02	.02	[−.02, .05]	Q_M (df = 1) = 0.30	Q_E (df = 39) = 245.02***
	Yes		−.02	.04	[−.11, .06]		

Note. $p < .05$ = *, $p < .01$ = **, $p < .001$ = ***

Table 7: Moderator Analysis for the Mixed Domain — Males Only.

Moderator		K	β	SE	95% CI	Test of Moderators	Test of Residual Heterogeneity
Sample Type	Intercept (CHS)	24	.02	.05	[−.07, .11]	Q_M (df = 2) = 0.65	Q_E (df = 21) = 66.29***
	CS		−.03	.06	[−.14, .07]		
	S		−.05	.06	[−.17, .07]		
Avrg. Payment	Intercept	3	.19	.14	[−.08, .45]	Q_M (df = 1) = 1.25	Q_E (df = 1) = 0.06
	Avrg. payment		−.01	.01	[−.02, .01]		
CAM	Intercept (CATB)	24	.03	.03	[−.04, .09]	Q_M (df = 3) = 2.77	Q_E (df = 20) = 75.96***
	CRT		−.08	.05	[−.18, .03]		
	NUM		−.10	.09	[−.27, .07]		
	RPM		−.03	.05	[−.13, .08]		
Decision Task	Intercept (ALT)	24	−.07	.05	[−.17, .02]	Q_M (df = 7) = 53.31***	Q_E (df = 16) = 22.82
	BLAT		−.03	.06	[−.16, .09]		
	CGT		.15**	.05	[.05, .26]		
	DTB		.30***	.07	[.17, .43]		
	GPIT		.06	.05	[−.04, .17]		
	IGT		.06	.05	[−.04 .16]		
	LT		.08	.06	[−.05, .20]		
	MPL		.04	.07	[−.10, .19]		
Certain Option	Intercept (No)	24	.11***	.03	[.05, .18]	Q_M (df = 1) = 14.40***	Q_E (df = 22) = 40.44**
	Yes		−.14***	.04	[−.21, −.07]		
Probabilities	Intercept (Changes)	24	.08*	.04	[.00, .15]	Q_M (df = 2) = 5.86*	Q_E (df = 21) = 45.54**
	Constant (33%)		−.10	.09	[−.27 .08]		
	Constant (50%)		−.10*	.04	[−.19, −.02]		
Payoff Safer Choice	Intercept (Changes)	24	.01	.03	[−.04, .06]	Q_M (df = 1) = 1.13	Q_E (df = 22) = 73.78***
	Constant		−.05	.05	[−.14, .04]		
Payoff Riskier Choice	Intercept (Changes)	24	.00	.02	[−.04, .05]	Q_M (df = 1) = 1.10	Q_E (df = 22) = 83.41***
	Constant		−.06	.06	[−.18, .06]		
Incentivized	Intercept (No)	21	−.04	.04	[−.13, .04]	Q_M (df = 2) = 1.21	Q_E (df = 18) = 49.92***
	Random		.06	.06	[−.05, .18]		
	Yes		.05	.06	[−.07, .16]		
Risk Averse Choices %	Intercept	22	.01	.10	[−.19, .21]	Q_M (df = 1) = 0.03	Q_E (df = 20) = 52.62***
	Risk averse choices %		−.00	.00	[−.00, .00]		
Primary purpose	Intercept (No)	24	−.00	.02	[−.05, .04]	Q_M (df = 1) = 0.14	Q_E (df = 22) = 84.38***
	Yes		−.03	.07	[−.16, .11]		
Beta Imputed	Intercept (No)	24	−.01	.02	[−.05, .04]	Q_M (df = 1) = 0.07	Q_E (df = 22) = 85.78***
	Yes		−.03	.10	[−.22, .17]		

Note. p < .05 = *, p < .01 = **, p < .001 = ***

Table 8: Moderator analysis for the mixed domain — females only.

Moderator		K	β	SE	95% CI	Test of Moderators	Test of Residual Heterogeneity
Sample Type	Intercept (CHS)	24	.04	.03	[−.02, .09]	Q_M (df = 2) = 1.35	Q_E (df = 21) = 36.04*
	CS		.00	.03	[−.06, .07]		
	S		−.04	.04	[−.12, .04]		
Avrg. Payment	Intercept	3	.01	.12	[−.21, .24]	Q_M (df = 1) = 0.00	Q_E (df = 1) = 0.16
	Avrg. payment		−.00	.01	[−.01, .01]		
CAM	Intercept (CATB)	24	.06***	.01	[.03, .09]	Q_M (df = 3) = 10.72*	Q_E (df = 20) = 28.22
	CRT		−.08**	.03	[−.14, −.02]		
	NUM		.04	.06	[−.07, .15]		
	RPM		−.05*	.03	[−.11, −.00]		
Decision Task	Intercept (ALT)	24	.10*	.04	[.02, .19]	Q_M (df = 7) = 34.15***	Q_E (df = 16) = 11.42
	BLAT		−.15*	.06	[−.27, −.03]		
	CGT		−.00	.05	[−.09, .09]		
	DTB		.00	.05	[−.10, .11]		
	GPIT		−.10*	.05	[−.19, −.01]		
	IGT		−.07	.04	[−.16, .02]		
	LT		−.09	.06	[−.20, .02]		
	MPL		−.09	.07	[−.22, .04]		
Certain Option	Intercept (No)	24	.10***	.01	[.07, .13]	Q_M (df = 1) = 23.32***	Q_E (df = 22) = 22.25
	Yes		−.08***	.02	[−.11, −.05]		
Probabilities	Intercept (Changes)	24	.10***	.01	[.07, .12]	Q_M (df = 2) = 23.33***	Q_E (df = 21) = 22.25
	Constant (33%)		−.12	.06	[−.25, .00]		
	Constant (50%)		−.08***	.02	[−.11, −.04]		
Payoff Safer Choice	Intercept (Changes)	24	.02	.02	[−.01, .06]	Q_M (df = 1) = 0.23	Q_E (df = 22) = 45.18**
	Constant		.01	.03	[−.04, .07]		
Payoff Riskier Choice	Intercept (Changes)	24	.02	.01	[−.01, .05]	Q_M (df = 1) = 0.86	Q_E (df = 22) = 44.96**
	Constant		.04	.04	[−.04, .12]		
Incentivized	Intercept (No)	21	.05*	.02	[.00, .09]	Q_M (df = 2) = 2.22	Q_E (df = 18) = 23.48
	Random		−.03	.03	[−.10, .03]		
	Yes		−.05	.04	[−.12, .02]		
Risk Averse Choices %	Intercept	22	.02	.09	[−.15, .20]	Q_M (df = 1) = 0.00	Q_E (df = 20) = 40.84**
	Risk averse choices %		−.00	.00	[−.00, .00]		
Primary purpose	Intercept (No)	24	.03*	.01	[.00, .06]	Q_M (df = 1) = 0.36	Q_E (df = 22) = 41.46**
	Yes		−.03	.04	[−.11, .06]		
Beta Imputed	Intercept (No)	24	.03*	.01	[.00, .06]	Q_M (df = 1) = 0.46	Q_E (df = 22) = 44.62**
	Yes		−.05	.07	[−.19, .09]		

Note. p < .05 = *, p < .01 = **, p < .001 = ***.

Table 9: Overview of studies included for the domain of losses.

Author	Year	N	Male	Female	MF-Ratio	Avrg Age	Sample Type	Payment	Avrg Pay $	CAM	Decision Task	Certain Option	Probabilities
Chapman et al (a)	2018	1000	NA	NA	NA	NA	CS	Yes	9.00	CATB	MPL	Yes	Constant(0.50)
Chen et al	2014	84	43	41	1.049	44.0	CS	NA	NA	CATB	CT	Yes	Changes
Frey et al	2017	1482	563	919	0.613	25.0	CS	Yes	NA	CATB	ALT	No	Changes
Kirchler et al	2017	603	253	350	0.723	23.5	S	Yes	12.16	CRT	LT	Yes	Constant(0.50)
Koch & Nafziger	2016	643	284	359	0.791	21.4	S	Yes	25.00	CRT	MPL	Yes	Constant(0.50)
Kurnianingsih	2015	33	14	19	0.737	68.7	CS	Yes	NA	CATB	LT	Yes	Changes
Levin & Hart	2003	30	11	19	0.579	6.0	CHS	Yes	NA	CATB	GGT	Yes	Constant(0.50)
Mather et al	2012	157	79	78	1.013	39.0	CS	Yes	NA	CATB	LT	Yes/No	Changes
Pachur et al	2017	118	76	42	1.810	47.4	CS	Yes	NA	CATB	LT	Yes/No	Changes
Park & Cho	2018	69	35	34	1.029	20.2	S	NA	NA	CATB	LT	Yes	Changes
Sytsma et al	2014	190	147	43	3.419	21.0	S	Yes	NA	RPM	EGRT	Yes	Constant
Tymula et al	2013	135	70	65	1.077	37.2	CS	Yes	NA	CATB	LT	Yes	Changes

Note. Not available (NA), cognitive ability measure (CAM), student sample (S), community sample (CS), children sample (CHS), cognitive ability test battery (CATB), ravens' progressive matrices (RPM), cognitive reflection task (CRT), multiple price list (MPL), cups task (CT), adaptive lottery task (ALT), lottery task (LT), gift gambling task (GGT), Eckel-Grossman risk task (EGRT).

Table 9, continued

Author	Year	Payoff Safer Choice	Payoff Riskier Choice	Incentivized	% Risk Averse Choices	Primary Purpose	R-Recode	R-Male-Recode	R-Female-Recode	Imputed-Beta
Chapman et al (a)	2018	Changes	Constant	Yes	NA	No	−.015	NA	NA	No
Chen et al	2014	Constant	Changes	NA	67	Yes	−.237	−.449	−.213	No
Frey et al	2017	Changes	Changes	Random	NA	No	−.052	.006	−.063	No
Kirchler et al	2017	Changes	Constant	Random	40	No	.157	.037	.163	No
Koch & Nafziger	2016	Changes	Constant	Random	52	No	.122	.175	.073	No
Kurnianingsih	2015	Changes	Changes	Random	NA	No	−.182	NA	NA	No
Levin & Hart	2003	Constant	Constant	Yes	100	Yes	−.250	NA	NA	No
Mather et al	2012	Changes	Changes	Random	100	No	−.060	.086	−.111	No
Pachur et al	2017	Changes	Changes	Random	50	Yes	−.159	−.026	−.189	No
Park & Cho	2018	Changes	Changes	NA	60	Yes	−.055	−.100	−.030	No
Sytsma et al	2014	Constant	Changes	NA	NA	No	−.230	−.255	.003	Yes
Tymula et al	2013	Constant	Changes	Random	NA	No	.055	NA	NA	Yes

Note. Not available (NA).

Table 10: Moderator analysis for the domain of losses.

Moderator		K	β	SE	95% CI	Test of Moderators	Test of Residual Heterogeneity
MF-Ratio	Intercept	11	.06	.07	[−.08, .21]	Q_M (df = 1) = 3.49	Q_E (df = 9) = 38.71***
	MF-Ratio		−.09	.05	[−.19, .00]		
Age	Intercept	11	.04	.12	[−.19, .27]	Q_M (df = 1) = 0.70	Q_E (df = 9) = 44.08***
	Avrg. age		−.00	.00	[−.01, .00]		
Sample Type	Intercept (CHS)	12	−.26	.22	[−.69, .18]	Q_M (df = 2) = 2.14	Q_E (df = 9) = 32.01***
	CS		.18	.23	[−.27, .63]		
	S		.28	.23	[−.18, .73]		
Avrg. Payment	Intercept	3	.00	.16	[−.31, .31]	Q_M (df = 1) = 0.34	Q_E (df = 1) = 8.96**
	Avrg. payment		.01	.01	[−.01, .02]		
CAM	Intercept (CATB)	12	−.05**	.02	[−.08, −.01]	Q_M (df = 2) = 41.50***	Q_E (df = 9) = 9.13
	CRT		.19***	.03	[.12, .25]		
	RPM		−.19*	.08	[−.33, −.04]		
Decision Task	Intercept (ALT)	12	−.05	.11	[−.27, .16]	Q_M (df = 5) = 6.61	Q_E (df = 6) = 23.61***
	CT		−.19	.19	[−.56, .18]		
	EGRT		−.18	.17	[−.51, .15]		
	GGT		−.20	.25	[−.68, .28]		
	LT		.04	.12	[−.20, .29]		
	MPL		.10	.14	[−.16, .37]		
Certain Option	Intercept (No)	12	−.05	.13	[−.32, .21]	Q_M (df = 2) = 0.34	Q_E (df = 9) = 41.16***
	Yes		.02	.15	[−.27, .30]		
	Yes/No		−.06	.18	[−.40, .29]		
Probabilities	Intercept (Changes)	12	−.08	.04	[−.16, .00]	Q_M (df = 2) = 10.36**	Q_E (df = 9) = 22.59**
	Constant		−.16	.11	[−.37, .06]		
	Constant (50%)		.15*	.06	[.03, .27]		
Payoff Safer Choice	Intercept (Changes)	12	−.00	.04	[−.09, .08]	Q_M (df = 1) = 2.96	Q_E (df = 10) = 40.93***
	Constant		−.15	.09	[−.32, .02]		
Payoff Riskier Choice	Intercept (Changes)	12	−.10*	.04	[−.18, −.02]	Q_M (df = 1) = 7.05**	Q_E (df = 10) = 27.71**
	Constant		.17**	.06	[.04, .30]		
Incentivized	Intercept (Random)	9	.01	.05	[−.08, .11]	Q_M (df = 1) = 0.47	Q_E (df = 7) = 33.48***
	Yes		−.07	.11	[−.29, .14]		
Risk Averse Choices %	Intercept	7	.21	.18	[−.15, .57]	Q_M (df = 1) = 1.91	Q_E (df = 5) = 15.78**
	Risk averse choices %		−.00	.00	[−.01, .00]		
Primary purpose	Intercept (No)	12	−.00	.04	[−.09, .08]	Q_M (df = 1) = 3.27	Q_E (df = 10) = 42.34***
	Yes		−.17	.09	[−.34, .01]		
Beta Imputed	Intercept (No)	12	−.04	.05	[−.13, .06]	Q_M (df = 1) = 0.29	Q_E (df = 10) = 46.45***
	Yes		−.06	.11	[−.28, .16]		

Note. p < .05 = *, p < .01 = **, p < .001 = ***

Table 11: Moderator analysis for the domain of losses — males only.

Moderator		K	β	SE	95% CI	Test of Moderators	Test of Residual Heterogeneity
Sample Type	Intercept (S)	8	−.02	.10	[−.23, .18]	Q_M (df = 1) = 0.13	Q_E (df = 6) = 28.58***
	CS		−.05	.15	[−.34, .24]		
CAM	Intercept (CATB)	8	−.07	.07	[−.21, .08]	Q_M (df = 2) = 4.77	Q_E (df = 5) = 12.64*
	CRT		.17	.12	[−.06, .41]		
	RPM		−.19	.16	[−.52, .13]		
Decision Task	Intercept (ALT)	8	.01	.04	[−.08, .09]	Q_M (df = 4) = 28.18***	Q_E (df = 3) = 1.01
	CT		−.49**	.16	[−.81, −.17]		
	EGRT		−.27**	.09	[−.45, −.08]		
	LT		.02	.06	[−.11, .14]		
	MPL		.17*	.07	[.03, .31]		
Certain Option	Intercept (No)	8	.01	.21	[−.40, .42]	Q_M (df = 2) = 0.53	Q_E (df = 5) = 29.05***
	Yes		−.11	.23	[−.56, .35]		
	Yes/No		.02	.27	[−.50, .55]		
Probabilities	Intercept (Changes)	8	−.07	.07	[−.21, .08]	Q_M (df = 2) = 4.77	Q_E (df = 5) = 12.64*
	Constant		−.19	.16	[−.52, .13]		
	Constant (50%)		.17	.12	[−.06, .41]		
Payoff Safer Choice	Intercept (Changes)	8	.05	.04	[−.02, .13]	Q_M (df = 1) = 15.40***	Q_E (df = 6) = 8.44
	Constant		−.37***	.09	[−.56, −.19]		
Payoff Riskier Choice	Intercept (Changes)	8	−.11	.07	[−.25, .03]	Q_M (df = 1) = 2.83	Q_E (df = 6) = 19.77**
	Constant		.22	.13	[−.04, .47]		
Risk Averse Choices %	Intercept	6	.02	.32	[−.61, .64]	Q_M (df = 1) = 0.02	Q_E (df = 4) = 17.02**
	Risk averse choices %		−.00	.00	[−.01, .01]		
Primary purpose	Intercept (No)	8	.01	.08	[−.14, .16]	Q_M (df = 1) = 1.92	Q_E (df = 6) = 24.36***
	Yes		−.20	.14	[−.48, .08]		
Beta Imputed	Intercept (No)	8	−.00	.06	[−.13, .12]	Q_M (df = 1) = 2.25	Q_E (df = 6) = 17.93**
	Yes		−.26	.17	[−.59, .08]		

Note. p < .05 = *, p < .01 = **, p < .001 = ***. Data available for the domain of losses was insufficient to investigate the influence of average payment as well as the incentive structure of the decision task used to measure risk aversion for males only.

Table 12: Moderator analysis for the domain of losses — females only.

Moderator		K	β	SE	95% CI	Test of Moderators	Test of Residual Heterogeneity
Sample Type	Intercept (S)	8	.11**	.04	[.03, .18]	Q_M (df = 1) = 13.40***	Q_E (df = 6) = 4.08
	CS		−.18***	.05	[−.28, −.09]		
CAM	Intercept (CATB)	8	−.08*	.03	[−.14, −.02]	Q_M (df = 2) = 15.50***	Q_E (df = 5) = 3.04
	CRT		.19***	.05	[.10, .29]		
	RPM		.08	.16	[−.24, .40]		
Decision Task	Intercept (ALT)	8	−.06	.15	[−.35, .22]	Q_M (df = 4) = 1.33	Q_E (df = 3) = 8.47*
	CT		−.15	.26	[−.66, .36]		
	EGRT		.07	.26	[−.44, .57]		
	LT		.06	.17	[−.28, .39]		
	MPL		.14	.21	[−.27, .55]		
Certain Option	Intercept (No)	8	−.06	.07	[−.20, .07]	Q_M (df = 2) = 4.84	Q_E (df = 5) = 6.50
	Yes		.13	.08	[−.03, .30]		
	Yes/No		−.08	.12	[−.32, .16]		
Probabilities	Intercept (Changes)	8	−.08*	.03	[−.14, −.02]	Q_M (df = 2) = 15.50***	Q_E (df = 5) = 3.05
	Constant		.08	.16	[−.24, .40]		
	Constant (50%)		.19***	.05	[.10, .29]		
Payoff Safer Choice	Intercept (Changes)	8	.01	.05	[−.10, .11]	Q_M (df = 1) = 0.60	Q_E (df = 6) = 18.22**
	Constant		−.11	.14	[−.39, .17]		
Payoff Riskier Choice	Intercept (Changes)	8	−.07*	.03	[−.13, −.01]	Q_M (df = 1) = 15.82***	Q_E (df = 6) = 3.28
	Constant		.19***	.05	[.10, .28]		
Risk Averse Choices %	Intercept	6	.34**	.11	[.12, .56]	Q_M (df = 1) = 6.31*	Q_E (df = 4) = 5.33
	Risk averse choices %		−.01*	.00	[−.01, −.00]		
Primary purpose	Intercept (No)	8	.03	.05	[−.07, .13]	Q_M (df = 1) = 2.20	Q_E (df = 6) = 16.38*
	Yes		−.18	.12	[−.41, .06]		
Beta Imputed	Intercept (No)	8	−.01	.05	[−.12, .09]	Q_M (df = 1) = 0.01	Q_E (df = 6) = 19.10**
	Yes		.02	.20	[−.37, .40]		

Note. $p < .05$ = *, $p < .01$ = **, $p < .001$ = ***. Data available for the domain of losses was insufficient to investigate the influence of average payment as well as the incentive structure of the decision task used to measure risk aversion for females only.