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Who's biased? A meta-analysis of buyer-seller differences in the pricing of lotteries

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A large body of empirical research has examined the impact of trading perspective on pricing of consumer products, with the typical finding being that selling prices exceed buying prices (i.e., the endowment effect). Using a meta-analytic approach, we examine to what extent the endowment effect also emerges in the pricing of monetary lotteries. As monetary lotteries have a clearly defined normative value, we also assess whether one trading perspective is more biased than the other. We consider several indicators of bias: absolute deviation from expected values, rank correlation with expected values, overall variance, and per-unit variance. The meta-analysis, which includes 35 articles, indicates that selling prices considerably exceed buying prices (Cohen's $d = 0.58$). Importantly, we also find that selling prices deviate less from the lotteries' expected values than buying prices, both in absolute and in relative terms. Selling prices also exhibit lower variance per unit. Hierarchical Bayesian modeling with cumulative prospect theory indicates that buyers have lower probability sensitivity and a more pronounced response bias. The finding that selling prices are more in line with normative standards than buying prices challenges the prominent account whereby sellers' valuations are upward biased due to loss aversion, and supports alternative theoretical accounts.

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When objects are traded in real-life settings, there is often an information asymmetry between buyers and sellers, whereby the latter know more about the objects than the former (Akerlof, 1970). This asymmetry can lead to an advantage for sellers as they can exploit it to their benefit, for instance by demanding higher prices (Stiglitz, 2000; Bae, Stulz, & Tan, 2008). However, trading also introduces dissimilarities between buyers and sellers due to each party viewing the same object differently. Specifically, depending on who owns the object and who is about to buy it, there are differences in the status quo (Gal, 2006) and in whether the transaction is viewed as a gain or a loss. Such disparities in perspective are known to be associated with systematic behavioral gaps (Kahneman & Tversky, 1979; Fagley, 1993; Kühberger, 1998; Levin, Schneider, & Gaeth, 1998). Indeed, it has been demonstrated that there is a reliable difference between selling prices (i.e., the minimal price sellers are willing to accept) and buying prices (i.e., the maximal prices buyers are willing to pay), even in settings where equal information is provided to sellers and buyers (Birnbaum & Stegner, 1979; Thaler, 1980; Kahneman, Knetsch, & Thaler, 1990; Carmon & Ariely, 2000; Johnson & Busemeyer, 2005; Johnson, Häubl, & Keinan, 2007; Morewedge, Shu, Gilbert, & Wilson, 2009; Schurr & Ritov, 2014). According to this *endowment effect*, sellers indicate higher prices than buyers.

The endowment effect was initially demonstrated with consumer products, such as pens, mugs, and sports tickets (Thaler, 1980; Kahneman et al., 1990), and the bulk of subsequent studies has focused on the pricing of products (see reviews in Horowitz & McConnell, 2002; Sayman & Öncüler, 2005; Tuncel & Hammitt, 2014). The goal of the current meta-analysis is to examine whether a robust buyer-seller valuation gap also exists for risky monetary lotteries, arguably the most common type of object investigated

in studies of economic decision making (e.g., Edwards, 1954; Kahneman & Tversky, 1979; Weber, Shafir, & Blais, 2004). Additionally, we investigate whether a potential gap reflects a psychological bias on the part of sellers or buyers. In contrast to consumer products monetary lotteries have a clearly defined "normative" value (i.e., their expected value), allowing one to assess whether buying or selling prices show a larger deviation from this standard. In other words, we examine whether sellers or buyers are more biased in their pricing decisions. Existing theoretical accounts for the endowment effect give rise to opposing predictions regarding this question, and hence the current investigation helps to evaluate these accounts.

Two previous reviews have analyzed selling and buying prices for both consumer products and monetary lotteries in a systematic fashion (Sayman & Öncüler, 2005; Tuncel & Hammitt, 2014). Our investigation goes beyond these analyses in the following ways. First, our review is more comprehensive, in that it includes not only studies in economics but also in psychology.[1] Second, in addition to quantifying the difference between selling and buying prices, we also evaluate and compare their accuracy.

We seek to address the following questions: Does the endowment effect also emerge for objects that return money? Kahneman et al. (1990) originally argued that the endowment effect only exists for non-monetary items, as the effect was assumed to be primarily driven by sellers having to relinquish an object they could utilize (Kahneman et al., 1990; see details below). Most other theoretical accounts of the endowment effect (e.g., Morewedge et al., 2009) suggest, on the other hand, that the effect is more general

[1] Specifically, Sayman and Öncüler (2005) considered only 7 independent studies of lotteries, while Tuncel and Hammitt (2014) limited their examination to the Econlit database of scientific papers and only examined 12 independent studies. Using a broader search strategy, we include data from 35 independent studies (as elaborated below).

and should manifest for monetary lotteries as well. Still, in Tuncel and Hammitt's (2014) meta-analysis of studies in economics, the buyer-seller price gap was smaller for lotteries than for other domains, and the lower error bound of the size of the gap approached zero.[2] This underlines the value of conducting an additional, more comprehensive, analysis.

Further, we ask whether sellers are more or less *biased* than buyers. According to the classical explanation of the endowment effect, the discrepancy is mainly due to a bias on the part of the sellers, whose price levels are upward-biased (for details see below; e.g., Kahneman et al., 1990). Others have proposed that both sellers and buyers are biased but have not offered predictions regarding whether the bias is more pronounced for one or the other (e.g., Johnson & Busemeyer, 2005; Schurr & Ritov, 2014). Still others have provided evidence that it may be buyers who are more biased (Trautmann et al., 2011; Yechiam, Abofol, & Pachur, in press), with selling prices being closer to the expected value of lotteries than buying prices (Yechiam et al., in press). In order to investigate this issue, we go beyond studying differences in price level between buyers and sellers and consider various indices of accuracy of the pricing responses, such as absolute accuracy (i.e., the difference of the prices from the expected values), relative accuracy (i.e., the ranking of prices relative to ranking by expected value), and variability.

The remainder of the article is organized as follows: The first section gives an overview of different theoretical accounts of the endowment effect and their predictions for our two research questions. The second section follows with a meta-analysis of the relevant literature; this section also reports a computational modeling analysis of buying

[2] Specifically, Tuncel and Hammitt (2014) focused on the ratio of selling to buying prices, and the lower error bound of the estimated ratio was 1.06.

and selling prices using Cumulative Prospect Theory (Tversky & Kahneman, 1992). We close by discussing the implications of our findings.

Accounts of Buyer-Seller Differences in Pricing

The strong and reliable difference between buying and selling prices – which was first demonstrated for common consumer goods such as coffee mugs and pens (Kahneman et al. 1990) – has captured the attention of behavioral scientists because it represents a violation of two major principles of neo-classical economics. First, in welfare analysis, buying and selling prices are usually assumed to converge to an equilibrium (Willig, 1976). Secondly, a buyer-seller asymmetry in prices implies a behavioral barrier to trading (e.g., Kahneman & Tversky, 1984; Dubourg, Jones-Lee, & Loomes, 1994), which in turn contradicts the presumed efficiency of market institutions (i.e., the Coase theorem; Coase, 1960).

There have been many theoretical accounts as to which mechanisms may give rise to the endowment effect, and these accounts also have testable predictions for the domain of monetary lotteries. The most common argument has been that sellers experience the act of selling an object as a loss whereas buyers do not perceive the money paid for an object as a loss (Kahneman et al., 1990; Camerer, 2004). Therefore, due to loss aversion (Kahneman & Tversky, 1979) – the tendency to subjectively inflate the value of negative outcomes compared to equivalent positive ones – the price indicated by sellers is higher. Hence, according to this argument, it is sellers who show a *bias*. Kahneman et al. (1990) further argued that loss aversion only emerges for goods that are purchased for utilization and not for exchange, as the latter are held exclusively for being substituted, and are

worthless if not given away. Hence under their "strict loss aversion" account there should be no endowment effect for monetary lotteries because they are only valuable when redeemed for cash (see also van de Ven et al., 2005). The theoretical predictions of the strict loss aversion account, as well as other accounts of the endowment effect, appear in Table 1.

Bateman, Kahneman, Munro, Starmer, and Sugden (2005) observed, however, that buyers experience the paying of money as a loss as well. Hence, they argue that both perspectives could lead to a bias, although for sellers the bias is larger (Bateman et al., 2005). We refer to this explanation as "relative loss aversion" for sellers. A related line of accounts similarly attributes a larger bias to sellers but suggests that it is caused by specific circumstances implicated in trading rather than by the fact that relinquishing an object is painful. For example, it has been suggested that the endowment effect is driven by sellers' (irrational) reluctance to make an exchange (e.g., Beggan, 1992; Mackenzie, 1997; see also Gal, 2006) and fear of making a bad deal (e.g., Brown, 2005). Under these views, both sellers and buyers are biased in pricing monetary lotteries, but the bias is assumed to be larger on the part of sellers.

Another account proposing that sellers tend to deviate more from normative prices highlights the role of the psychological experience of ownership in producing the endowment effect. For example, it has been suggested that owners may come to identify themselves with the object and this may increase its value (Morewedge et al., 2009). Ownership can enhance the subjective value of the object due to the generation of positive associations between one's self and the object (Maddux et al., 2015; Morewedge & Giblin, 2015; and see also Symons & Johnson, 1997; Cunningham, Turk, Macdonald,

& Macrae, 2008) or simply due to greater exposure: Merely paying attention to an object has been found to increase its liking (Dhar & Simonson, 1992). Hence, under this account sellers also deviate more from the normative price of an object than buyers, though it is the mere ownership and not the act of selling that leads to this difference.

Alternatively, it has been argued that both sellers and buyers are biased, but neither is more biased than the other. One account that falls into this category is the proposal that the endowment effect results from an overgeneralization from real-world trading situations, where exaggerating the price can be a reasonable strategy in the first initial step of a negotiation process for sellers, while making a low first offer can be a reasonable initial step for buyers (e.g., Brookshire & Coursey, 1987; Hausman, 2012).[3] Also falling into this category are studies demonstrating that sellers and buyers differ in their consideration of positive and negative features of the object (Birnbaum & Stegner, 1979; Johnson & Busemeyer, 2005; Johnson et al., 2007; Ashby, Dickert, & Glöckner, 2012; Pachur & Scheibehenne, 2012; Ashby, Walasek, & Glöckner, 2015).

According to a less common view, sellers are less biased than buyers. Yang, Vosgerau, and Loewenstein (2013) suggested that buyers exhibit extreme risk aversion for monetary lotteries, leading to valuations that fall well below their normative prices. Yang et al. (2013) argued that this extreme risk aversion is due to buyers being overly sensitive to making a "bad deal", a case where the object is sold far below market value. Sellers, by contrast, do not show this inflated degree of risk aversion, because they can

[3] Relatedly, it has been argued that the endowment effect might be the product of misunderstanding concerning experimental instructions (see Plott & Zeiler, 2005; though see Isoni et al., 2011 for conflicting findings). Somewhat inconsistent with both approaches, the classic endowment effect has been shown to occur even following repeated market trials (e.g., Kahneman et al., 1990; Knetsch, Tang, & Thaler, 2001), though some studies find that it is reduced when trials are repeated (e.g., Coursey et al., 1987; List & Shogren, 1999).

only gain from such a bad deal. Similarly, in the context of ambiguous lotteries (in which the probability of outcomes is not known), Trautmann, Vieider, and Wakker (2011) found that buyers tend to display extreme ambiguity aversion, and suggested that this reflects a bias on the part of buyers due to loss aversion for the ambiguous loss (see also Trautmann & Schmidt, 2012).

The notion that sellers are less biased than buyers is also implied by the loss attention model of Yechiam and colleagues (e.g., Yechiam & Hochman, 2013a,b). In a review of the literature, Yechiam and Hochman (2013a) showed that many of the behavioral differences observed between tasks with gains and losses can be understood as resulting from the fact that losses lead to greater task attention. For instance, individuals were found to exhibit increased autonomic arousal following losses, as evidenced by an increased heart rate and pupil diameter (Satterthwaite, et al., 2007; Hochman & Yechiam, 2011; Yechiam, Telpaz, & Hochman, 2014), and this was associated with increased accuracy (Yechiam, Retzer, Telpaz, & Hochman, 2015). Also, individuals were found to invest more time and provide more elaborate responses in tasks that include losses (Porcelli & Delgado, 2009; Xue et al., 2009; Yechiam & Telpaz, 2013). To the extent that sellers are more likely to frame the transaction in a loss-like manner (Kahneman et al., 1990), they might show greater accuracy (i.e., less pricing bias) than buyers due to increased attention to the task, as found in other tasks involving losses. Note that this prediction is opposite to the one following from a "strict loss aversion" account, according to which sellers (but not buyers) are biased, and, all things being equal, should provide prices that are further away from the normative price of the object.

Another prediction implied by the loss attention account is that accuracy differences between buyers and sellers should be reduced when attention to the task is increased (as implied by the diminishing marginal benefit of attentional investment under the Yerkes-Dodson curve; see Kahneman, 1973; Yechiam & Hochman, 2014).[4] Attention could be increased, for instance, by incentivization (e.g., Baumeister, 1984; Ashton, 1990; Libera & Chelazzi, 2006; Ariely, Gneezy, Loewenstein, & Mazar, 2009). On the other hand, incentivization may also elevate concerns of social desirability and self-presentation (see e.g., Vieider, 2012) and trigger emotional reactions that increase heuristic processing (Rottenstreich & Hsee, 2001; Pachur, Hertwig, & Wolkewitz, 2014). These processes can decrease accuracy (e.g., Trautmann, Vieider, & Wakker, 2008), which could mask or interfere with the effect of incentivization on attention. To test these contrasting predictions in our meta-analysis, we examined the moderating effect of incentivization (e.g., using the Becker, DeGroot, and Marschak, 1964, procedure) on buyer-seller differences in accuracy.

In summary, the various accounts discussed in this section differ widely with regard to whether an endowment effect is expected to emerge for monetary lotteries and whether the price gap is due to a bias on the part of sellers or buyers (as indicated in Table 1).

[4] Kahneman's (1973) model of attention predicts that task attention has an inverted U-shaped effect on task performance (following Yerkes & Dodson, 1908). Accordingly, a manipulation that increases attention should influence particularly those individuals who initially allocated little attention. Consequently, individual difference in performance due to attention investment should be reduced (see Yechiam & Hochman, 2014, Figure 1).

Previous Studies of Pricing Bias and the Present Analysis

Few empirical studies have attempted to address the question of whether buyers or sellers are more biased. Using consumer products as stimuli, Novemsky and Kahneman (2005) compared selling and buying behavior to participants' choices between an object and varying amounts of money. Choice equivalents for the objects in the latter condition were determined as the midpoint between the lowest monetary amount accepted and the highest amount rejected. As it turned out, buying prices were close to the choice equivalents, with both being well below the sellers' prices. This might suggest that sellers are more biased in comparison to individuals making pricing choices with no trading perspective (this finding was not replicated, however, by Knutson et al., 2008, or by Ashby, Glöckner, and Dickert, 2011).

Other studies, using monetary lotteries as stimuli and different approaches reached opposite conclusions. In their pioneering study, Knez, Smith, and Williams (1985) first asked their participants to provide the lowest selling price they would consider and the highest buying price they would consider for a lottery. Participants then made repeated market decisions, involving the possibility to make selling and buying bids for this lottery. As it turned out, selling bids deviated less frequently from the initially stated selling price than buying bids did from the initially stated buying price (34% versus 47%). This suggests that selling prices reflect an object's actual worth more accurately than buying prices. In another study, De Martino, Kumaran, Seymour, and Dolan (2009) found that selling prices were closer to a price that participants provided after careful deliberation (which in turn was close to the object's expected value) than buying prices were.

In light of these mixed findings, in the current meta-analysis we took a different approach to evaluate the accuracy of buying and selling prices. Instead of examining the similarity of buying and selling prices to subjective prices elicited in a different (non-trading) context, we used the deviation of the prices from the expected values of the traded lotteries as a measure of accuracy. The expected value is commonly considered as the normative price for a risky lottery (Edwards, 1954; Kahneman & Tversky, 1979; and see also Wedell & Bockenholt, 1990; Knutson, Taylor, Kaufman, Peterson, & Glover, 2005; Levin, Weller, Pederson, & Harshman, 2007). If decisions are elicited in the context of an incentive-compatible mechanism (under which a decision maker has no incentive to under- or over-price an object relative to one's actual subjective price), then any deviation from the expected value means that the decision maker will lose money in the long run. To maximize payoff in this case, a price should therefore approximate the expected value of a lottery as closely as possible.

We used two indices of accuracy that are based on this approach. The first is the absolute deviation of prices from the expected value of the lottery (i.e., *absolute accuracy* with respect to expected value). A possible problem with interpreting this index is that it is sensitive to changes in the mean level of prices due to risk aversion (i.e., reduced sensitivity to outcome as a function of its size), which may mask the effect of other biases.[5]

[5] For instance, assume that both buyers and sellers are subject to risk aversion, which leads to a downward bias on their mean pricing decision (as suggested by Barkan, Danziger, Ben-Bashat, & Busemeyer, 2005; Carpenter, Verhoogen, & Burks, 2005). At the same time, sellers might also show a bias due to loss aversion, which increases the mean price. Because of the simultaneous negative and positive bias, sellers' mean prices may be on the mark in terms of expected value, and thus in theory they may be normatively correct, although they are still cognitively biased.

Second, we also examined *relative accuracy,* an index used in the marketing literature for assessing pricing accuracy (Conover, 1986; Monroe & Lee, 1999). It is defined as one's sensitivity (expressed in the price provided) to the objects' rank order determined according to their expected value, and is typically measured by the rank correlation between a series of indicated and expected prices (Conover, 1986). Akerlof (1970) argued that due to information asymmetry, sellers often rank traded objects more accurately than buyers, leading to a trading advantage. A feature of the relative accuracy index is that on the one hand, if the price provided is close to the expected value, then it will show higher relative accuracy. On the other hand, this index is relatively robust to deviations of the mean in the studied conditions, for instance due to risk aversion, since the correlational measure is unaffected by the mean (except for the case of a ceiling or a floor effect, which leads to a reduced range).

In addition, we compared the variability of buying and selling prices across people. Variance across different individuals' prices results both from individual differences in how an object is subjectively valued and from noise (error). Assuming no disparity between sellers and buyers in the former, higher accuracy will also lead to lower variance. We therefore analyzed differences in the pricing variance across participants, as well as differences in variance per-unit (coefficient of variation), a measure of variance that is insensitive to disparities in mean price level between perspectives (e.g., the endowment effect).

Finally, to examine the psychological origins of buyer-seller gaps in pricing level and accuracy, we modeled the pricing decisions with *cumulative prospect theory* (CPT; Tversky & Kahneman, 1992) and specifically its typical reduction for positive outcomes,

which is formally equivalent to a rank-dependent utility model (Quiggin, 1982). In brief, this model decomposes valuations of risky options in terms of the decision maker's degree of (a) outcome sensitivity, captured by parameter α, that also indicates the amount of risk aversion (values of $\alpha < 1$ indicate risk aversion and values of $\alpha > 1$ indicate risk seeking); and (b) probability sensitivity, captured by parameter γ (with values deviating from 1 indicating increasingly lower probability sensitivity). In addition, we estimated a noise parameter σ, and a response bias parameter β (see Appendix section for details). All four parameters were estimated separately for buying and selling prices, allowing us to assess differences between perspectives.

Present Meta-Analysis

To find relevant articles, we employed both ISI Web of Science and Google Scholar, using the keywords "WTA" (Willingness to Accept), "WTP" (Willingness to Pay), and either "lottery" or "gamble" (last search May 2016). We also submitted announcements to the mailing lists of the Judgment and Decision Making Society and of the Economic Science Association. Additionally, we included all of the articles reported in a recent meta-analysis on buyer-seller differences in pricing (Tuncel & Hammitt, 2014). No restrictions were applied in terms of language and foreign abstracts were translated.

The following eligibility criteria were used: With respect to *study type*, we included only studies that compared buying and selling prices (i.e., we excluded studies that examined only selling or only buying prices), and where the same lotteries were used to elicit both. We did not include conditions in which participants had to choose between

a lottery and a monetary amount (since this is neither buying nor selling). No publication date or publication status restrictions were imposed. With respect to *types of participants*, we included all participants, and all incentivization methods.

With regard to *types of outcome measure*, we included all studies where participants were required to provide prices for lotteries that offered some monetary outcome at some probability (ranging from 0 to 1). We only included studies in which the outcome was monetary (i.e., we excluded studies with non-monetary objects, such as consumer products). Additionally, we only included studies where participants were provided with explicit information about probabilities and outcomes (thus excluding uncertain or ambiguous monetary lotteries). Finally, we did not include studies in which the response scale constrained the indicated price below the expected value of the object (thereby setting an artificial boundary to the gap in pricing) or where the scale was different for sellers and buyers. Methods of the analysis and inclusion criteria were specified in advance and documented. Eligibility assessment was performed independently in an unblinded standardized manner by two authors. Disagreements were resolved by consensus.

We used a data extraction protocol based on the Cochrane Consumers and Communication Review Group's data extraction template. One author extracted the data from included studies and the other author checked the extracted data. If buying or selling prices were not provided in an article, we requested the data from the corresponding author. If we obtained no response and none of the relevant indices was reported (i.e., neither WTA and WTP, nor their ratio WTA/WTP), then the article was not included.

Information was extracted from each included study with regards to: (1) The traded lotteries (probabilities and outcomes, number of lotteries, currency, and format, e.g., as a lottery or a bargaining chip), (2) whether incentivization was provided or not, (3) participants' pricing decisions, and (4) sample size. The primary dependent variables were sellers' and buyers' pricing decisions. Additionally, each article was reviewed to determine whether participants were randomly allocated to the buying and selling conditions or not.

Based on participants' pricing decisions, we calculated the following indices: a) absolute accuracy – defined as the discrepancy of prices from the expected value of the respective lottery, b) relative accuracy – defined as the rank correlation between pricing decisions and the lotteries' expected values, calculated for each participant. Additionally, we included two second-order indices, namely, the variance across participants' pricing decisions and the variance per unit (i.e., coefficient of variation).

We further examined the moderating effect of incentivization (e.g., with the Becker, DeGroot, and Marschak, 1964, or *BDM* procedure). Additionally, for the endowment effect we examined the moderating effect of price level (across the buying and selling conditions). In order to test for potential publication biases, we plotted the effect size (standardized mean difference) of each study by its respective standard error. The symmetry of such 'funnel plots' indicates whether there is a publication bias in favor of studies with higher standard errors (Egger, 1997). This examination was conducted using the *metafunnel* and *metabias* commands in STATA.

The meta-analysis was based on all relevant studies reported in the included articles. To examine the differences between buying and selling prices and between these

prices and the lotteries' expected value, we used the Mantel-Haenszel method (Mantel & Haenszel, 1959; Greenland & Robins, 1985), which is a corrected inverse variance procedure. For the comparison of prices between conditions and the examination of the effect of incentivization we used STATA's *metan* command developed by Harris et al. (2008), with default settings (i.e., assuming fixed effects and using Cohen's estimate of standardized effect size) and stratified by whether incentivization was provided or not. For studying continuous moderating effects (of price level) we used STATA's *metareg* command originally developed by Sharp (1988; see also Harbord & Higgins, 2008), with default settings. However, because in the latter analysis the within-study standard error could not be estimated, we instead used the inverse mean sample size over conditions within study *j*: $1/((N_{j,s} + N_{j,b})/2)$; the subscripts *s* and *b* are used to refer to sellers and buyers, respectively. Finally, for comparing the relative accuracy of prices across studies we used a multi-level modeling framework. This analysis was conducted for those studies for which raw data were available, and is recommended over standard meta-analytic summary in this case (Hedges & Olkin, 2014; Erez, Bloom, & Wells, 1996). Non-parametric tests were used to compare the variance in the buying and selling conditions across studies.

On the basis of our search and inclusion criteria, we identified 35 articles, encompassing a total of 45 studies published between 1967 and 2016. Figure 1 provides a complete flow diagram of the search process (as prescribed in Moher, Liberati, Tetzlaff, & Altman, 2009). One article that met all inclusion criteria but where there was no randomization (selling condition always followed the buying condition in a within-subject design) was excluded (Shavit, Sonsino, & Benzion, 2002). The 35 analyzed

articles included 3,469 participants providing selling prices and 3,452 participants providing buying prices. The studies included both between-subject and within-subject designs, as well as both hypothetical and incentivized decisions. The data reported in Table 2 is averaged across different lotteries administered to the same participants; between-subject conditions are noted. In addition, we were able to obtain raw data for 13 studies – five of which have not yet been published – allowing for in-depth analyses.

As shown in Table 2, from the 45 studies two only reported the WTA/WTP ratio (which will be denoted as ψ), and additional data was not available from the authors. Therefore, while the examination of ψ included all 45 studies, for the examinations of the difference between WTA and WTP, as well as their differences from the expected value, the analysis incorporated 43 studies.

Selling Prices Exceed Buying Prices

Figure 2 shows the effect sizes of the discrepancies between selling and buying prices. As can be seen, in almost all studies selling prices are higher than buying ones, with an overall standardized mean difference (i.e., Cohen's d) of .58 ($CI_{95\%}$[.53, .63], $p <$ .001; see Figure 2). The mean ratio of the selling/buying price ψ was about 2 ($M = 2.01$; $CI_{95\%}$ [1.59, 2.44]). There was no effect of incentivization on the standardized mean difference ($SMD_{unincentivized} = .58$, $CI_{95\%}$[.42, .64]; $SMD_{incentivized} = .57$, $CI_{95\%}$[.48, .65]). We also assessed the amount of heterogeneity in the studies (Higgins & Thompson, 2002; Higgins, Thompson, Deeks, & Altman, 2003), which was considerable ($I^2 = 86.3\%$); no significant difference in heterogeneity between unincentivized and incentivized studies was observed ($p = .79$).

As can be seen in Table 1, a few articles did not report standard deviations of the pricing decisions and it was impossible to recover this information. In these cases we used mean imputation, a procedure known to return accurate results (Furukawa et al., 2006). Furthermore, excluding these studies yielded highly similar results (standardized mean difference = .75, $CI_{95\%}$[.69, .82], $p < .001$), except that the effect of incentivization was significant, indicating that the difference between selling and buying prices was larger when incentivization was not provided ($SMD_{unincentivized} = .84$, $CI_{95\%}$[.75, .92]) relative to when it was ($SMD_{incentivized} = .63$, $CI_{95\%}$[.53, .72].

Additionally, we tested the robustness of ψ to varying price levels (i.e., the average of the nominal buying and selling prices). Note that the absence of an effect of price level on ψ implies that the difference between buying and selling prices increases proportionally with increasing price level. This pattern is observed in the data: For example, in Table 2 there is a correlation of 0.55 ($p = .0001$) between the averaged buying and selling prices (i.e., price level) and the difference between buying and selling prices. To test whether there is nevertheless a moderating effect of price level on ψ, a meta-regression was conducted. As expected, no significant effect of price level was found ($p = .11$). An examination of publication bias was conducted using Egger's method (Egger, 1997). As shown in the left panel of Figure 3, no asymmetry was visually apparent and no significant publication bias was detected ($p = .85$; Egger, 1997).

Selling Prices are Closer to the Expected Value

To quantify the amount of bias in selling and buying prices, we first compared the prices to the lotteries' expected values. Table 2 shows the average expected value for the

various lotteries in each study. As can be seen in the rightmost columns of Table 2, in 32 of the 41 experimental studies for which WTA, WTP, and expected value were reported, the prices set by sellers tended to be closer to this normative standard than the prices set by buyers.

In order to corroborate this pattern statistically, and to test for a moderating effect of incentivization, we performed a similar meta-analysis as we had with the difference in buying and selling prices. In contrast to the previous analysis, we now predicted the absolute deviation of buying and selling prices from the expected value, imputing mean standard deviations where they were missing as in the previous analysis. Figure 4 presents the difference between the absolute distance of the selling price from the expected value and the equivalent distance of the buying price (a negative effect size implies a smaller distance from the expected value for sellers). Our analysis showed that selling prices were closer to the normative standard than buying prices: The overall standardized mean difference (Cohen's d) was -.44, $CI_{95\%}$[-.49, -.38, $p < .001$; see Figure 4). Importantly, however, there was also an effect of incentivization, with the difference between selling and buying prices in accuracy being substantially larger in studies in which no incentivization was provided ($SMD_{unincentivized} = -.57$, $CI_{95\%}$[-.64, -.50]) compared to those that provided incentivization ($SMD_{incentivized} = -.23$, $CI_{95\%}$[-.31, -.15]).

There was considerable heterogeneity across studies ($I^2 = 89.8\%$), and this held both for studies with incentivization ($I^2 = 88.9\%$) or without incentivization ($I^2 = 89.0\%$), $p < .001$. As for the gap between buying and selling prices analyzed in the previous section, we tested whether there was a publication bias for the pattern that selling prices deviate less from the expected value than buying prices. As shown in Figure 3, there was

no asymmetry in SMDs and thus as outlined in the preceding section, no evidence for a publication bias (p = .65).

Sellers Show Higher Relative Accuracy

Another facet of the accuracy of pricing decisions is relative accuracy, the degree to which participants rank objects according to their expected value (Conover, 1986; Monroe & Lee, 1999). A rigorous statistical test of relative accuracy requires individual-level (raw) data and thus could be conducted only for a subset of the studies reported in Table 2. Yechiam et al. (in press) examined relative accuracy differences between buyers and sellers for the data of Pachur and Scheibehenne (2012) and Ashby et al. (2012). In the current review we also include the data from Birnbaum and Yeary (1998), Ashby et al. (2011, unpublished), Shahrabani et al. (2008a), Yechiam et al. (in press), and Abofol (2016, unpublished). Relative accuracy was determined for each individual participant by calculating the rank correlation (i.e., Spearman's ρ) between the indicated price and the expected value of each lottery. If a person correctly orders the lotteries by their expected values, then this produces a ρ^2 of 1 and an error rate (ε) of 0 (where $\varepsilon = 1 - \rho^2$).[6]

Table 3 reports the mean ε by condition for each of the 10 studies for which raw data was available and multiple lotteries were priced. In all of these studies ε was smaller for sellers than for buyers, reflecting higher relative accuracy for sellers. To quantify this effect, we performed a meta-analysis using a multi-level modeling framework. Specifically, we predicted ε by condition on Level 1, with a random effect of study on Level 2, and with a random effect of subject nested within studies, allowing slopes and

[6] In order to calculate ε, we estimated ρ^2 for each participant, separately by condition and block (where relevant), and then averaged across participants and conditions.

intercepts to vary between subjects, and employing robust standard errors. Because raw data was only available for a subset of the studies in Table 2 we could not examine moderating effects (e.g., incentivization) in a robust manner.

As expected, there was a significant effect of condition, with sellers showing lower ε than buyers, $b = .03$ ($CI_{95\%}$ [.02, .05]), $z = 4.50$, $p < .001$. Thus, it appears that in line with the results of Yechiam et al. (in press), sellers show a small, though robust, advantage over buyers not only in making pricing decisions that are closer to the expected value, but also in terms of how their pricing decisions are correlated with the normative ranking of the lotteries. Furthermore, we find the random effect of study to be significant (random effect estimate = .10, $CI_{95\%}$ [.06, .18]), indicating the presence of heterogeneity between studies and hinting that future examinations of this effect might look for potential moderating factors.[7]

Sellers Show Higher Variance but Lower Variance per Unit

As indicated in Table 2, in 18 out of the 25 studies in which standard deviations for the prices were reported, they were *higher* for sellers than for buyers (two-tailed binomial test against 50%, $p = .04$). This could be the result of higher random error (or bias) in individual participants' selling prices (inconsistently with the notion that sellers provide more accurate prices). Alternatively, the differences in variance might simply be the result of the tendency of selling prices to be higher than buying prices. Generally,

[7] For the data in Table 3, there was a positive correlation (on average) between ε and absolute accuracy, both for both sellers ($r = .58$; $CI_{95\%}$ [.40, .75]) and buyers ($r = .53$; $CI_{95\%}$ [.24, .81]), indicating that the indices of absolute and relative accuracy are correlated. This was also confirmed in a multi-level analysis as above, regressing ε on absolute accuracy and condition, as well as their interaction. The effect of absolute accuracy was significant, indicating a positive relationship between ε and absolute accuracy, $b = .01$ ($CI_{95\%}$ [.002, .019]), $z = 2.50$, $p = .01$. Neither the effect of condition nor its interaction with absolute accuracy was significant, ps > .39.

higher values are associated with greater variance (Bedeian & Mossholder, 2000; Weber, Shafir, & Blais, 2004), a well-known phenomenon that forms the basis for variance-stabilizing transformations (Dodge, 2003). Consistent with the latter interpretation, for the studies reporting standard deviations in Table 2, the mean buying and selling price and the pooled standard deviation of buying and selling prices were positively correlated ($r = 0.77$, $p < .001$).

One way to further distinguish between the two interpretations for the higher standard deviations of selling prices is to examine differences in variance calculated *per unit*. The variance per unit is also known as the coefficient of variation (CV; sometimes referred to as the relative standard deviation). It is calculated by normalizing the standard deviation by the average of each group (e.g., in a study j, $CV_{j,s} = SD_{j,s}/Mean_{j,s}$), with larger scores reflecting higher variance. In 88% of the studies that reported standard deviations in Table 2, the CV was lower for sellers than for buyers (two-tailed binomial test against 50%, $p < .001$). This suggests that sellers not only provide more accurate prices, but also show lower dispersion per unit in pricing.

Analyzing Buying and Selling Prices with Cumulative Prospect Theory

For the CPT analysis, we focused on the studies listed in Table 3, for which raw data were available.[8] Further, we only considered responses for lotteries producing gains and therefore excluded the lotteries incurring losses in Shahrabani et al. (2008a). Overall, the analysis involved 10 studies. The parameter estimation was conducted using a

[8] We also conducted the analyses including the studies by Trautmann and Schmidt (2012), Trautmann et al. (2011, Study 1 & 8) and Wieland et al. (2014, Study 2), for which raw data were available as well. The parameter estimation, however, did not show acceptable convergence (indicated by the Gelman-Rubin statistic > 1.1; see Kruschke, 2014). This is likely due to the fact that these studies used only a single identical lottery for all participants.

hierarchical Bayesian approach (e.g., Kruschke, 2014; Scheibehenne & Pachur, 2015), which yields posterior distributions of the parameters. More details, including a formal description of the model implementation, can be found in the Appendix.

Table 4 reports the medians of the posterior distribution of the study-level means for each of the four parameters, separately for selling prices (WTA) and buying prices (WTP). As can be seen, although there was some variability across studies, the results indicate that overall, sellers showed a clear tendency for risk seeking (indicated by the α parameter being > 1), whereas buyers showed a clear tendency for risk aversion (indicated by the α parameter being < 1). Further, there were also differences on the γ parameter, with sellers showing higher probability sensitivity (indicated by a higher γ). Finally, sellers and buyers also differed on the response bias parameter β, which was consistently and considerably more pronounced (and negative) for buyers than for sellers.

To obtain a better understanding of the origins of the buyer-seller differences in accuracy (i.e., deviation from the lotteries' expected value), we calculated how strongly the parameters estimated for the buying and selling price conditions deviated from the parameters of an unbiased model –that is, one that produces the expected value without error (with $\alpha = 1$, $\gamma = 1$; $\sigma = 0$, and $\beta = 0$). Figure 5 plots the differences between the buying and selling conditions in the absolute deviation for each of the parameters. Overall, the analyses suggest that although sellers deviated from the unbiased model more in terms of risk aversion (α), this was apparently more than compensated by buyers' stronger deviation on probability sensitivity (γ) and response bias (β). That is, buyers' lower pricing accuracy seems to be driven by their lower probability sensitivity and a

stronger distortion of their subjective valuation of a lottery when translating it into a response.

With respect to probability sensitivity, note that for moderate to high probabilities the lower probability sensitivity on the part of buyers implies stronger underweighting of these probabilities, which is conducive to a buying price that is lower than the expected value of the lottery; for lotteries with rare events (i.e., that have a low probability), in contrast, reduced probability sensitivity implies stronger overweighting of these events, which can lead to a buying price that is closer to the expected value. Indeed, a review of Table 2 shows that in the common case where sellers were closer to the expected values, 23 out of 32 studies involved lotteries with moderate to high probabilities (i.e., ≥ 0.4). By contrast, from the 9 studies where buying prices were closer to the expected value mark, 7 involved lotteries with low probabilities (i.e., < 0.4), $\chi^2 = 7.28$, $p = .007$. Thus, the difference between buyers and sellers in probability sensitivity points to a boundary condition for the absolute accuracy advantage of sellers, which seems to be more pronounced for lotteries with medium to large probabilities.[9]

Discussion

Using a meta-analytic approach, we examined whether a gap between buying and selling prices – which is usually studied in the context of consumer products (see e.g., Sayman, & Öncüler, 2005; Tuncel & Hammitt, 2014) – also exists for well-defined monetary lotteries. Our review and analyses highlight that for lotteries there is a considerable gap in prices between sellers and buyers, consistent with the endowment

[9] Still, this conclusion should be cautiously stated because the latter post-hoc analysis pools together studies that used a single lottery and studies with multiple lotteries as well as studies with one possible outcome versus those with multiple outcomes (across which the probability is averaged).

effect. This implies that the endowment effect emerges even when the endowed object has only monetary consequences, speaking to the robustness of the effect.

While the classical view of the endowment effect suggests that the bias is on the side of sellers (Thaler, 1980; Kahneman et al., 1990), our findings highlight that for lotteries sellers actually showed higher accuracy in pricing than buyers, in several respects. First, they exhibited higher absolute accuracy: There was closer alignment of selling prices with the lotteries' expected values. Second, sellers exhibited higher relative accuracy, indicating higher sensitivity with regard to differences in the expected values of lotteries. Third, sellers showed lower dispersion per unit of pricing.

Finally, we found evidence that these effects were moderated by whether the pricing task was incentivized or not. Specifically, under incentivization the distance between selling and buying prices was reduced, suggesting that strategic influences exacerbate the gap between sellers and buyers (Brookshire & Coursey, 1987; Hausman, 2012).[10] Additionally, the divergence of buyers' and sellers' pricing decisions from the expected value was smaller under incentivization. Importantly, though, even under incentivization, both the discrepancy between buying and selling prices and the buyer-seller differences in accuracy were robust and sizeable.

Our analysis indicates that for monetary lotteries divergences between pricing decisions of buyers and sellers occur on a broader scale than suggested in the literature. Most previous analyses of buying and selling prices have focused on the finding that sellers attach a higher value to objects than buyers (i.e., the endowment effect; see

[10] Note, however, that this was found only for the subset of studies that reported indices of variance. Moreover, incentivized studies may have used lotteries with lower expected values, and this might have contributed to the difference between studies due to incentivization (however, we did not find a general effect of price level on the size of the endowment effect).

reviews in Horowitz & McConnell, 2002; Rick, 2011). Extending this focus, we highlight additional disparities between buyers and sellers that occur simultaneously with the endowment effect and have a clear impact on the price elicited.

Possible Causes for the Buyer-Seller Gap in Pricing Accuracy

As noted above, one possible reason for the differences between buyers and sellers in accuracy is that the former are more risk averse than the latter (Yang et al., 2013). Our CPT analysis indeed revealed stronger risk aversion for buyers (Table 4), indicating that this is one of the factors that pulls buying prices down. Nevertheless, this analysis also showed that sellers had a commensurate degree of risk seeking (see Table 4 and Figure 5). As such, differences in risk attitude cannot explain sellers' greater absolute accuracy. However, the CPT analysis pointed out two other aspects in which buyers were indeed more biased than sellers: a) they showed lower probability sensitivity, implying more pronounced underweighting of events with medium to high probability; and b) a more pronounced (negative) response bias.

Yang et al. (2013) suggested when an object is highlighted as involving risk (e.g., in the common labeling of a risky option as a lottery ticket or a gamble) buyers are driven by an aversion to making a "bad deal". Arguably, such an aversion might lead to a reduction of the price irrespective of risk level. This interpretation of Yang et al.'s account seems consistent with our finding of a more pronounced response bias for buyers, which implies reduced prices irrespective of risk level.

Another approach to explain the buyer-seller differences we identified is Yechiam and Hochman's (2013a) loss attention account, according to which sellers might be more

sensitive to the incentive structure because they perceive the transaction as a possible loss. In principle, this could explain why sellers showed higher accuracy, and why the difference between perspectives in terms of accuracy was reduced in studies where participants were incentivized. This account is also in line with the higher probability sensitivity found for sellers.

The loss attention approach is also attractive because it points to possible mediators and boundary conditions that could be tested in future research. Specifically, Yechiam and Hochman (2013a) suggested three mediators for the effect of losses (see also Porges, 1992): i) Increased energetic investment (e.g., autonomic arousal), ii) increased deliberation time, and iii) strategic changes that promote continued investment of attention (e.g., a person leaning forward in her chair which in turn strengthens attention). With respect to the endowment effect, the only mediating factor that has been investigated so far is deliberation time. In two studies Yechiam et al. (in press) found that sellers take longer to provide a price than buyers, suggesting that they deliberate more (this was replicated by Abofol, 2016, while a re-analysis of Ashby et al., 2011 does not indicate a significant difference between buyers and sellers in response time). Yechiam et al. (in press) also found that the accuracy difference between buyers and sellers was reduced in tasks where participants were encouraged to deliberate, suggesting that the effect is driven by a disparity in the spontaneously allocated deliberation time. Potentially, other manipulations that increase task attention (see Bateman, Day, Jones, & Jude, 2009; Engelmann & Hollard, 2010) may have a similar effect of reducing the accuracy gap.

Might the Buyer-Seller Gap in Accuracy Generalize to Consumer Products?

As pointed out in the introduction, our review focused on buyer-seller differences in pricing of monetary lotteries, thus allowing an assessment of the accuracy of buying and selling prices. Can the current findings – particularly the increased accuracy found for sellers on various indices – be generalized to consumer products, the domain in which the endowment effect was originally discovered? Yang et al. (2013) proposed that highlighting the risk component of an object is essential for the tendency of buyers to considerably pull down the price, which suggests that the bias on the part of buyers is not likely to emerge for consumer products. On the other hand, if accuracy differences are due in part to reduced probability sensitivity for buyers, as we observed, then it might be argued that they are relevant to consumer products as well, as they might or might not meet one's expectations. Furthermore, if the difference between sellers and buyers is more general, such as reflecting differences in attentional investment, then a decreased bias for sellers should also emerge in the pricing of consumer products.

As noted above, although it is difficult to assess accuracy for consumer products in an absolute sense, one can examine the sensitivity to changes in features of the traded objects. Several experiments in this domain have found that sellers are more sensitive to variance in relevant features of the object, which is consistent with higher pricing accuracy on their part (Carmon & Ariely, 2000; Nayakankuppam & Mishra, 2005; Weaver & Frederick, 2012; Irmak, Wakslak, & Trope, 2013). For example, Weaver and Frederick (2012) observed that sellers are more sensitive to differences in store-price labels for a given product. Carmon and Ariely (2000) found that selling prices of baseball tickets were more closely related than buying prices to the relevant properties of the

tickets, such as game significance and whether a participant had tracked the team throughout the season.

The current findings are also consistent with the main results of studies on "coherent arbitrariness" (e.g., Ariely, Loewenstein, & Prelec, 2003; Simonson & Drolet, 2004, Tufano, 2010; Fudenberg, Levine, & Maniadis, 2012). In these studies, participants are asked to make pricing decisions after having been exposed to an arbitrary number (e.g., the last two digits of a person's social security number). Buyers are typically more affected by such arbitrary values than sellers (Simonson & Drolet, 2004, Fudenberg et al., 2012; Maniadis, Tufano, & List, 2014; but see also Sugden, Zheng, & Zizzo, 2013). Thus, buyers seem more easily distracted by off-task cues, which can lead them to err in their assessments of worth.

Another context in which buyers' lower accuracy in pricing may come into play during trading is overbidding in auctions. Overbidding is commonly exhibited by buyers (Kagel & Levin, 1993). For example, Malmendier and Szeidl (2008) found that in 43% of the eBay auctions they examined, the final price for an object was higher than the fixed price for which the same item was sold on the very same webpage at the same time.[11] Indeed, Malmendier and Szeidl (2008) demonstrated that auction markets are often designed to exploit the behavior of buyers, who strongly depart from rational behavior. While this and similar regularities have previously been attributed to an information asymmetry between buyers and sellers, our analysis suggests that they may be more prevalent and exist even when buyers and sellers have similar knowledge levels.

[11] Typically, overbidding is assumed to be a result of the inherent competition in auctions, or "auction fever" (Delgado, Schotter, Ozbay, & Phelps, 2008). Under the loss-attention account, this sort of competition is considered an off-task consideration, and it is assumed that for buyers such off-task considerations may bias the price to a greater degree than for sellers.

Limitations

One major limitation of our study is that our analysis of the accuracy of buying and selling prices relied on the expected value as a normative benchmark. Ceteris paribus, under conditions of incentive compatibility (e.g., the BDM procedure) setting a price at the expected value should in the long run maximize one's payoff. On the other hand, actual trading also involves social interaction. The eventual success of a bid depends on how the other party responds, and this can be influenced by one's stated price. Thus, it is possible that participants generalized strategies that they had previously (and successfully) used in social contexts to the laboratory context. This suggests that in future research it will be important to test whether buyers also show a greater bias (and perform worse than sellers) in real-world contexts, in which they barter with social agents. Although, as noted above, relative to sellers buyers seem to deviate more strongly from normative standards even in more applied settings (e.g., Simonson & Drolet, 2004, Fudenberg et al., 2012; Weaver & Frederick, 2012), this result should to be confirmed in carefully planned experiments.

Another limitation refers to the fact that due to the requirement of having data on the individual level, the analyses of relative accuracy and the CPT analyses could be conducted only for a subset of the studies. We cannot exclude that this subset is not fully representative of all included studies. Still, the conclusions drawn from the relative accuracy analysis and the CPT analysis were consistent with those drawn from the analysis of absolute accuracy (which was based on all studies), with both showing that selling prices were more aligned with the lotteries' expected values than buying prices.

Finally, as with any meta-analysis one should consider the possibility of a file-drawer effect. Our usage of Egger's analysis only partially protects us from this possibility by checking that the results are not due to an over-representation of small-sample studies (Egger, 1997). To counter the risk of a selection bias, we also included unpublished papers. Furthermore, given that with the exception of Yechiam et al. (in press) none of the articles included in our analysis had examined the accuracy of buyers' and sellers' pricing decisions, it seems unlikely that the data is censored based on null effects on the indices that we used to measure accuracy.

Conclusions

Our results confirm that even when buyers and sellers evaluate objects that have precisely quantified attributes – monetary lotteries – they price the objects considerably differently. In line with the endowment effect, which has often been demonstrated for consumer products, selling prices for lotteries were consistently higher than buying prices. Importantly, we also compared buying and selling prices to normative standards and found that selling prices more closely approximated both the value and rank of the lottery in terms of expected value. Selling prices of a lottery also exhibited lower per-unit variance than buying prices. Our modeling analyses with CPT showed that sellers had higher probability sensitivity and a lower response bias, suggesting that the differences in pricing are not simply a manifestation of buyers' extreme risk aversion. Overall, our review reveals several robust, but previously neglected, differences between buying and selling prices which suggest – inconsistent with the common loss aversion account of the endowment effect – that the psychological bias is on the part of the buyer.

Appendix: Modeling Buying the Selling Prices with Cumulative Prospect Theory

According to CPT, the subjective valuation, V, of a lottery with m outcomes $x_m > \ldots > x_1 \geq 0$ (as all studies included in our analysis involve lotteries with positive outcomes, we focus on the gain domain only) and corresponding probabilities $p_m \ldots p_1$ is given by

$$\mathrm{V} = \sum_{i=1}^{m} v(x_i)\pi_i \ . \tag{A1}$$

v is a *value function* satisfying $v(0) = 0$, which translates objective outcomes into subjective values. It is defined as

$$v(x) = x^{\alpha}, \tag{A2}$$

where parameter α governs the curvature of the value function. With values of $\alpha < 1$, the function is concave, indicating risk aversion, with values of $\alpha > 1$, the function is convex, indicating risk seeking ($\alpha = 1$ yields risk neutrality).

π is the decision weight of the outcome, which is a function of the outcomes' probabilities. The decision weights are defined as

$$\begin{aligned} \pi_m &= w(p_m), \\ \pi_i &= w(p_i + \ldots + p_m) - w(p_{i+1} + \ldots + p_m), \end{aligned} \tag{A3}$$

where w is the *weighting function*, which implements a rank-dependent translation of objective probabilities. The decision weights represent the marginal contribution of the outcomes' probability to the total probability of obtaining a better outcome. Several functional forms of the weighting function have been proposed. We used the one-parameter weighting function proposed by Tversky and Kahneman (1992), which is defined as

$$w(p) = \frac{p^{\gamma}}{(p^{\gamma} + (1-p)^{\gamma})^{1/\gamma}}\ , \tag{A4}$$

where the parameter γ governs the curvature of the weighting function. With values of γ < 1 the function is inverse S-shaped, indicating overweighting of small probability and underweighting of moderate to large probabilities. With values of γ > 1 the function is S-shaped, indicating underweighting of small probability and overweighting of moderate to large probabilities.

The pricing decisions were modeled by assuming that they were drawn from normal distribution with mean *V* and standard deviation σ. The parameter σ can thus be interpreted as the amount of unsystematic error in the response. To obtain predictions P for the pricing decisions on the monetary scale, we transformed the valuations using a response rule that is the inverse of the value function (Equation A2):

$$\mathrm{P} = \mathrm{V}^{\frac{1}{\alpha}} + \beta\ , \tag{A5}$$

where β is a constant, which can be interpreted as response bias (cf. Birnbaum & Beeghley, 1997; Birnbaum, Yeary, Luce, & Zhao, in press; Pachur & Scheibehenne, 2016). Overall, there were thus four parameters, estimated separately for buying and selling prices and for each participant: α, γ, β, and σ.

The parameters were estimated using a hierarchical Bayesian approach (e.g., Scheibehenne & Pachur, 2015). Bayesian parameter estimation yields a posterior probability distribution of each parameter and allows to quantify the most likely parameter value, as well as the uncertainty associated with the estimate (indicated by the dispersion of the distribution). The advantage of a hierarchical approach is that individual parameters are partially pooled through group-level distributions, thus improving the

reliability of the estimates compared to the traditional, nonhierarchical approach. The hierarchical structure was implemented such that individual-specific parameters were assumed to stem from an overarching distribution representing the level of each study (i.e., we assumed separate group-level distributions for each individual study). In addition, the study-specific parameters were assumed to stem from a second, overall group-level distribution (separately for buying prices and selling prices). To obtain overall estimates for the parameters (i.e., that aggregate across all studies), we repeated the analysis without the study level (but still estimating posterior distributions for each participant), thus obtaining a group-level distribution for each parameter, separately for buying and selling prices.

The priors for the individual-level parameters α, γ, and β were set to uniform probability distributions spanning reasonable ranges found in previous research. Specifically, the ranges were 0–2 for α and γ, and -20 to +20 for β. The study-level means of these parameters were assumed to be normally distributed, as were the means of the overall group-level means. For the latter, a mean of 0 and a variance of 1 were assumed. The parameters on the study level were linked with the individual level through probit transformations, yielding a range between 0 and 1 (Scheibehenne & Pachur, 2015; see also Rouder & Lu, 2005). In order to extend the range of these distributions from 0 to 2 for α and γ and -20 to +20 for β, we interposed an additional linear linkage function. The prior on the individual level for σ was assumed to be gamma distributed, with a mode on the study-level assumed to be drawn from a normal distribution and a standard deviation drawn from a gamma distribution. On the overall group level, the mean of the normal distribution was assumed to be drawn from a normal distribution with mean 0 and a

standard deviation of 1. For σ as well, the study level was linked with the individual level through a probit transformation, and the range was extended to be between 0–10 using a linear linkage function. The group-level priors of all standard deviations were gamma distributed, with uniform priors on the mode and standard deviation.

The joint posterior parameter distributions were estimated using Monte Carlo Markov Chain methods implemented in JAGS, a sampler that utilizes a version of the BUGS programming language (version 3.4.0) called from Matlab. We ran a total of 80,000 representative samples (distributed across 8 chains), which were drawn from the posterior distributions after a burn-in period of 1,000 samples in each chain. To reduce autocorrelations during the sampling process, we recorded only every 10th sample. The sampling procedures were efficient, as indicated by low autocorrelations of the sample chains, Gelman-Rubin statistics, and visual inspections of the chain plots.

Figure A1 shows the results of the posterior predictive check (e.g., Kruschke, 2014) of CPT. Displayed are the mean (across samples) predicted valuations (each dot represents an observed pricing decision) as a function of the observed buying prices (in blue) and selling prices (in red), separately for each of the 10 studies. As can be seen, the model captures the data rather well. To further evaluated the fit of the CPT model, we compared it to the fit of an EV model (i.e., with $\alpha = 1$, $\gamma = 1$, $\beta = 0$), in which only the noise parameter σ was estimated. As it turned out, the deviance information criterion (DIC; lower values indicate a better fit; see Spiegelhalter, Best, Carlin, & Van der Linde, 2002), an index of model fit that takes into account model complexity, was considerably lower for the CPT model than for the EV model, both for the selling prices (DIC = 105,182 vs. 123,725) and the buying prices (DIC = 90,464 vs. 134,659).

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Table 1. Theoretical predictions regarding the emergence of a price gap between sellers and buyers for monetary lotteries, and the assumed source of the bias (relative to the expected normative price).

Account	Predicted price gap for lotteries	Primary source of bias in pricing
Strict loss aversion interpretation – loss aversion for sellers (e.g., Kahneman et al., 1990)	No	Sellers
Relative loss aversion for sellers (e.g., Bateman et al., 2005)	Yes	Sellers
Mere ownership (e.g., Morewedge et al., 2009)	Yes	Sellers
Overgeneralization from real-world trading situations (e.g., Brookshire & Coursey, 1987)	Yes	No prediction
Varied attention to positive and negative features (e.g., Birnbaum & Stegner, 1979)	Yes	No prediction
Risk/loss aversion for buyers (e.g., Trautmann et al., 2012; Yang et al., 2013)	Yes	Buyers
Loss attention for sellers (e.g., Yechiam et al., in press),	Yes	Buyers (moderated by incentivization)

Table 2. Studies comparing selling prices (Willingness to Accept; WTA) and buying prices (Willingness to Pay; WTP) of monetary lotteries. The columns denote the format in which the object was presented (as a lottery or bargaining chip; *P* indicates the mean probability of gaining a reward), the sample size (N) for the WTA and WTP conditions, whether the study was incentivized, and mean expected value (EV) of the lottery (lotteries); followed by the mean WTA and WTP (with standard deviations in brackets), the ratio of these prices (ψ = WTA/WTP), and their absolute deviation (*D*) from the EV.

Study	Format (*P*)	$N_{WTA/WTP}$	Incentivized	EV	WTA	WTP	ψ	WTA-*D*	WTP-*D*
Coombs et al., 1967	Lotteries (0.50)	40/40	No	\$0.75	1.04	0.29	3.51	0.29	0.75
Knetsch & Sinden, 1984[B]	Lottery	64/64	No	*NA*	5.18	1.28	4.05	-	-
Harless, 1989	Lottery (0.50)	28/28	No	-\$0.17	*NA*	*NA*	2.73	-	-
Singh, 1991	Lottery (0.50)	231/231	No	\$2.5	*NA*	*NA*	1.27	-	-
Birnbaum & Sutton, 1992	Lottery (0.50)	100/100	No	\$54	52.25	42.66	1.22	1.75	11.34
Kachelmeier & Shehata, 1992, Group 7	Lottery (.50)	15/15	Yes	\$10.00	11.13	6.07	1.83	1.13	3.93
Kachelmeier & Shehata, 1992, Group 8	Lottery (.50)	13/13	Yes	\$10.00	10.60	5.12	2.07	0.60	4.88
Eisenberger & Weber, 1995,	Lottery (.50)	67/67	Yes	\$5.00	6.64	4.51	1.47	1.64	0.49
van Dijk & van Knippenberg, 1996[ψB]	Bargaining chip (1)	33/33[**]	No	*f* 3.50	3.76	3.05	1.23	0.26	0.45
Birnbaum & Beeghley, 1997	Lotteries (.33)	46/46	No	\$46.82	40.87	30.26	1.35	5.96	16.56
Mueser & Dow, 1997 [B]	Lotteries (.73)	134/134	No	\$4.56	4.94	3.57	1.38	0.38	0.99
Birnbaum & Yeary, 1998[R]	Lotteries (.33)	67/67	No	\$90.63	71.76 (23.30)	47.12 (28.89)	1.52	18.87	43.51
Borges & Knetsch, 1998, Study 1	Lottery (0.50)	28/28	No	\$10	10.50	5.43	1.93	0.50	4.57
Borges & Knetsch, 1998, Study 2	Lottery (1/participants)	45/45	No	*NA*	1.87	1.14	1.64	-	-

Weber et al., 2000	Lotteries (.50)	94/94	Yes	€ 50	52.63	44.93	1.17	2.63	5.08
Anderhub et al., 2001	Lottery (.50)	61/61	Yes	NIS 75	71.09 (10.99)	50.59 (9.02)	1.41	-3.91	24.41
Peters et al., 2003, Study 1	Lotteries (.28)	166/166	No	$15.13	9.98	5.77	1.73	5.15	9.36
Peters et al., 2003, Study 2	Lottery (.05)	56/56	Yes	$5.00	15.04	2.14	7.03	10.04	2.86
Peters et al., 2003, Study 3	Lottery (.05)	35/35	Yes	$5.00	18.41	2.19	8.41	13.41	2.81
Peters et al., 2003, Study 4	Lotteries (.07)	163/163	No	$2.96	4.24	2.43	1.74	1.28	0.53
Blondel & Levy-Garboua, 2004[B]	Lotteries (.62)	32/30	Yes	$4.87	5.47	2.67	2.05	0.60	2.20
van De Ven et al., 2005, Study 1[B]	Bargaining chip (*)	20/23	No	€5.50	5.58 (2.25)	1.91 (1.86)	2.92	0.08	3.59
van De Ven et al., 2005, Study 2[B]	Bargaining chip (1)	44/44**	Yes	€1.80	1.89 (0.14)	1.61 (0.31)	1.17	0.09	0.19
Shavit et al., 2006	Lotteries (0.33)	51/51	Yes	NIS 78	74.80 (18.08)	75.59 (15.89)	0.99 0.99	3.20	2.41
Traub & Schmidt, 2006	Lotteries (.40)	23/23	Yes	£20.50	19.46 (13.27)	15.13 (11.38)	1.88	1.04	5.37
Shahrabani et al., 2008[aψR]	Lotteries (.38)	51/51	Yes	NIS 71.52	75.52 (65.43)	69.93 (43.78)	1.08	4.00	1.59
Shahrabani et al., 2008b[ψ]	Lotteries (.33)	95/95	Yes	NIS 81.67	85.38 (72.17)	60.75 (30.22)	1.41	3.71	20.92
Okada, 2010[B]	Lottery (*)	47/51	Yes	$4.50	3.44	2.34	1.47	1.06	2.16
Shavit et al., 2010	Lotteries (.33)	86/86	Yes	NIS 25.33	27.19 (13.80)	26.20 (17.62)	1.04	1.86	0.87
Ashby et al., 2011, Study 2[BR]	Lotteries (.50)	29/30	No	€8.05	6.57 (3.05)	4.61 (2.62)	1.43	1.48	3.44
Ashby et al., 2011, Study 3[BR]	Lotteries (.50)	43/37	No	€8.05	6.21 (2.98)	3.88 (3.02)	1.60	1.84	4.17
Trautmann et al., 2011, Study 1 & 8[BR]	Lottery (.50)	90/59	No	€50.0	24.59 (6.69)	11.86 (6.82)	2.07	25.41	38.14
Ashby et al., 2012, Study 1[R]	Lotteries (.50)	84/84	No	$10.83	8.56 (8.37)	6.18 (7.08)	1.39	2.27	4.65
Ashby et al., 2012, Study 2[BR]	Lotteries (.46)	26/26	Yes	€4.38	5.13 (3.45)	2.78 (2.95)	1.85	0.75	1.60
Pachur & Scheibehenne, 2012***[R]	Lotteries (.37)	152/152	No	€28.18	28.66 (24.60)	19.47 (18.96)	1.47	0.48	8.71
Weaver & Frederick, 2012, Study 3a[B]	Lottery (.33)	77/77**	Yes	$0.83	1.08 (1.02)	0.70 (0.79)	1.54	0.25	0.13
Weaver & Frederick, 2012, Study 3b[B]	Lottery (.33)	184/184**	No	$83.0	55.67 (53.13)	19.67 (38.03)	2.83	27.33	63.33

Trautmann & Schmidt, 2012*MR*	Lottery (.50)	295/299	No	€50.0	49.43 (24.15)	26.71 (20.99)	1.85	0.57	23.29
Sugden et al., 2013*B*	Lottery (.33)	108/120	Yes	£6.2	6.11 (3.38)	2.19 (2.36)	2.79	0.09	3.92
Wieland et al., 2014, Study 2*BR*	Lottery (.50)	118/116	No	$50.0	40.77 (20.22)	18.50 (20.40)	2.20	9.23	31.50
Drouvelis & Sonnemans, 2015	Lotteries (.50)	114/114	Yes	€2.92	3.09 (1.26)	2.29 (1.10)	1.35	0.17	0.64
Abofol, 2016*R*	Lotteries (.37)	47/47	No	NIS 28.18	29.46 (6.59)	21.54 (6.33)	1.37	1.28	6.64
Bayrak & Kriström, 2016	Lottery (.50)	92/92	Yes	SEK 15	17.59 (7.17)	12.88 (7.60)	1.34	2.59	2.12
Yechiam et al., 2016, Study 3BR	Lotteries (.37)	27/27	No	NIS 28.18	29.49 (24.41)	19.69 (19.74)	1.49	1.31	8.49
Yechiam et al., 2016, Study 4R	Lotteries (.37)	48/48	No	NIS 28.18	28.96 (25.31)	21.86 (19.73)	1.32	0.78	6.32

* - In these experiments the lottery involved a random chance to get a value in a certain range.
** - Equal sample sizes assumed, as only total *N* was reported.
*** - We include only those valuations that were made when full descriptive information was provided.
ψ - This study included binomially distributed probabilities.
NA – Not available
B – Indicates a between-subject design.
M – Indicates a mixed (i.e., between-within) subjects design or where both between-subjects and within-subjects designs were run in the same study and are reported averaged across the two.
R – Indicates raw data was available.

Table 3. Mean error (ε) for selling prices (WTA) and buying prices (WTP) and the correlation between the absolute accuracy and ε (*D*ε) by study and condition; 95% confidence intervals are in brackets.

Study	WTA ε	WTP ε	WTA *D*ε	WTP *D*ε
Birnbaum & Yeary, 1998	.79 (.74, .85)	.80 (.75, .85)	.12	.05
Shahrabani et al., 2008a	.29 (.24, .35)	.32 (.26, .39)	.19	.29
Ashby et al., 2011, Study 2	.90 (.85, .95)	.93 (.88, .98)	.53	.51
Ashby et al., 2011, Study 3	.92 (.89, .95)	.95 (.93, .97)	.55	-.29
Ashby et al., 2012, Study 1	.27 (.22, .31)	.29 (.25, .33)	.76	.69
Ashby et al., 2012, Study 2	.38 (.29, .48)	.42 (.34, .49)	.80	.85
Pachur & Scheibehenne, 2012*	.08 (.07, .09)	.14 (.12, .15)	.70	.82
Yechiam et al., 2016, Study 3	.07 (.06, .09)	.19 (.13, .26)	.72	.63
Yechiam et al., 2016, Study 4	.14 (.10, .19)	.16 (.12, .20)	.75	.89
Abofol, 2016	.09 (.07, .12)	.13 (.10, 16)	.63	.82

* - Only including valuations made when full descriptions were provided for consistency across studies.

Table 4. Medians (95% highest density intervals are in brackets) of the posterior distribution of the study-level means of the parameters of the cumulative prospect theory analysis, separately for the selling price (WTA) and buying price (WTP) conditions.

Study	Model parameter							
	α (risk aversion)		γ (probability sensitivity)		σ (noise)		β (response bias)	
	WTA	WTP	WTA	WTP	WTA	WTP	WTA	WTP
Ashby et al., 2011, Study 2	1.23 [0.96, 1.54]	0.51 [0.27, 0.77]	0.89 [0.68, 1.14]	1.01 [0.68, 1.44]	5.38 [3.00, 6.81]	6.18 [4.42, 7.54]	-0.94 [-1.83, -0.07]	-2.16 [-3.11, -1.22]
Ashby et al., 2011, Study 3	0.01 [0.01, 0.20]	0.19 [0.01, 0.63]	0.52 [0.42, 0.62]	0.46 [0.34, 0.59]	5.23 [5.20, 5.27]	5.23 [5.19, 5.27]	-0.88 [-1.57, -0.23]	-1.04 [-1.94, -0.19]
Ashby et al., 2012, Study 1	0.97 [0.88, 1.06]	0.87 [0.80, 0.95]	0.66 [0.59, 0.75]	0.55 [0.48, 0.62]	0.97 [0.01, 3.42]	4.62 [3.89, 5.04]	-0.88 [-1.58, -0.23]	-2.44 [-3.53, -1.44]
Ashby et al., 2012, Study 2	0.94 [0.78, 1.10]	0.75 [0.56, 0.97]	0.93 [0.75, 1.15]	1.42 [1.14, 1.71]	5.22 [3.93, 5.96]	5.65 [4.80, 6.20]	0.09 [-1.09, 1.32]	-2.22 [-3.30, -1.15]
Shahrabani et al., 2008a	0.87 [0.50, 1.32]	0.95 [0.70, 1.27]	0.92 [0.79, 1.13]	1.06 [0.90, 1.29]	4.91 [4.66, 4.98]	5.00 [4.92, 5.03]	-0.52 [-2.27, 1.77]	-0.44 [-2.91, 2.13]
Birnbaum & Yeary, 1998	2.00 [1.80, 2.00]	1.16 [0.63, 1.81]	0.61 [0.49, 0.80]	0.36 [0.27, 0.44]	4.99 [4.93, 5.01]	4.99 [4.94, 5.01]	-3.34 [-7.61, -0.67]	-2.72 [-5.82, 0.30]
Yechiam et al., 2016, Study 3	1.94 [1.51, 2.00]	0.25 [0.01, 0.87]	0.80 [0.72, 0.90]	1.15 [0.50, 1.81]	5.09 [4.99, 5.16]	5.00 [4.64, 5.12]	-0.59 [-1.64, 0.58]	-4.83 [-8.09, -2.25]
Yechiam et al., 2016, Study 4	1.95 [1.70, 2.00]	0.64 [0.14, 1.13]	0.75 [0.62, 0.89]	0.53 [0.41, 0.70]	4.97 [4.84, 5.05]	2.33 [0.05, 4.39]	-0.72 [-1.78, 0.44]	-2.89 [-3.91, -1.95]
Pachur & Scheibehenne, 2012	2.00 [1.94, 2.00]	0.52 [0.36, 0.68]	0.87 [0.81, 0.93]	0.54 [0.49, 0.61]	5.08 [5.06, 5.09]	4.90 [4.71, 5.02]	-1.10 [-1.92, -0.34]	-4.27 [-4.93, -3.65]
Abofol, 2016	1.90 [1.72, 2.00]	0.73 [0.48, 0.96]	0.82 [0.73, 0.93]	0.55 [0.46, 0.66]	5.04 [4.95, 5.10]	5.05 [4.90, 5.13]	-1.49 [-2.69, -0.50]	-3.93 [-5.07, -2.86]
Overall parameters	1.57 [1.47, 1.67]	0.69 [0.61, 0.77]	0.78 [0.74, 0.81]	0.65 [0.59, 0.71]	0.01 [0.01, 0.01]	0.01 [0.01, 0.01]	-1.01 [-1.35, -0.68]	-3.39 [-3.85, -2.96]

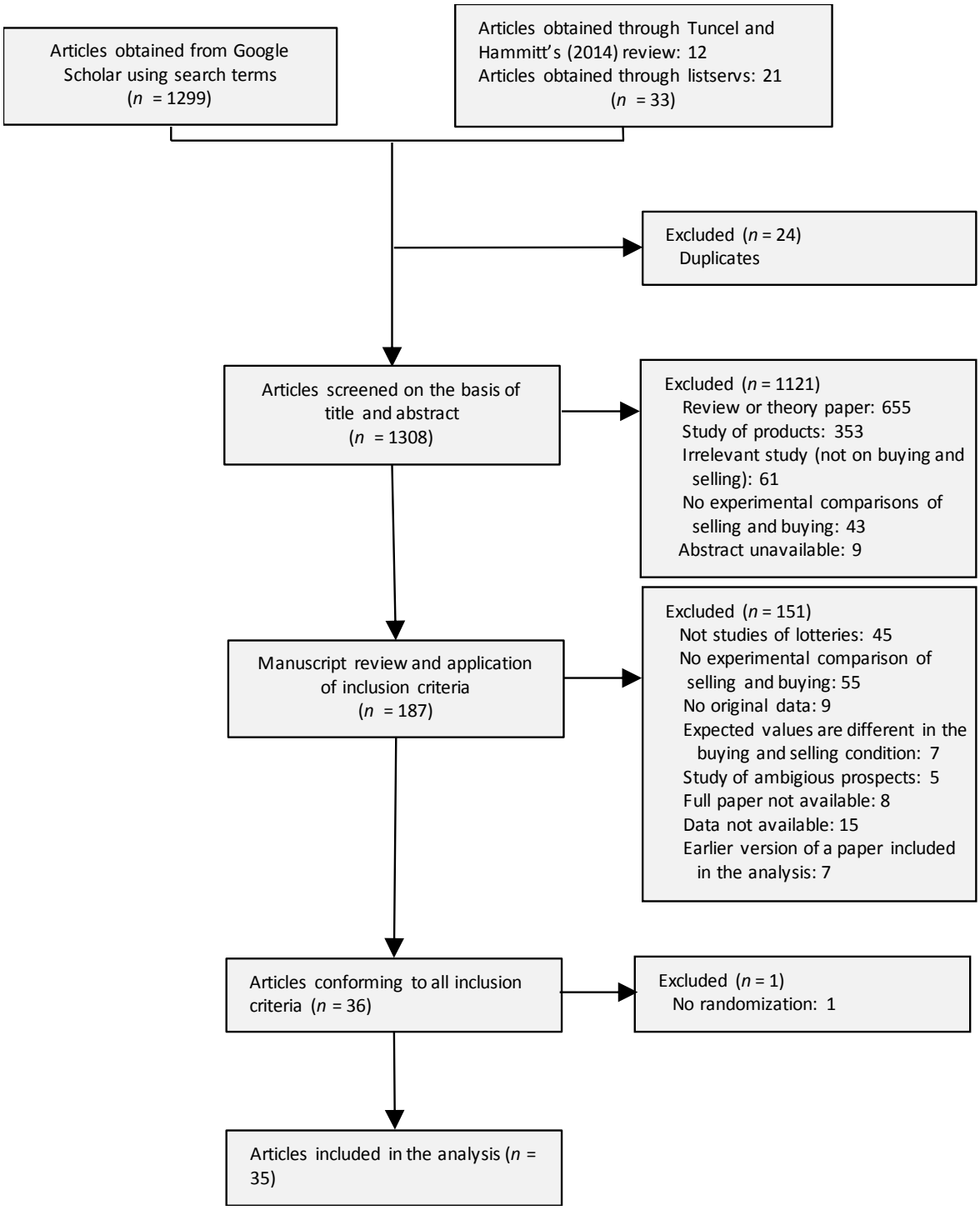

Figure 1. Flow diagram of the literature search.

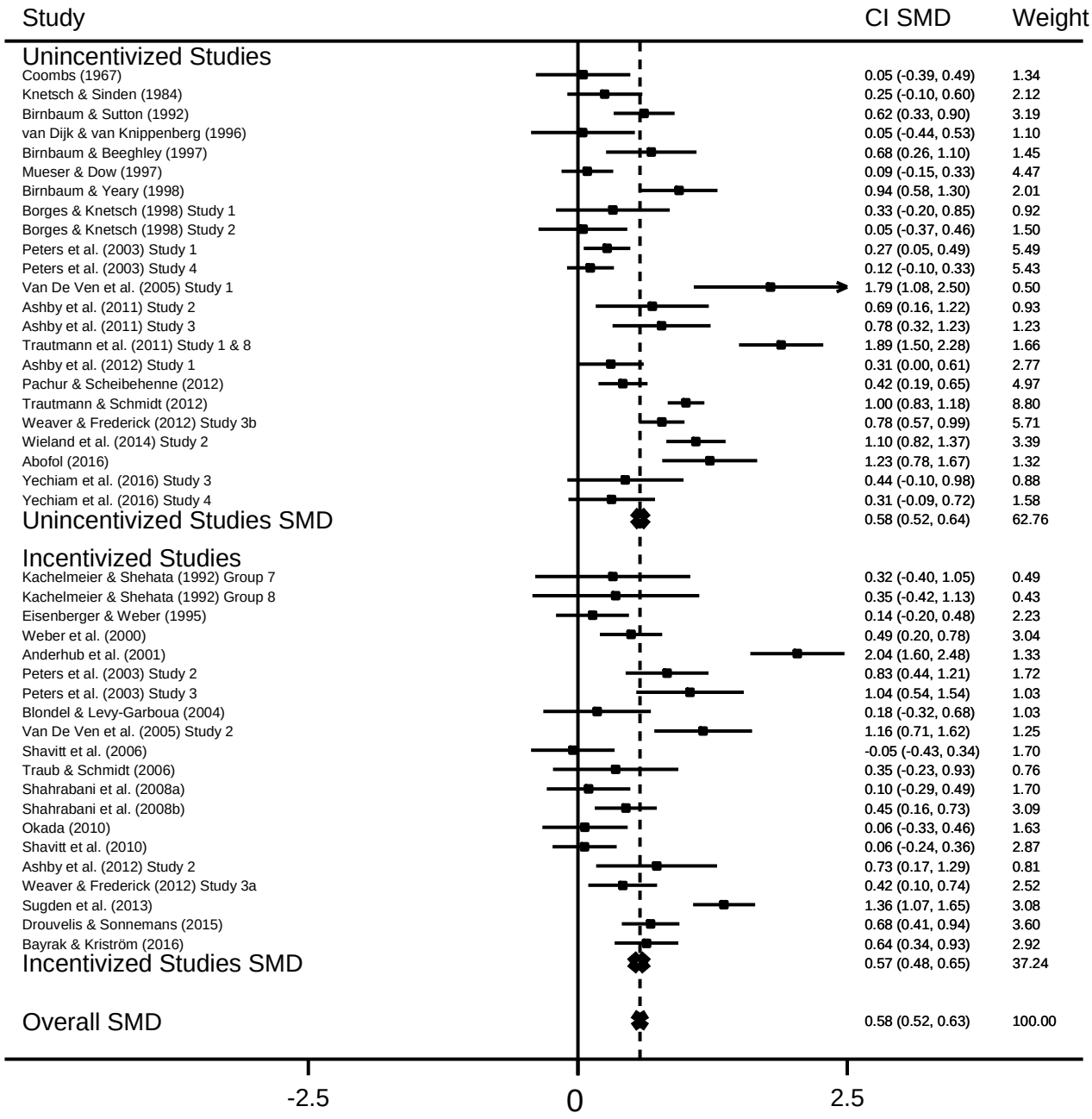

Figure 2. Estimates of the standardized mean difference (SMD) between buying and selling prices grouped by whether the studies provided incentivization or not. SMDs falling to the right of zero indicate higher selling prices than buying prices. Error bars represent 95% confidence intervals (CI) around the SMD and the dashed line represents the mean SMD. The right hand side presents the SMD and CI in brackets for each study and the percent weight assigned to each study in the meta-analysis (based on the number of participants).

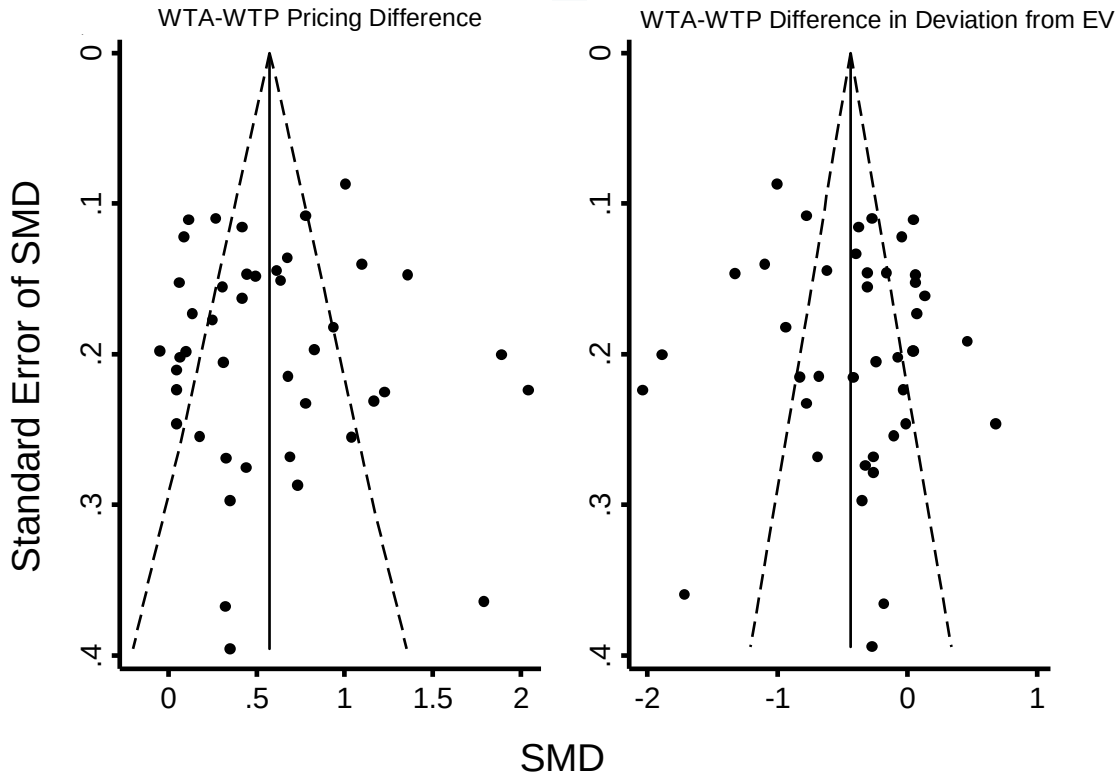

Figure 3. Funnel plots displaying the standard error of the standardized mean difference (SMD) in each study, plotted as a function of the SMD of the study for the WTA-WTP pricing difference (left panel), and the WTA-WTP difference in deviation from expected value (right panel); the solid line indicates the average SMD and the dotted lines the predicted 95% confidence intervals.

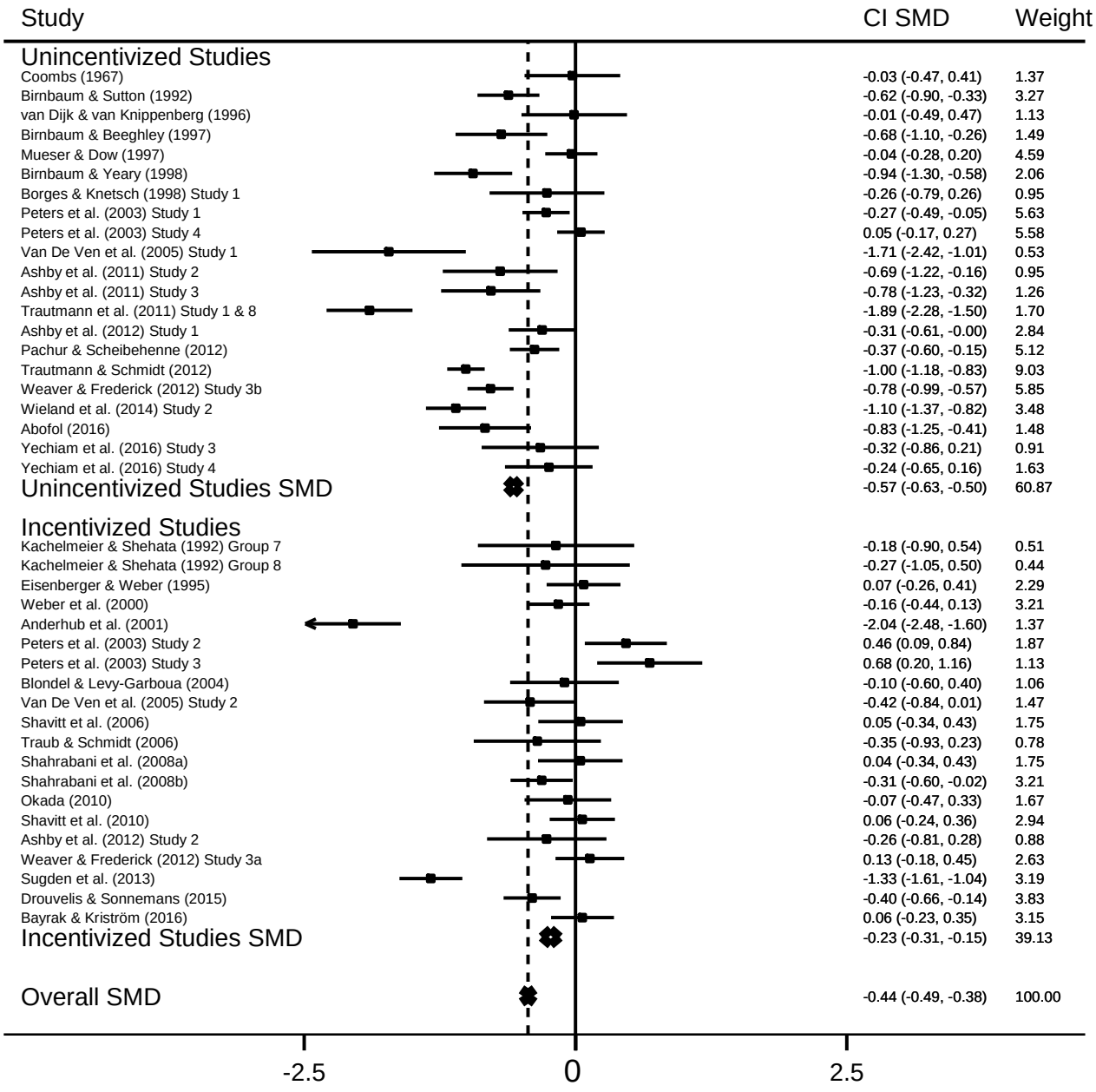

Figure 4. Estimates of the standardized mean difference (SMD) between buying and selling prices in their absolute distance from the expected value, grouped by whether the studies provided incentivization or not. SMDs falling to the left of zero indicate less deviation from the expected value by sellers. Error bars represent 95% confidence intervals (CI) around the SMD and the dashed line represents the mean SMD. The right hand side presents the SMD and CI in brackets for each study and the percent weight assigned to each study in the meta-analysis (based on the number of participants).

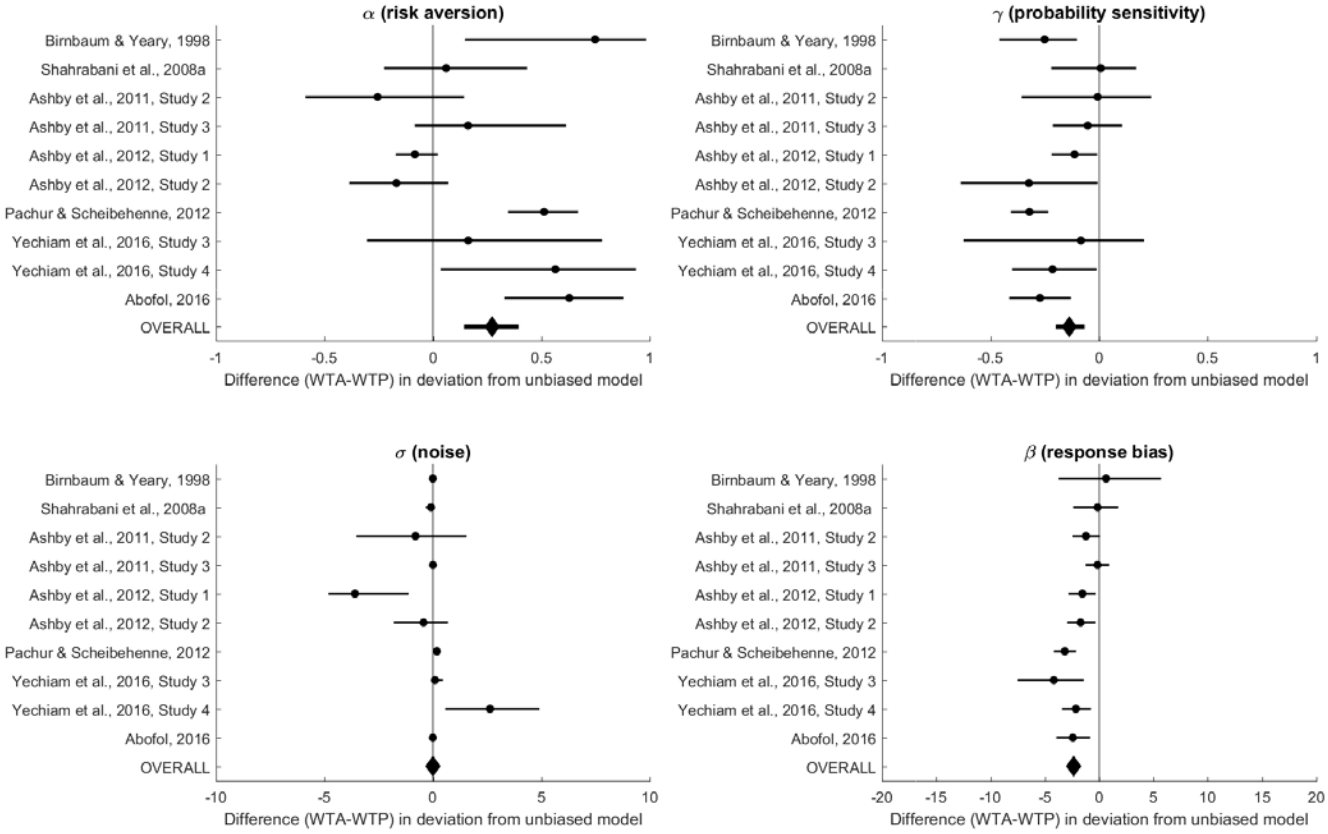

Figure 5. Medians and 95% highest density intervals of the posterior distributions of the differences between selling and buying prices (WTA – WTP) in terms of the absolute deviations of the parameter values from an unbiased model (i.e., $\alpha = 1$, $\gamma = 1$, $\sigma = 0$, $\beta = 0$). Values falling to the right of zero indicate greater bias for sellers, values falling to the left of zero indicate greater bias for buyers.

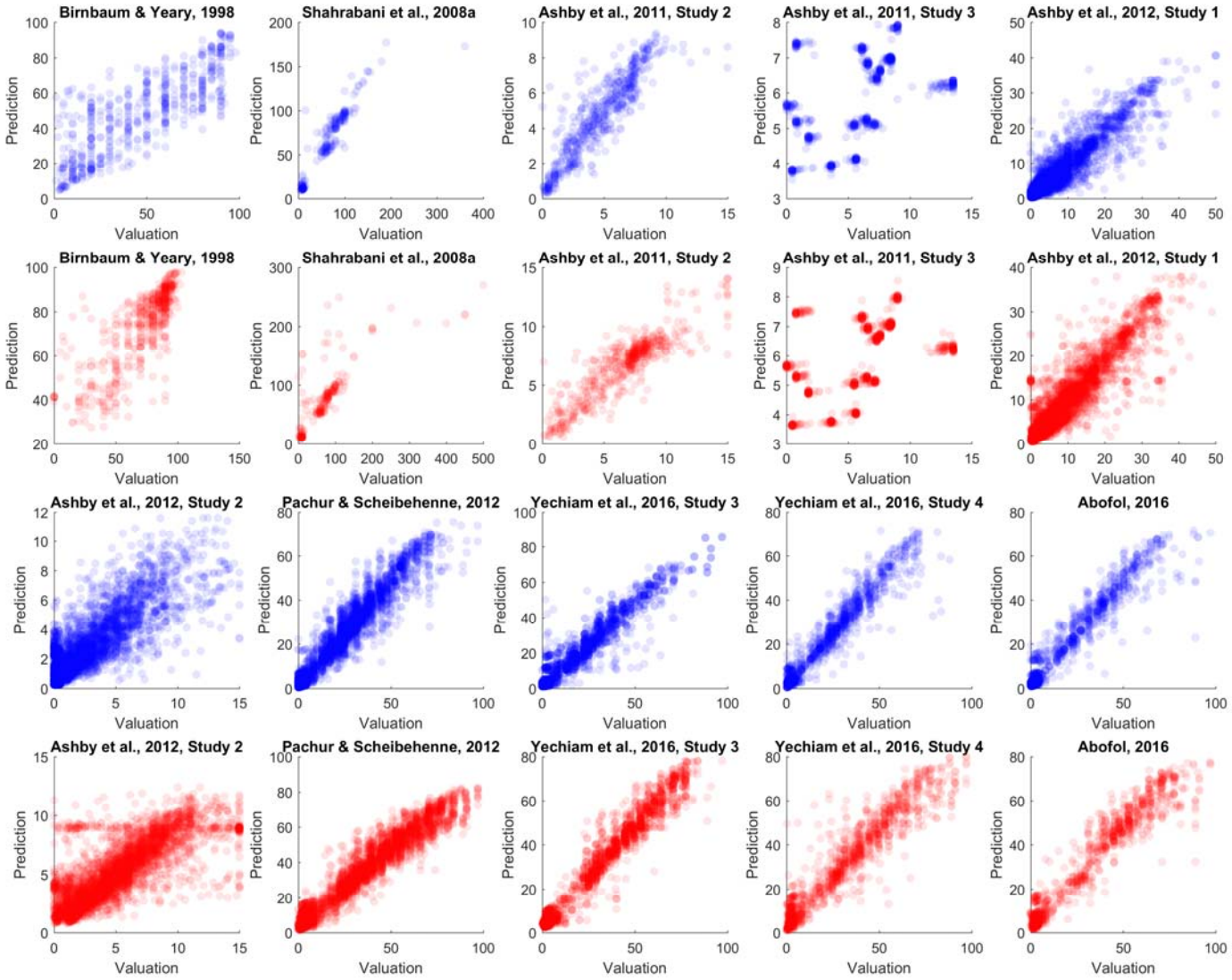

Figure A1. Posterior predictive checks for the CPT model. Shown are mean pricing decisions (across the different samples of the posterior distribution) predicted from the model as a function of each observed pricing decision, separately for buying prices (blue) and selling prices (red). Each dot represents an individual pricing decision.