

Web Appendix to
Endowment Effect Theory, Subject Misconceptions and Enhancement Effect Theory: A
Reply to Isoni, Loomes and Sugden

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This Web Appendix supplements our published Reply (Plott and Zeiler 201x) in two ways. In Section I, we provide a more detailed study of the lottery data, analyzing the individual lottery valuations as opposed to the aggregates reported in our Reply. The disaggregated data provides additional support for the conjecture that misconceptions about random devices appear to cause a shifting in subject beliefs about lottery outcomes that is correlated with selling (“willingness to accept”; WTA) and buying (“willingness to pay”; WTP) roles, and it assesses the impact of these misconceptions on WTA and WTP measures. While WTA-WTP gaps might be evident in aggregate lottery valuations, the analysis reported here suggests that the “question-influenced beliefs” conjecture is a viable alternative explanation to the theory that the gap reflects a special shape of preference relations. In Section I, we refine this conjecture and offer an analysis of the lottery data that supports it. The combined implication is that the lottery data do not unambiguously support theories developed to extend endowment effect theory (EET) to the case of lotteries.

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The key to further investigation and testing seems to be methods of controlling beliefs and correcting misconceptions about random devices and probabilities. In Section II, we discuss some of the diverse literature that provides clues about how to control for such misconceptions. This experimental literature suggests that our procedures are ill-equipped to elicit lottery valuations for the purpose of testing EET (or almost any preference-based theory). We provide the beginnings of an analysis that would be required to generate a set of controls to remove misconceptions related to random devices.

I. Boundary Valuation Asymmetries

In Section III of our Reply we provided the first steps of an analysis of the footprints of contamination in the lottery data. Section III(A) of our Reply reveals substantial irrationality in Andrea Isoni, Graham Loomes and Robert Sugden's (ILS) (201x) and our lottery data (PZ 2005). Subjects frequently bid outside the bounds of the lottery value support in the certainty lottery rounds (1, 2, 4 and 5).¹ Sections III(B) and III(C) of our Reply continue with an analysis of the asymmetry in boundary valuations, defined as those valuations that lie exactly on or outside the bounds of the lottery value support.² Most importantly, we reported the presence of boundary valuation asymmetries: the tendency for subjects to value the lottery at or above the lottery value support in WTA rounds and at or below the support in WTP rounds. Table 1 below expands on Table 2 of our Reply and demonstrates that the asymmetry that appears in the aggregate data also appears in most individual lottery rounds.

¹ We adjusted our definition of irrationality to account for the fact that ILS limit valuations to increments of five pence.

² In Section III(D) of our Reply we report widespread inconsistency in risk preferences, another footprint of misconceptions.

Given the experimental environment and given appropriate simplifying assumptions about risk preferences, these subjects do not exhibit sophisticated beliefs over lottery outcomes, which represent probability distributions over the state space. Specifically, they are acting as if they can accurately guess the lottery outcome. We reported this phenomenon in our data supplement. We also find it in the data reported by ILS, which demonstrates that their experiment did not remove contamination as we defined the term.

		WTA BOUNDARY VALUATIONS				WTP BOUNDARY VALUATIONS			
		#7	#8	#9	#10	#11	#12	#13	#14
ILS (N=100)	lottery value support (£)	[0,3]	[0,2]	[0.5,2.5]	[0,4]	[1,4]	[1,3]	[1.5,3.5]	[1,5]
	upper	14%**	5%	5%	5%	5%	2%	5%	3%
	lower	0%	0%	7%	0%	8%***	18%***	15%**	15%***
PZ (2005) (N=74)	lottery value support (\$)	[0,7]	[0,5]	[-4,8]	[0,10]	[1,8]	[1,6]	[-3,9]	[1,11]
	upper	8%**	7%**	0%	8%	1%	1%	0%	7%
	lower	1%	0%	4%	1%	7%**	7%**	1%	1%

Note: "Upper" ("lower") indicates the proportion of subjects who valued the non-degenerate lottery at or above (below) the upper (lower) bound of the lottery value support. The asterisks denote results of tests of equal proportions (* denotes significance at the 10 percent level, ** at the 5 percent level and *** at the 1 percent level). For upper boundary valuations, Ho: proportion of valuations at or above upper bound in WTA = proportion of valuations at or above upper bound in WTP; Ha: proportion at or above upper bound in WTA rounds > proportion at or above upper bound in WTP. For example, 14 percent at or above the upper bound in ILS's round 7 is compared to 5 percent at or above the upper bound in ILS's round 11. Similar tests are performed on lower boundary valuations (Ho: proportion of valuations at or below lower bound in WTA = proportion of valuations at or below lower bound in WTP; Ha: proportion at or below lower bound in WTA rounds < proportion at or below lower bound in WTP). For lotteries with negative or zero lower bounds, the frequency represents offers of \$0.

Table 1 reveals that subject beliefs appear to be directly influenced by whether they are placed in the position of seller or buyer. We define "boundary valuation asymmetry" as the asymmetric tendency for subjects to be more likely to report boundary valuations at or above the upper bound in selling (WTA) rounds and at or below the lower bound in buying (WTP) rounds. For example, 14 percent of ILS's subjects reported boundary valuations at or above the upper bound when valuing as sellers in round #7 and no subject chose the lower bound of zero. By comparison, when valuing the matched lottery as buyers in round #11, 5 percent reported boundary valuations at or above the upper bound and 8 percent chose the lower bound or below.

The results of one-tailed tests of equal proportions are displayed in Table 1. Five of the eight tests using ILS's data resulted in a statistically significant difference (at the 5 percent level); four of the eight tests using our data produced similar results. In short, when subjects report valuations as sellers, subjects are more likely to believe that the lottery outcome will be the higher payoff. Conversely, when subjects report valuations as buyers, they are more likely to believe that the lottery outcome will be the lower payoff.

Boundary asymmetries naturally imply the existence of "boundary gaps." An upper boundary gap is measured using only pairs of individual values for which the valuation as seller is on or above the upper bound and the valuation of the same individual as a buyer is below the upper bound. Similarly, to measure lower boundary gaps, we use only pairs for which the valuation as buyer is on or below the lower bound and the valuation as seller is above the lower bound. Boundary gaps suggest that the same subject perceives the same lottery as involving different subjective probabilities depending on whether the subject is valuing the lottery as a seller or a buyer.

Table 2 displays gaps, as measured by ILS, using a variety of subsets of the data. The first row of each panel ("all ILS data" and "all PZ data") reports gaps using all the data. These correspond to the gaps reported by ILS.³ The second row in each panel reports upper boundary gaps. The results demonstrate that the magnitude of gaps in the full dataset is driven substantially by relatively few individual ratios with seller valuations that are based on extreme beliefs. Likewise, the third row in each panel displays lower boundary gaps and reveals a similar impact by relatively few individual ratios with buyer valuations that are based on an extreme belief. The fourth row further demonstrates the impact of extreme asymmetric beliefs on lottery gaps. When

³ ILS reported gaps separately for our Type A and Type B lotteries. We pooled these subsets to construct Table 2.

those individuals exhibiting extreme beliefs of any kind as buyer or seller are removed from the data, the magnitudes of the gaps drop substantially.

TABLE 2					
BOUNDARY GAPS					
ILS LOTTERY DATA					
	L3/L6	L7/L11	L8/L12	L9/L13	L10/L14
MEAN WTA/WTP RATIO (MEDIAN RATIO WITH RESULTS FROM ONE-TAILED SIGNED RANK TEST^b)					
All ILS data	2.19 (1.33***) N=100	1.53 (1.26***) N=100	1.37 (1.16***) N=100	1.11 (1.00) N=100	1.46 (1.11***) N=100
Upper boundary gap	10.58 (2.67**) N=7	2.42 (2.03***) N=12	2.76 (3.00*) N=4	2.20 (2.33*) N=4	4.38 (5.00*) N=4
Lower boundary gap	6.43 (2.50***) N=15	4.01 (4.00**) N=8	2.27 (2.24***) N=18	1.71 (1.67***) N=15	3.06 (2.50***) N=15
Both valuations inside the bounds	1.36 (1.15*) N=78	1.26 (1.16***) N=81	1.16 (1.04***) N=80	1.00 (1.00) N=83	1.16 (1.03) N=83
PZ (2005) LOTTERY DATA (POOLED ACROSS TYPE A AND B LOTTERIES)					
	L3/L6	L7/L11	L8/L12	L9/L13	L10/L14
MEAN WTA/WTP RATIO (MEDIAN RATIO WITH RESULTS FROM ONE-TAILED SIGNED RANK TEST)					
All PZ data	1.53 (1.15***) N=71 ^a	1.56 (1.20***) N=74	1.50 (1.20***) N=74	1.68 (1.03***) N=73	1.32 (1.04***) N=74
Upper boundary gap	2.16 (1.60**) N=5	2.15 (2.00**) N=5	1.77 (1.44*) N=4	N=0	1.83 (1.47*) N=4
Lower boundary gap	N=0	4.40 (5.00**) N=5	4.00 (4.05**) N=5	N=0	8.00 (8.00) N=1
Both valuations inside the bounds	1.49 (1.10***) N=65	1.31 (1.15***) N=63	1.29 (1.17***) N=64	1.68 (1.03***) N=73	1.20 (1.00**) N=67

^a Ratios for three subjects are undefined because lottery valued at \$0 as buyer in Round 6. In Round 13, one buyer valued the lottery at \$0. The sign test includes the \$0 bids.

^b H₀: adjusted WTA and WTP come from identical distributions (results from one-tailed test)

Importantly, boundary gaps demonstrate evidence of misconceptions and do not lend support to the preference function assumed by EET. In the absence of special assumptions about the preference relation, an individual who values a lottery on the boundary of the value support should reveal the same value regardless of whether in the role of buyer or seller. This implies that boundary gaps are different from the standard interpretation of a valuation gap: a gap

between WTP and WTA for the *same* good.⁴ Individuals revealing boundary gaps view the lottery from the buying perspective as a different lottery than the one considered from the selling perspective, even though the lotteries are identical (save the addition of some amount to both outcomes). In other words, boundary gaps imply that the actual properties of the lottery as perceived by the individual have changed from round to round and from selling perspective to buying perspective, presumably due to misconceptions about randomness. Hence, the very concept of a valuation gap is inappropriate.

The existence of the boundary gaps and the substantial reduction in gap magnitude when only non-suspect data are included suggest that misconceptions about the random device play a central role in the lottery valuation gaps. Furthermore, the existence of boundary asymmetries has substantial implications for the use of lotteries in the measurement of WTP-WTA gaps. If misconceptions about the random device cannot be controlled, and in particular, if the systematic violation of sophisticated beliefs cannot be avoided, then, as a matter of principle, lottery valuations should not be used to measure WTA-WTP gaps, which assume that individuals value the same good as buyer and as seller. If the roles of seller and buyer trigger a change in subjective probabilities for the same lottery, then the lottery valued from the buying perspective is not the same as the lottery valued from the selling perspective. Unless subjects view the good as the same good from both perspectives, testing EET or even measuring a valuation gap using lotteries is impossible. Amos Tversky and Daniel Kahneman (1991) were wise to move the science to the study of commodities when developing the foundations from which EET was constructed.

⁴ Very few ILS subjects valued the lotteries at or above the upper bound as both buyer and seller (2 for L3/6 and L7/11; 1 for L8/12, L9/13 and L10/14) and at or below the lower bound as both buyer and seller (0 for L3/6, L7/11, L8/12 and L10/14, and 2 for L9/13). The same is true for our subjects (upper bound: 1 for L3/6, L7/11 and L8/12; 0 for L9/13 and 2 for L10/14; 0 for all lotteries for the lower bound).

Finally, while gaps exist in the valuations that remain after removing suspect valuations, conclusions drawn from any remaining gap have questionable reliability if applied to EET. It is reasonable to believe that the forces that compel the reporting of suspect valuations might influence the valuations of subjects who stayed inside the bounds. More work is required to determine whether gaps would remain after properly controlling for misconceptions about random devices. In Section II, we discuss how our revealed theory methodology illuminates avenues through which the research can proceed.

II. Revealed theory methodology and controlling for lottery misconceptions

Our study was based on the intuition that subject misconceptions about the preference elicitation device systematically impact valuations. Importantly, we recognized that there is no theory of misconceptions. To approach this seemingly intractable problem, we developed a “revealed theory” approach that rests on the assumption that procedures used by experimentalists to control for misconceptions in some sense reveal a theory of misconceptions. Our strategy was to cast a wide net by examining theories and employing procedures that others had suggested or used in relation to misconceptions and the preference elicitation device. Using this method, we incorporated them all into a single set of procedures with the hope that misconceptions about the elicitation device might be adequately controlled. As we did not intend to use the lottery data to test EET, we did not develop procedures to control for misconceptions about random devices associated with lotteries.

When we employed the revealed theory procedures in mug rounds, the valuation gap disappeared. Thus, our mug data demonstrate that the mug experiments do not support EET. Given that there is no well-defined theory of misconceptions that can be specified as a theoretical

alternative to EET, however, the data fall short of supporting a conclusion that the gap in mug valuations is caused by some specific theory of misconceptions. Instead, application of the revealed theory method produces a collection of potential theories (PZ 2005, p. 531). This implies that no clear theory of misconceptions can be formulated to apply in all circumstances and that the set of controls will depend on the features of the experiment that might lead to misconceptions, including features of the goods. For these reasons, to correctly apply revealed theory methodology, one must appeal to the literatures that specifically address features that might trigger misconceptions.

Neither PZ (2005) nor ILS apply revealed theory methodology in the lottery round design. Neither design considers the literature that explores possible misconceptions associated with special features of lotteries. It is well known that lotteries can trigger difficulties in addition to any misconception that might relate to the elicitation device and that these must be addressed before reported valuations can be used to test any theory of preference. Experimenters have studied important issues related to the random process and its role in influencing subjects' beliefs (i.e., subjective probabilities) about what actions might be optimal. Depending on the factors that influence beliefs as subjects face lotteries, values placed on the same lottery can change from round to round, as we demonstrated in the previous section. The experimenter, being unable to observe the subject's changing beliefs, unknowingly collects data that are contaminated for the purpose of testing any theory assuming consistent preferences. This problem is especially troublesome when the theory rests on a particular shape of preference, as does prospect theory.

To properly apply revealed theory methodology to remove misconceptions about random devices in order to test theories of preferences over lotteries, the literature warns that one must attend to numerous types of misconceptions related to random devices. The challenge seems to

stem from difficulties some individuals have with the notion of randomness itself. For example, some of our subjects reported believing that they could accurately guess the lottery outcomes, a belief supported by ILS's and our lottery data. If a subject believes he can accurately predict the outcome of a particular lottery and the prediction depends on whether he owns the lottery, then the subject's (unobserved) subjective probabilities, and thus the subject's valuation of the same lottery, might change from round to round. Such changing beliefs can be motivated by imagined patterns in historical data, theories based on the physical properties of random devices, or even impulses that cause people to believe that some outcomes are more likely than others. Such beliefs are symptomatic of a disconnect between the probabilities as understood by the experimenter and the actual beliefs held by subjects.

The nature of this disconnect requires study and, in fact, has been studied in a variety of ways. One of the most dramatic examples of the disconnect is the number of offers to pay more for a lottery than the maximum it could pay (or asking for less than the minimum payoff), as observed by both ILS and us. Gideon Keren and Martijn Willemsen (2008) connect this mistake to misconceptions over random devices. Colin F. Camerer (1989) and Peter Bossaerts and Plott (2004) report findings suggesting that individuals tend not to accept the notion of independence. How to train subjects away from these tendencies is not obvious, but the literature suggests ideas including the use of formal training models (Theo Offerman et. al. 2009) and training methods that work through subject involvement in the lottery procedures (Christina Fong and Kevin McCabe 1999).

While on the one hand paradoxes (e.g., Maurice Allais 1953; Daniel Ellsberg 1961) and anomalies (e.g., overconfidence, beliefs relating to low probability events) abound, several findings suggest that attitude formation has an underlying structure that leads to the eventual

understanding of or an effective way of dealing with random processes (Wolfgang Gaissmaier and Lael J. Schooler 2008; Gerd Gigerenzer et. al. 2008). Adrian R. Camilleri and Ben R. Newell (2009) give subjects an opportunity to value hundreds of lotteries.⁵ Gerrit Roth (2005) has directly studied whether observed lottery gaps are related to the underlying riskiness of lotteries. The application of revealed theory methodology to lottery rounds should take into account these and other such studies in fashioning controls for misconceptions about randomness.

⁵ By comparison, ILS's and our lottery data are collected after only two unpaid practice rounds.

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