A meta-analysis of loss aversion in risky contexts

Lukasz Walasek[A] Timothy L. Mullett[B] Neil Stewart[B]

[A] Department of Psychology, University of Warwick

[B] WBS, University of Warwick

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Abstract

Loss aversion is widely regarded as the most robust and ubiquitous finding in behavioural economics. According to the loss aversion hypothesis, the subjective value of losses exceeds the subjective value of equivalent gains. One common assumption in the literature is that this asymmetry represents a fundamental and stable feature of people's preferences. In cumulative prospect theory, loss aversion is captured by the lambda (λ) parameter, which controls the steepness of the value function for losses. Estimates of λ by Tversky and Kahneman (1992) found evidence for considerable overweighting of losses in risky choice ($\lambda = 2.25$). But others find very different levels of loss aversion, with some reporting weak loss aversion or even loss neutrality. In order to assess what is the average level of λ reported in the literature, we set out to conduct a meta-analysis of studies in which λ parameter of the cumulative prospect theory parameter was estimated from individual choices between risky prospects. We draw three conclusions. First, surprisingly few studies have estimated λ using risky choices, and there are only a few datasets suitable to perform model fitting. Second, much of the data are of poor quality, making it impossible to obtain precise estimates of the prospect theory's parameters. Third, using a random-effect meta-analysis upon the available data, we found a small λ of 1.31, 95% CI [1.10, 1.53].

Keywords: loss aversion, meta-analysis, risk, valuation, cumulative prospect theory

A meta-analysis of loss aversion in risky contexts

"The concept of loss aversion is certainly the most significant contribution of psychology to behavioural economics" (p. 300, Kahneman, 2011)

One of the most ubiquitous hypotheses in behavioural sciences is that the subjective value of losses outweighs the subjective value of equivalent gains (Kahneman & Tversky, 1979; Köbberling & Wakker, 2005; Novemsky & Kahneman, 2005, but see Gal & Rucker, 2017). The principle of loss aversion has found considerable empirical support in both risky and riskless contexts, and its influence is clearly visible in theoretical developments of psychological and economic models of choice behaviour (Camerer, 2005; Kahneman, 2003; Kőszegi & Rabin, 2006; Rabin, 2000; Usher & McClelland, 2001). Loss aversion is an integral part of prospect theory and, later, cumulative prospect theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992; henceforth PT and CPT), the most influential descriptive model of choice under risk and uncertainty. In both versions of the model, loss aversion is represented by the lambda parameter (λ), which scales the psychological value of losses compared to equivalent gains. For example, a person with a λ of 2 would be expected to be indifferent about a gamble involving a fair coin toss offering a gain of \$20.00 if the coin lands heads but a loss of \$10.00 if it lands tails. Therefore for an individual whose $\lambda = 2$, the hedonic impact of a given loss (e.g. -\$10.00) looms twice as large as the hedonic impact of the same size gain (e.g. + \$10.00).

One dominant interpretation of loss aversion is that it captures a fundamental feature of people's preferences. According to this view, asymmetric weighting of gains and losses is a stable individual difference representing an inherent property of most, if not all, decision makers. A widely accepted magnitude of loss aversion is the parameter estimate of $\lambda = 2.25$ obtained by

Tversky and Kahneman (1992, henceforth T&K92), which signifies that losses loom more than twice as much as equivalent gains. Over the years, a number of efforts have been made to test the descriptive validity of CPT in risky contexts, estimating λ (as well as other parameters of the model) at both the individual and aggregate level. There have been no meta-analyses of the estimates of λ in risky choice. The goal of the present work is therefore to establish what is the average level of estimated λ, based on the published work that used parametric methods to fit prospect theory to people's choices and valuations of risky prospects.

In order to position our work in the broader literature, we begin with a concise summary of the origins of loss aversion (for comprehensive reviews see Brooks & Zank, 2005; Camerer, 2005; Gal & Rucker, 2017; Köbberling & Wakker, 2005; Novemsky & Kahneman, 2005; Rick, 2011; Schmidt & Zank, 2005; Yechiam, 2018). In our review, we discuss the empirical evidence behind the existence and estimated magnitude of loss aversion. At the same time, we describe a range of significant issues that have been raised with regards to the descriptive value of gain-loss asymmetry in risky choice and valuation of risky assets. Building on this research, we propose a meta-analytic approach to quantify the degree to which people exhibit loss aversion when trading off gains and losses under condition of risk.

Brief History of Evidence for Loss Aversion

The focus of the present paper is on the estimates of loss aversion parameter, λ, as defined within the PT and CPT. We therefore take the original formulation of the PT (Kahneman & Tversky, 1979) as the starting point for the loss aversion hypothesis (see Yechiam, 2018 for a more extensive historical overview). The key assertion of the model is that of reference dependence—people do not integrate outcomes with their expected impact on future total wealth, but rather evaluate them with respect to a neutral reference point. From a given reference point, an outcome can be regarded as a gain or a loss, and within the PT (and CPT), losses loom larger than gains. Tversky and Kahneman (1979) introduced a reference dependent value function, which translates gains and losses into the subjective equivalents. They argued that the value function for losses is steeper than the value function for gains, and that this asymmetry accounts for the finding that most people reject fair bets of the form (*x*, .50; -*x*, .50). Figure 1 shows an example value function with λ = 2.25. For example, when choosing between $0 for certain and a lottery offering 50% chance of winning $10 and a 50% chance of losing $10, most decision makers prefer the safe $0 option. Figure 1 shows how the subjective value for the lottery is constructed. Here, because the psychological value of the loss is 2.25 times greater than the psychological value for the gain, the overall subjective value is negative.

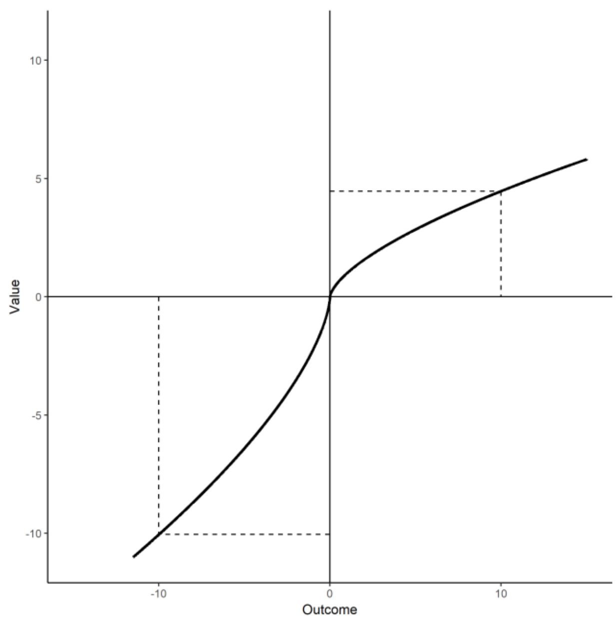

Figure 1. CPT value function.

In one of the first empirical attempts to estimate λ, T&K92 recruited 25 graduate students to take part in a one-hour long experimental session. Participants in their study were asked to make a series of hypothetical choices between a risky lottery (involving only gains, only losses, or both gains and losses) and different positive amounts of money for certain. In the first stage of the experiment, seven certain outcomes were chosen to be logarithmically spaced between the highest and the lowest outcome of the risky alternative. In the second stage, the choices were repeated, but available choices consisted of seven new certainty equivalents that were linearly spaced between a value 25% higher than the lowest amount accepted in the first stage, and a value that was 25% lower than the highest amount accepted in the previous part. In this way, T&K92 identified the lowest amount that would be accepted instead of the gamble and the highest amount that would be rejected in favor of the gamble, and took the average of these as the certainty equivalent of the gamble. In total, T&K92 estimated certainty equivalents for 28 positive, 28 negative, and, critically for the estimation of loss aversion, eight mixed prospects. The median parameters estimated by fitting CPT to these data revealed the median λ value of 2.25.

Since T&K92's seminal work, much evidence in support of loss aversion was generated through the research of decision making and valuation in riskless contexts. Thaler (1980) famously argued that loss aversion is necessary to explain the asymmetry in valuation between owners and non-owners (i.e., the endowment effect). According to this account, the disparity between the willingness to accept (WTA) of sellers and willingness to pay (WTP) of buyers emerges because sellers regard the transaction as a potential loss, whereas buyers see it as a potential gain. Loss aversion can therefore explain why WTAs exceed WTPs in many contingent valuation studies. In the most famous example, Kahneman, Knetsch, and Thaler (1991) have shown that sellers demanded much more money to keep a university branded coffee mug than buyers were willing to pay to acquire it. Participants who were merely offered a choice between money and the mug behaved similarly to buyers, supporting the idea that sellers perceive a transaction as a potential loss (Tversky & Kahneman, 1991). A number of studies have demonstrated that the endowment effect is robust, and that the WTA/WTP ratio exceeds 1 across a variety of items, including basketball tickets (Carmon & Ariely, 2000), gift certificates (Sen & Johnson, 1997), collectable cards (List, 2003), chocolate (Reb & Connolly, 2007) wine (van Dijk & van Knippenberg, 1998), lottery tickets (Knetsch & Sinden, 1984), clean air (Cummings & Brookshire, 1986), and LEGO (Walasek, Rakow, & Matthews, 2015). The ratio of WTA and WTP for any product is commonly regarded as a measure of loss aversion, and similarly to risky contexts, it is believed to equal approximately 2.

Loss aversion proved to be particularly useful for explaining a range of phenomena in choice behaviour, both in the lab and in the field. Loss aversion has been used to provide a psychological mechanisms behind the status-quo bias (Samuelson & Zeckhauser, 1988), the equity premium puzzles (Benartzi & Thaler, 1995), sellers' behaviour in the housing markets (Genesove & Mayer, 2001), disposition effect (Barberis & Xiong, 2009), anomalies in the labour supply (Camerer, 2001), and many others. Within this broad stream of research, two assumptions dominate how loss aversion is interpreted and implemented in theorizing about decision makers' choice and valuation. First, people are generally assumed to be loss averse. That is, their preferences are characterized by an asymmetric weighting of gains and losses[1]. Second, the

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[1] A competing view could be that loss aversion represents some form of error of the decision making apparatus or an emotional response to the outcomes (Camerer, 2005). Nonetheless, whichever definition one assumes, it is still widely agreed on that loss aversion represents a stable individual difference in perception of gains and losses.

magnitude of loss aversion is believed to be reflected in the estimates of λ parameter of the PT and CPT. This means that the ratio of losses to gains is about 2:1, which corresponds to empirical findings described above—estimates of λ by T&K92 and the sizes of the WTA/WTP ratios (Nilsson, Rieskamp, & Wagenmakers, 2011). In fact, the two measures are positively correlated (Spearman's $\rho = 0.635$), which suggests that a common psychological basis underpins oversensitivity to losses in risky and riskless contexts (Gächter, Johnson, & Herrmann, 2007).

The observation that negative events outweigh positive events is not limited to judgment and decision making. Existing research suggests that negative events are more potent and salient, and that this negativity bias can influence individual's physiological responses, attention, learning, information search, or impression formation (for a review see Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001; Rozin & Royzman, 2001). What separates loss aversion from these accounts is that there never was clear a psychological theory about the causes of loss aversion (Gal, 2006; Gal & Rucker, 2017). The theory of loss aversion was devised to account for irregularities in the choice data and therefore its value was purely descriptive. The lack of a clear definition of loss aversion has led to paradoxical situations in which the same phenomena are simultaneously explained by loss aversion *and* are regarded as evidence for loss aversion (e.g., the endowment effect).

Multiple research projects focused on uncovering the sources of the gain-loss asymmetry. Since the estimates of loss aversion tend to vary within a population, much of this work aimed to identify psychological or biological markers that correlate with loss averse behaviour in risky and riskless contexts. Multiple mechanisms and systems have been put forward and include emotions (Bibby & Ferguson, 2011; Sokol-Hessner, Camerer, & Phelps, 2013), genetic predispositions (Ernst et al., 2014), emotional attachment (Ariely, Huber, & Wertenbroch, 2005), attention allocation (Carmon & Ariely, 2000), memory retrieval (Johnson, Häubl, & Keinan, 2007), personality traits (Boyce, Wood, & Ferguson, 2016), affective forecasting errors (Kermer, Driver-Linn, Wilson, & Gilbert, 2006), uncertainty (Loomes, Orr, & Sugden, 2009; Walasek, Wright, & Rakow, 2014), as well as brain activation in regions responsible for reward sensitivity (Tom, Fox, Trepel, & Poldrack, 2007) and emotion processing (De Martino, Camerer, & Adolphs, 2010). Clearly, virtually any variable that is associated with loss averse behaviour is added to the list of its proximal causes. Once again, in most cases the prevalent assumption is that decision makers exhibit some degree of loss aversion in their choices and valuations.

Criticism of Loss Aversion

More recently, some authors have begun to question the descriptive value of loss aversion in risky contexts[2]. A number of studies found no evidence of loss aversion, both in typical tasks of risky choice (Ert & Erev, 2008, 2013) and in experiments in which the probabilities and outcomes associated with different lotteries need first to be learned by sampling information from each alternative (i.e., decision from experience, see Table 1 in Yechiam & Hochman, 2013 for a summary; Yechiam & Telpaz, 2013). These studies demonstrate that the magnitude of the observed loss aversion, at least on aggregate level, can be largely driven by the features of the

[2] Loss aversion has also been criticised as an explanation of the endowment effect. This paper focuses mainly on risky context and hence we do not summarize this research here. For more detail, a reader can refer to the work of Morewedge, Shu, Gilbert and Wilson (2009), as well as Plott and Zeiler (2005; 2007)

elicitation task. Ert and Erev (2011) identified six such methodological attributes which, if present, can lead people to exhibit stronger aversion to the risk of losing money. For example, in a study conducted by Ert and Erev (Study 4, 2011), the loss aversion parameter was estimated using a choice list task. Participants were presented with a list of choices between pairs of gambles. Each offered a 50% chance of losing some amount and a 50% chance of gaining some amount. The choice was made between a safe gamble (with a small gain and small loss) and risky gamble (with a large gain and large loss). Choices only differed in the size of the large gain in the risky gamble, with the large gain increasing down the list. Ert and Erev manipulated the rank position in the list of choices of a critical common choice in which the two gambles on offer had the same expected value. The results showed a contrast effect. Participants demonstrated absolute loss aversion by choosing the safe option more often than the risky one in the critical choice when the list mainly contained choices with higher large gains for the risky gamble. But participants showed no absolute loss aversion by being indifferent between the risky and safe gamble when the list contained as many choices where the large gain for the risky gambles was smaller or as choices where the large gain was larger. Such examples suggest that loss aversion is highly malleable and that the degree to which people avoid losses in risky choice largely depends on the context determined by the features of the elicitation procedure (Mukharjee, Sahay, Pammi, & Srinivasan, 2017; Walasek & Stewart, 2015, 2018a; Yechiam & Hochman, 2013a).

Given these problems, are the estimates of λ reported in the literature close to the figure of 2.25 that was originally estimated by T&K92? With respect to riskless context, there are currently three published meta-analyses of the WTA/WTP gap. All report a considerable magnitude of loss aversion—Horowitz and Mcconnell (2002) found the median of the

WTA/WTP ratio to be 2.60, whereas Tunçel and Hammitt (2014) reported geometric mean of 3.28[3]. However, all authors found a large amount of heterogeneity in the aggregate estimates between the available studies. Overall, the gap appears to be smaller when experiments involve real out-of-pocket costs (Sayman & Öncüler, 2005), ordinary market products (Horowitz & McConnell, 2002), or when participants already have experience in valuing goods (Tunçel & Hammitt, 2014). Clearly, a wide range of variables have a profound impact on the participants stated WTPs and WTAs.

As we noted earlier, no meta-analysis exists for the estimation of λ in risky choice (or valuation)[4]. However, several existing overviews of the aggregate parameter estimates demonstrate a considerable amount of heterogeneity (Booij, Van Praag, & Van De Kuilen, 2010; Fox & Poldrack, 2008; Sokol-Hessner et al., 2009). The aggregate estimates of λ include findings of strong loss aversion (λ = 2.54 in Abdellaoui et al., 2007) weak loss aversion (λ = 1.38 in Harrison & Rutström, 2008), or even no evidence of loss averse behaviour (λ = 1.00, Rieskamp, 2008). It is clear, however, that these estimates are not comparable for a number of reasons. First and foremost, aggregate estimates obtained by different authors were estimated by

[3] Meta-analysis of Sayman and Öncüler (2005) does not include aggregate estimates. However, the effect of perspective (i.e. buyer vs. seller) is a significant predictor in their regression analysis.

[4] Note that we are not referring here to studies that required participants to value or exchange lottery tickets. We do consider, however, studies that used valuation methods (e.g., certainty equivalence) as it is possible to estimate parameters of the CPT with such data.

fitting different versions of the CPT, which can influence the final result (we return to this issue later on). Second, individual fits are often noisy and positively skewed, and hence studies reporting mean parameter values can be particularly misleading. Last but not least, substantial differences in the elicitation tasks could also influence the magnitude of loss aversion.

Current Meta-Analysis

For the purpose of our analysis, data from each existing study had to meet three basic criteria. First, since our goal was to determine the aggregate level of estimated loss aversion in the literature, our data had to come from published research. Second, parametric estimates of loss aversion in risky contexts must be based on the elicitation method that employs mixed lotteries (i.e., gambles with both gain and loss components). Without including mixed gambles, λ cannot be estimated, and so data that consisted solely of gain- or loss-only lotteries were not considered (Köbberling & Wakker, 2005). Third, because one cannot compare λs across different variants of CPT, we require raw choice data which we use to estimate one common variant of CPT across all data sets. Fourth, our approach involved fitting the model to data using maximum likelihood estimation (MLE). For this reason, we exclude a small number of studies which estimate parameters using an adaptive series of questions (Mohammed Abdellaoui, Bleichrodt, & L'Haridon, 2008; Wakker & Deneffe, 1996),

Method

Data Collection. We conducted our literature search in three steps. First, we obtained data from twelve articles reported by Fox and Poldrack (see Table 11.3, p. 138; 2009), of which six met our criteria for inclusion in the meta-analysis because they used a parametric methods to estimate parameters of CPT. Second, we approached the community of judgment and decision, sending a request on the 3rd of November, 2014 (http://mail.sjdm.org/mailman/listinfo/jdmsociety) asking for raw data that matched our criteria. Out of all responses, six unique articles were identified as appropriate. Finally, we conducted a comprehensive search through the Web of Science records using the "loss aversion" keyword as the topic category. This search produced 2053 results. Abstracts of all articles were read by the first author, who identified 115 potentially useful data sources. Further in-depth evaluation of each article revealed that 29 contained data suitable for estimating CPT parameters, and we contacted all corresponding authors of these works asking for raw data. Due to variety of reasons (e.g., data were lost, lack of ethical approval for data sharing, no access to individual level data, lack of response from all authors, poor documentation supplementing data)[5], in the end, we were left with 19 data sets from 17 published articles (two articles contained two unique datasets).

Model. There are at least 256 possible variants of the CPT, depending on the parametric form of the utility function, probability weighting function and probabilistic choice rule (Stott, 2006). The choice of the exact functional form can influence the quality of the model fit and therefore the value of the parameters that are estimated. We opted for specification that is closest to the most widely-recognized version of the CPT offered by T&K92. In the following section, we describe our modelling approach but also note where we depart from this specification due to constraints imposed by the available data.

[5] In most cases where data could not be shared with us, fewer than 10 years (APA limit for retention of raw data) have passed since the relevant studies were conducted.

We begin with the basic assumption of the CPT, which states that the subjective value of a mixed gamble with possible outcomes $x_1 \leq \cdots \leq x_k \leq 0 \leq x_{n+1} \leq x_n$ and their respective probabilities $p_1 \ldots p_n$ is:

$$V = \sum_{i=1}^{k} \pi_i^- v(x_1) + \sum_{j=k+1}^{n} \pi_j^+ v(x_j) \tag{1}$$

The decision weights π^+ and π^- are derived from a rank transformation of the outcomes' probabilities. Following T&K92

$$\begin{gathered}\pi_1^- = w^-(p_1)\\ \pi_n^+ = w^+(p_n)\\ \pi_i^- = w^-(p_1 + \cdots + p_i) - w^-(p_1 + \cdots + p_{i-1}) \quad for\ 1 < i \leq k\\ \pi_j^+ = w^+\left(p_j + \cdots + p_n\right) - w^+\left(p_{j+1} + \cdots + p_n\right) \quad for\ 1 < j \leq k\end{gathered} \tag{2}$$

with $w^+(\cdot)$ *and* $w^-(\cdot)$ representing probability weighting function for gains and losses. These equations have the effect of transforming the cumulative probability of receiving an outcome at least as extreme as x_i instead of transforming raw probabilities.

Similar to T&K92, we used a single parameter probability weighting function,

$$w(p) = \frac{p^\gamma}{[p^\gamma + (1-p)^\gamma]^{1/\gamma}} \tag{2}$$

where γ controls a degree of overweighting and underweighting of small and large probabilities. We used a single parameter to estimate the subjective weight of probabilities over gains and losses.

The value function is concave for gains and convex for losses. Additionally, the λ parameter determines steepness the loss function and represents loss aversion. Unlike the original CPT, we did not assign individual parameters to gain and loss (i.e., α and β) function and instead used a single parameter α for both.

$$v(x) = \begin{cases} x^{\alpha} & x \geq 0 \\ -\lambda|x|^{\beta} & x < 0 \end{cases}$$

Fixing $\alpha = \beta$ is essential if λ is to have meaning. Without this, λ is an arbitrarily defined by the unit of currency (see Wakker, 2010, Observations 9.6.2 and 9.6.3, and Stewart, Scheibehenne & Pachur, 2017). Additionally, a faster rate of decreasing marginal utility for losses than gains, which could be represented by α smaller than β, also captures loss averse behaviour (Nilsson et al., 2011; Pachur & Kellen, 2013). The ratio of $\alpha/\beta$and λ therefore trade-off against each other and in this case obscure estimates of λ.

Using logit choice rule, the probability of selecting lottery A over lotter B is given by:

$$P(A,B) = \frac{1}{1+e^{-s[v^{-1}(V_A)-v^{-1}(V_B)]}}, \quad (1)$$

with the sensitivity parameter s. We have departed from the usual form here by using the inverse value function $v^{-1}(\cdot)$ to transform the psychological values back into their certainty equivalents. Stewart, Scheibehenne, and Pachur (2017) explain how this keeps the power α out of the units of s, so s is measured in $1/\$$ instead of $1/\$^{\alpha}$. Without this change it is meaningless to compare values of λ over individuals with different αs (just as meaningless of asking which is bigger, 2 miles or 7 tons?). This allows s to be compared across individuals with different values of α, and removes the correlation between α and s.

Analyses. Using model specification outlined above, we estimated the maximum likelihood parameters for each individual in the 19 data sets from 17 articles. We used original estimates from T&K92 as our starting parameters, with the exception of the noise parameter (s), which was chosen from powers of 10 to produce the most evenly distributed choice probabilities in each study. The list of starting values for s is listed in Table S1 in Supplementary materials. In the case of studies that used Accept/Reject elicitation methods that involve only two probabilities

(50% and 100%), we used a simplified version of the model, fixing the γ parameter of the probability weighting function to 1. We performed this analysis using both the optim package in R (version 2.15; R Core Team, 2014), as well as fminsearch in Matlab. Both functions use the Nelder-Mead optimization algorithm (Lagarias, Reeds, Wright, & Wright, 2006; Nelder & Mead, 1965). To help avoid local minima, the algorithm was restarted three times, continuing from the previous maximum. In instances where the algorithms arrived at a different solution, we selected parameters from the package that achieved higher likelihood.

For each study, we calculated median λ and used bootstrapping to obtain 95% confidence intervals. We then applied random/mixed-effects meta-analysis to all datasets (Viechtbauer, 2010).

Results and Discussion

Coding the Experimental Attributes. For each study, we list major attributes of the experimental design, including characteristics of the elicitation methods. The coding was performed by the first two authors independently and the final list was agreed on collectively. Breakdown of the attributes is presented in Table 1.

= Insert Table 1 about here =

Study Characteristics. Table 1 shows that 9 (52%) studies drew their subjects from the student population and 8 (48%) from the general population. Across all studies, sample sizes varied from 16 to 235 participants. Use of real incentives was common, with only two studies using hypothetical choices. However, we found that the structure of the incentive mechanism varied greatly between the studies. This is problematic since the method used to incorporate real monetary outcomes in the experimental design can influence people's preferences in risky context (Hertwig & Ortmann, 2001). Consider the case of the endowment available to the participants prior to the elicitation task. In most instances, the purpose of such an endowment is to ensure nobody can end up with a negative balance at the end of the experiment. However, even if we accounted for different currencies and exchange rates, we could not accommodate subtle but important differences in our coding scheme. For example, in some studies the money was provided to the participants one week before the study (Canessa et al., 2013; Tom et al., 2007) to avoid the experience of windfall gains that can influence propensity to take risks (Thaler & Johnson, 1990). Yet in other studies, the earnings from the elicitation task were combined with extra income from additional, unrelated tasks (Chib, De Martino, Shimojo, & O'Doherty, 2012). Despite the fact that most studies allowed for part of the endowment to be lost, other mechanisms were put in place to ensure no participant could end up spending money out of their own pocket. For example, in some studies the money lost could be earned back by working in the lab or was compensated by allowing participants to play out an additional lottery in the gain-only domain. In sum, we could not identify even two studies that implemented an identical incentive structure and therefore any coding scheme that separates studies into incentivized and not incentivized would be inadequate.

Elicitation methods. Table 1 shows that elicitation methods included choices between pairs of lotteries (35% of studies), statements of certainty equivalence (12%), or decisions to accept or reject mixed lotteries (53%). Even within these categories, methodologies differed in several important ways. For accept or reject lotteries—the most popular method in our sample—participants were presented with a series of mixed lotteries where gains and losses can occur with equal probability (i.e. 50%). Studies differ in the number of trials, the number of possible responses (e.g., “accept vs. reject” or “weakly accept vs. strongly accept vs. weakly reject vs. strongly reject”) and whether trials included cases where the mixed lottery was paired with a non-zero outcome. The same issue applies to the distributions of monetary values that were used to construct possible lotteries. Distributions of gains and losses are a source of powerful context effects, which can influence the degree of loss aversion exhibited by the participants (Walasek & Stewart, 2015, 2018a). In the data available to us, we found a great deal of heterogeneity. For example, Sokol-Hessner et al. (2009) used gains ranging from $2 to $12 (in $2 increments), whereas available losses were determined by multiplying these values by a factor ranging from 0.5 to 2, in increments of 0.125. Such a method (see also Sokol-Hessner et al., 2012) results in skewed distributions of gains and losses. Whereas many of the remaining authors used uniform distributions of gains and losses in their studies, the ranges of values were often asymmetric (Chib et al., 2012; Tom et al., 2007).

Model Fitting Results. Median estimated parameter values for each study are displayed in Table 2 together with the 95% bootstrapped confidence intervals.

= Insert Table 2 about here =

We found value functions that were convex, linear and concave in our sample. For the probability weighting function, in six out of seven studies we found that people, on aggregate, overweighted small probabilities and underweighted large probabilities. This is consistent with findings in other studies (Gonzalez & Wu, 1999).

With respect to loss aversion, our aggregate estimates of λ visibly vary between the studies. Our results show that in some studies participants exhibited a very strong aversion to losses (λ_{max} = 3.45), yet in some participants showed the reverse of loss aversion (λ_{min} = 0.65). We also found a considerable amount of heterogeneity within each study. As Table 2 shows, the confidence intervals for λ often encompass both loss neutrality (λ ~ 1) and considerable loss aversion (λ > 2). The confidence intervals incorporated loss neutrality in 11 of the 19 datasets. In contrast, in only seven cases did our confidence intervals include the value of 2.25. In light of this clear heterogeneity, we performed a random-effect meta-analysis to determine the weighted average parameter of λ. The model confirmed that a large portion of variability in the estimated loss aversion is attributable to the between-study heterogeneity (τ^2 = 0.15). Indeed, the Q statistic is higher than could be expected by chance, $Q(18) = 227.26$, $p < .001$ (Cumming, 2014). The weights of λs in individual studies are displayed in the forest plot in Figure 2. Two dotted vertical lines indicate loss neutrality (λ = 1) and the original estimate of T&K92 (λ = 2.25). The overall weighted estimate of λ in our meta-analysis is 1.31. Notably, the confidence intervals on the final estimate span from λ of 1.10 to 1.53. Thus, despite the fact that a large amount of uncertainty remains with regards to the final estimate of λ, the 95% confidence intervals do not include λ of 2.25.

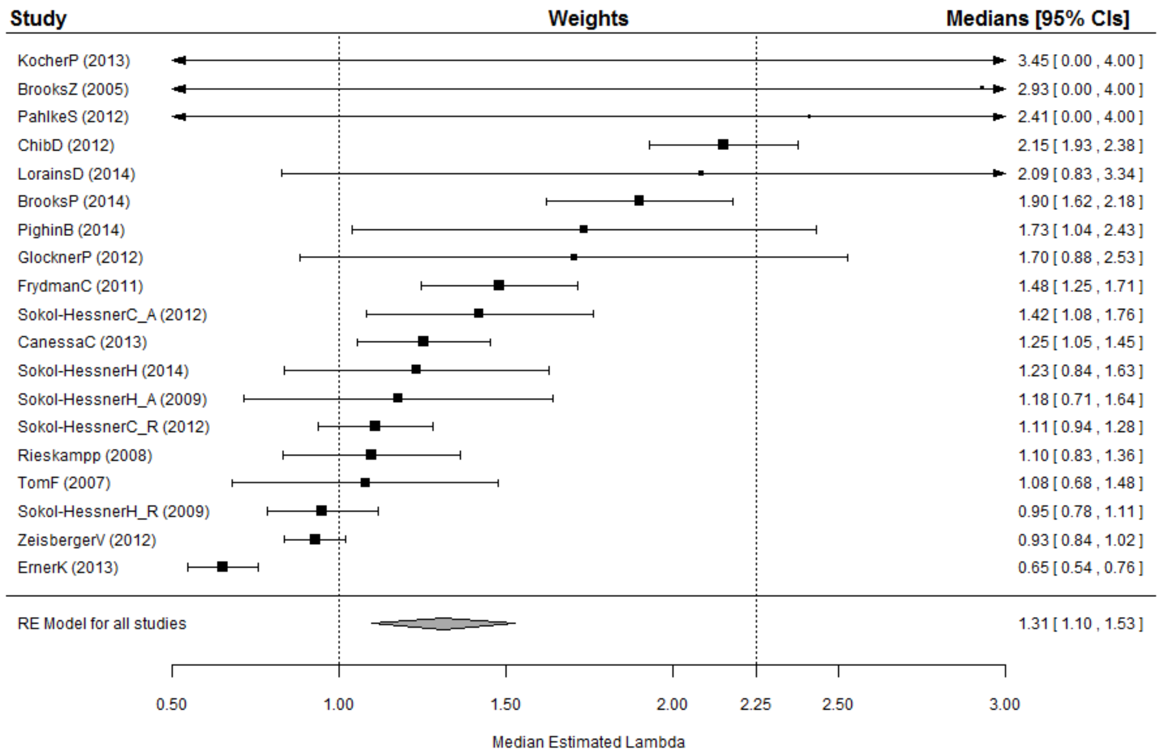

Figure 2. Forest plot of median values of λ across all studies. Weights were estimated using a random-effect meta-analysis. Confidence intervals that extend beyond the scale are indicated by arrows.

Imprecise estimates of loss aversion carry little weight in determining the aggregate model estimate. Nonetheless, it is worrying that in four studies that found losses weighting twice as much as gains, the confidence intervals are also relatively large. In a typical meta-analysis, this could be attributed to noisy estimates on account of a small sample size. In our case, it is likely that the stimuli used to reveal people's preference were not sufficiently diagnostic to estimate a true value of λ. Despite this, we investigated whether there is a relationship between the precision of the estimates and the size of the loss aversion parameter. A non-parametric correlation between standard errors and median λ revealed a considerable positive correlation ($\rho = 0.739, p < .001$).

Figure 3 shows a funnel plot of our data (λ plotted against the inverse of standard error), after excluding two studies with very large standard errors (standard errors of 390.25 and 10288.77 in Pahlke, Strasser, and Vieider (2012) and Brooks, Peters, and Zank (2014), respectively. Though funnel plots with few studies can be misleading (Anzures-Cabrera & Higgins, 2010), we do observe more studies in the lower right region of the plot. That is, studies with larger aggregate λ had the most variance.

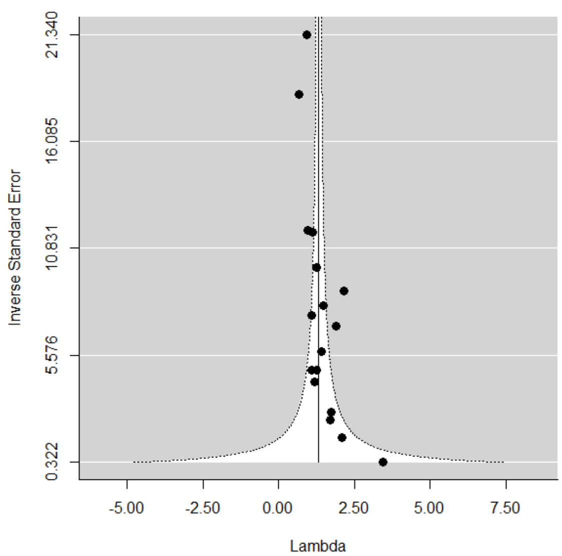

Figure 3. Funnel plot of median lambda estimates and the inverse of standard error for each study, excluding Brooks et al., (2014) and Pahlke et al., (2012. The vertical line marks the overall estimate of lambda.

General Discussion

When facing risky prospects, are people generally loss averse? In order to answer this question, we used a meta-analytic framework to compare estimates of the CPT's λ parameter in 17 published studies (19 data sets in all). Despite controlling for the functional form of the CPT and fitting it to individual responses, we observed a considerable amount of both within- and between-study heterogeneity. The end result of the random-effect meta-analysis revealed a median λ of 1.31 95% CI [1.10, 1.53]. Even with a high level of uncertainty surrounding our final estimate, the observed median λ is significantly lower than the original estimate of 2.25 obtained by T&K92. In other words, while it seems that there is a lot of noise in the estimates of loss aversion, we can be at least confident that aggregate λ is much lower than 2. It is important to note that any interpretation about the population-level magnitude of loss aversion must take into account the range of methodological issues that influence estimates of λ from risky choice and valuations. Broadly, these problems arise from the difficulty in estimating parameters of a complex model such as CPT, which are further exacerbated by the features of the elicitation tasks themselves.

First of all, the results of any maximum likelihood estimation will be highly dependent on the choice of the model—the exact combination of the parametric forms of the value and probability weighting functions, as well as the stochastic choice rules (Stott, 2006). In our approach, we chose the formulation that was closest to the original version of the CPT (Tversky & Kahneman, 1992) whilst avoiding the problems in estimation that have been revealed since then (Stewart, Scheibehenne, & Pachur, 2017; Wakker, 2010). The issue of parameter trade-offs in CPT is particularly problematic since it undermines the validity of λ as a direct representation of loss averse behaviour. Indeed, the overweighting of losses relative to gains can be captured by different combinations of parameter values, including the asymmetry in the curvature of the value function for gains and losses (α and β), as well as different elevations of the probability weighting function (γ and δ) (Pachur & Kellen, 2013). In the present study we avoided the issue of parameter trade-off in case of loss aversion by constraining $\alpha = \beta$ and $\gamma = \delta$. However, had we defined loss aversion using these pairs of parameters, our estimates of loss aversion would likely be very different. All three mechanisms described above are unique in that they assume different forms of transformations to the values and probabilities.

Another troubling point concerns the volume of potentially “poor” individual model fits. In our meta-analysis, we avoided making any arbitrary decisions about exclusion criteria. We included all estimates of λ in our meta-analysis, regardless of the quality of each participant’s responding. At the same time, we minimized the possibility of extreme parameter values driving our results by using medians, bootstrapped confidence intervals, and random-effect meta-analysis. However, excluding participants based on the pattern of their decisions is not uncommon[6]. In the original publications, individuals who showed no variability in their responding (Lorains et al., 2014; Sokol-Hessner et al., 2009), failed to respond within a set time limit (Frydman, Camerer, Bossaerts, & Rangel, 2011; Kocher, Pahlke, & Trautmann, 2013; Sokol-Hessner et al., 2013), violated monoticity in choice (Kocher et al., 2013), or were insufficiently motivated (Zeisberger, Vrecko, & Langer, 2012) could be excluded. In most cases, we did not have enough information to replicate exclusion criteria employed by other authors.

All of the issues discussed above may contribute to noisy model fits. As it is clearly visible in Figure 2, some studies show an extremely high level of variability in estimated λ. One interpretation could be that this uncertainty represents different levels of diversity in sensitivity to losses within studied samples. This seems extremely unlikely considering the size of these discrepancies. For example, it is surprising to see that the tendency to exhibit loss aversion

[6] These are reasons separate from those directly affective model fits

among the undergraduate students from the University of Amsterdam was over twice as variable (Kocher et al., 2013) as the estimates of students from the University of Verona (Pighin, Bonini, Savadori, Hadjichristidis, & Schena, 2014). An alternative explanation is that the sources of the heterogeneity (i.e., very low and very high magnitudes of λ) within these samples represent poor model fits. The amount of poor fits can be partially driven by problematic participants (see above) as well as the design of the elicitation task itself. If the combination of outcomes and probabilities does not sufficiently constrain the parameter space, it is more likely to produce unreliable (i.e., biased) parameter estimates. In fact, recent efforts illustrate that λ suffers from poor recoverability and that most stimuli sets in the literature produce estimates with a large amount of error (Broomell & Bhatia, 2014; Nilsson et al., 2011; Walasek & Stewart, 2018b)[7]. As a result of the observed heterogeneity, some studies contribute very little to the final estimate of λ in our meta-analysis. Taken together, very few studies offer a strong contribution to our understanding of the general level of loss aversion in the population.

Even in instances when there is relatively little variability in estimated λs, we still find considerable between-studies differences in obtained medians. Meta-analytical framework offers an exciting opportunity to investigate possible moderators of this variability (Cumming, 2014). In the context of risky choice, the magnitude of loss aversion could be influenced by the incentive structure of the task, population characteristics or the type of elicitation task itself

[7] One approach to determine uncertainty of individual model fits is to use Hierarchical Bayesian modelling. Nonetheless we opted for MLE method as this is the most widely used approach in the field, which makes our conclusions more comparable to the findings of others.

(Bardsley et al., 2010; Hertwig & Ortmann, 2001). It is therefore particularly disappointing that our data could not be subjected to any tests of meta-regression models. We have shown (see Table 1), studies considered in the present paper offer either too much or too little heterogeneity in features of their design. Consider the realization of monetary losses in the previous work. Recent research suggests that when monetary losses are truly experienced, people's attitude towards risk changes. Imas (2016) showed that when losses are deducted from one's endowment, participants exhibit lower propensity to take risks on subsequent trials. If such losses are not realised until the end of the study (i.e., paper losses), on the other hand, participants become motivated to recuperate and consequently show an increase in risk seeking behaviour. Based on these findings, one could predict that estimates of λ will be lower when the lotteries are not played out at the end of each trial. Among studies included in the present meta-analysis, this hypothesis cannot be evaluated, since in only one experiment gambles were played out for real outcomes following each decision. Even then, however, deduction could be interpreted as mere "paper losses" since no money had to be physically taken away from the participants. The impact of losses is further complicated by the incentive structures. Primarily due to ethical considerations, real out-of-pocket losses were not permitted in most studies reported here. Table 1 summarizes only some of the key features of the incentive mechanisms, and it is clear that the number of unique combinations is as high as the total number of studies. As such, we were unable to determine whether the between-study variability in estimated λ can be in part attributed to how participants experienced the risk of losing money. More generally, this presents a problem to all studies interested in observing and quantifying loss averse behaviour. If loss aversion requires real and tangible sense of losing one's personal money, then it seems that very few studies are in a position to claim that they created conditions necessary to elicit it.

Our meta-analysis consists of datasets that come from seventeen published articles. This may appear low in the context of other meta-analyses in behavioural sciences, many of which focus on experimental effects that are much less established than loss aversion. However, our approach differed considerably from other meta-analytical approaches in that we fitted model to individual responses of each study. This created two issues with regard to data availability. First, as we discovered, surprisingly few studies involve choices about mixed lotteries. The majority of papers that explored parametric forms of CPT focused on the gain-only domain, merely estimating the probability weighting or the value function for gains. Second, while there were relatively few works that included mixed lotteries and were therefore suitable for our review, even fewer datasets were accessible to us. Disappointingly few researchers were able or willing to share their raw data with us. This is worrisome, given how many research articles in psychology have failed to replicate in recent years (Open Science Collaboration, 2015).

Despite a multitude of methodological and theoretical issues, how should our perception of loss aversion in the behavioural sciences change in light of these results? The exact question, and possible answers, depend on the interpretation of what loss aversion really stands for. As we have demonstrated, there is much confusion in the past literature about the interpretation of loss aversion. Our conclusion is that if loss aversion is interpreted entirely as the asymmetric steepness of the value functions for gains and losses of the CPT, then the existing evidence shows that people exhibit weak loss aversion in risky choice. At the same time, present work is insufficient to provide a very precise estimate of loss aversion in the population. Large variability for estimates of λ in most studies suggest that the methods for eliciting attitudes towards monetary gains and losses may not be appropriate. Considerable between-study differences also suggest that unobserved variables can drive the overall sensitivity to losses within a given sample. Given the scarcity of data, it is not possible to determine whether loss aversion in a risky context is a stable property of people's preferences. At the very least, our work adds to the growing body work that challenges the notion that loss aversion is robust, ubiquitous or even well-understood phenomenon (Gal & Rucker, 2017; Walasek & Stewart, 2015; Yechiam, 2018).

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Table 1

Studies used in the present meta-analysis and a summary of the key features of their designs.

Author(s)	Year	N	Sample	Currency	Endowment	Incentive	Exchange Rate	Elicitation Task	N Trials	Min Gain	Min Loss	Max Gain	Max Loss
BrooksP	2014	90	Students	GBP	17	Random trial	1:1	Choice	105	15	15	15	15
BrooksZ	2005	49	Students	GBP	10	Random trial	1:1	Choice	106	1	1	15	9
CanessaC	2013	56	General	L	unknown	All trials	1:1	Accept/Reject	104	1	1	99	99
ChibD	2012	32	General	USD	40	Random trial	1:1	Accept/Reject	512	10	5	40	47
ErnerK	2013	235	Students	EUR	20	None	1:1	CE	43	1	1	60	60
FrydmanC	2011	90	Students	USD	25	Random trial	1:1	Accept/Reject*	140	2	1	30	24
GlöcknerP	2012	66	Students	EUR	22	Random trial	100:1	Choice	138	1200	-1000	1200	???
KocherP	2013	42	Students	EUR	5	Random trial	1:1	Choice	29	0.60	1	200	20
LorainsD	2014	38	General	AUD	0	None	NA	Accept/Reject	49	15	5	45	35
PahlkeS	2012	48	General	EUR	0	Random 3 trials	1:1	Choice	40	1	1	25	20
PighinB	2014	26	Students	EUR	32	Random trial	1:1	Accept/Reject	256	2	2	32	32
Rieskamp	2008	30	Students	EUR	15	Random trial	200:1	Choice	180	1	1	100	100
Sokol-HessnerC	2012	47[d]	General*	USD	105	Random 30 trials	1:1	Accept/Reject*	150	1	0.25	28	44.80
Sokol-HessnerH	2009	60[d]	General*	USD	30	Random 28 trials	1:1	Accept/Reject*	140	2	0.5	30	24
Sokol-HessnerH	2014	22	General	USD	45	Random 18 trials	1:1	Accept/Reject*	180	2	0.50	30	24
TomF	2007	16	General	USD	30	Random trial	1:1	Accept/Reject	256	10	5	40	20
ZeisbergerV	2012	73	Students	EUR	14	Random trial	1:1	CE	24	5	5	60	60

Note. Author names = the last name of the first author followed by the first letter of the second author's last name. Year = year of publication. N = total number of participants included in the raw data file. The exact number of participants reported in each paper may differ depending on the authors' exclusion criteria. Superscript "d" signifies that the sample contained within subject manipulation and that two samples were treated as separate in the analysis. Sample = student or general population. General* is used when the exact composition of the sample was unknown. Currency = currency used in the study for both payments and the elicitation tasks. Endowment = the amount of money given to the participants prior to completing the elicitation task. This does not factor in additional money received at the end of the study or in exchange for completing additional tasks. Note that in the case of ZeisbergerV, participants received four and ten Euros in two sessions, respectively. Incentive = the number of trials in the elicitation task that were played out for real outcome. Exchange rate: conversion rate used to convert money earned from outcomes used in the elicitation task. Elicitation Task = method of eliciting participants' preferences over risky prospects. Accept/Reject* corresponds to designs where the alternative to the (x, 0.5, y) gamble was not always a certain 0 outcome. N Trials = number of trials used in the elicitation task. Not always constant in each study. Min Gain, Min Loss, Max Gain, Max Loss = maximum and minimum non-zero gains and losses of the gambles used in the elicitation tasks.

Table 2. Median estimated CPT parameter values, with 95% bootstrapped confidence intervals.

Author(s)	Lambda [95% CIs]	Alpha [95% CIs]	Gamma [95% CIs]
BrooksP	1.9 [1.65; 2.24]	1.01 [0.98; 1.07]	NA
BrooksZ	2.93 [1; 17.16]	1.6 [0.99; 2.01]	1.2 [1.08; 1.34]
CanessaC	1.25 [1.07; 1.41]	0.8 [0.54; 1.01]	NA
ChibD	2.15 [1.89; 2.33]	0.96 [0.78; 1.1]	NA
ErnerK	0.65 [0.56; 0.77]	1.04 [1.01; 1.09]	0.69 [0.64; 0.72]
FrydmanC	1.48 [1.3; 1.75]	1.19 [1.08; 1.8]	NA
GlöcknerP	1.7 [0.98; 2.32]	0.61 [0.5; 0.67]	0.82 [0.74; 0.86]
KocherP	3.45 [2.81; 9.77]	1.28 [0.78; 2.26]	0.81 [0.55; 0.89]
LorainsD	2.09 [1.14; 2.63]	1.59 [0.73; 2.79]	NA
PahlkeS	2.41 [1.73; 3.35]	1 [0.98; 1.03]	0.67 [0.55; 0.86]
PighinB	1.73 [1.03; 2.17]	0.79 [0.25; 1.05]	NA
Rieskamp	1.1 [0.76; 1.31]	1 [0.86; 1.09]	0.77 [0.65; 0.88]
Sokol-HessnerC_A	1.42 [1.09; 1.79]	0.91 [0.84; 0.96]	NA
Sokol-HessnerC_R	1.11 [0.93; 1.24]	0.95 [0.88; 1.04]	NA
Sokol-HessnerH09_A	1.18 [1.01; 1.73]	0.87 [0.81; 0.99]	NA
Sokol-HessnerH09_R	0.95 [0.76; 1.11]	0.9 [0.81; 0.98]	NA
Sokol-HessnerH14	1.23 [0.88; 1.73]	0.96 [0.83; 1.21]	NA
TomF	1.08 [1; 1.63]	0.48 [0; 0.98]	NA
ZeisbergerV	0.93 [0.83; 1.01]	0.96 [0.93; 0.97]	0.86 [0.78; 0.89]

Note. Author names = the last name of the first author followed by the first letter of the second author's last name. Letters A and R represent different conditions from the same study.

Appendix I

Table S1. Starting parameters for sensitivity (s) parameter of the choice rule.

Author(s)	Sensitivity (s) starting value
BrooksP	0.1
CanessaC	0.01
ChibD	0.1
FrydmanC	0.1
GlöcknerP	0.001
KocherP	0.1
LorainsD	0.1
PahlkeS	0.1
PighinB	0.1
Rieskamp	0.01
Sokol-HessnerH09	0.1
Sokol-HessnerC	0.1
Sokol-HessnerH14	0.1
TomF	0.1
ErnerK	10
BrooksZ	1
ZeisbergerV	10

Note. Author names = the last name of the first author followed by the first letter of the second author's last name.