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A Dual-Role Analysis of Game Form Misconception and Cognitive Bias in Financial and Economic Decision Making

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A Dual-Role Analysis of Game Form Misconception and Cognitive Bias in Financial and Economic Decision Making

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Dedication

This dissertation is explicitly dedicated to my parents: Dr. Emeka and Dr. Chika Nwadiora, easily the two strongest people alive today. To my siblings: Emeka II, Chinwe and Ikechukwu. To my numerous nieces and nephews: Kia, Dante, Ashley, Ike Jr., Kory, and Skylar, as well as my uncle & cousins in Maine and the majority of my family who still resides in the motherland of Nigeria. The man who holds on OFO can not get lost in the journey.

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Abstract

The endowment and the framing effect are widely examined cognitive biases. The experimental economics literature, using choice data gathered through an elicitation device, commonly finds evidence of these biases. Recent work by Cason & Plott (2014) shows that the interpretation of choice data as consistent with biases related non-standard preference theory could also be consistent with confusion or misconception of the game type used to elucidate preferences. I use the Cason and Plott card auction framework to analyze offers of buyers and sellers in an experimental setting with subjects from the University of New Orleans simulating 97 sellers and 90 buyers. The two games have symmetric payoffs in order to examine cognitive biases given subjects' misconception of the game form. Subjects of both games display misconception of game form that explains both endowment and framing effects by rational confused choice; however, buyers display a much greater dispersion of offers than sellers. I estimate card implied valuation of sellers and buyers given game form misconception and find no statistical endowment effect, but I do find valuation is more uncertain in the buyer's game. The theory of Rational Inattention predicts this lack of offer symmetry is due to the additional cognitive steps necessary in calculating buyer offers.

Keywords: Behavioral Economics; Behavioral Finance; Cognitive Bias; Game Form Misconceptions; Endowment Effect; Framing Effect

I. Introduction

Researchers are increasingly testing economic theories by controlling the economic environment and repeatedly observing individual behavior. Experimental economics gives researchers the opportunity to state an economic theory ex ante and evaluate how individual behavior compares and contrasts with the proposed theory. One of the fundamental tenants of classical economic theory is the theory of rational choice, which states that individuals will make choices consistent with maximizing expected utility. Much empirical work is at odds with utility maximizing behavior, so economists, have for decades attempted to reconcile theory with empirical observation. Behavioral economics utilizes psychological insights such as cognitive bias to supplement existing economic theory to more accurately predict individual decision making.

Cognitive biases are systematic deviations from optimal behavior. These biases have serious implications for financial and economic policy decisions, as well as understanding individual investment behavior. This dissertation will focus on two of the most common cognitive biases; the endowment effect, and the framing effect. This paper attempts incorporate game form misconceptions of Cason & Plott (2014), in an effort to shed light on the existence and relative magnitude of such biases.

One of the principle messages of Cason & Plott (2014) is that choice data from elicitation devices such as the Becker–DeGroot–Marschak (BDM, 1964)[1] need to be interpreted carefully, specifically as they relate to preference revelation. Game form misconceptions can lead to individuals making choices out of confusion, rather than choices that reveal their true preferences. This concept

[1] The BDM framework is an incentive compatible mechanism where there the dominate strategy is for individuals to bid/offer the objects true price. A Vickrey auction is a BDM device.

should take special precedence when the choice data is non-optimal or non-utility maximizing. In any experimental setting, it is logical to assume some measure of confusion or misconception amongst the subjects. This paper uses the Plott & Cason (2014) experimental framework from both the buyer and the sellers' points of view to distinguish possible biases from the game form misconceptions that Plott & Carson identify in their seller only game.

I attempt to isolate the role of the subject with two experiments types. In the sellers game I elicit his Willingness-To-Accept (WTA). In the buyers games I elicit his Willingness-To-Pay (WTP). The Plott & Cason BDM type setup is used for each game. The payoffs of both games are structured to be symmetric and use instructions that are simple and similar. Following the BDM mechanism, both experiments have the same dominant offer strategy that is for a subject to offer a price equal to the true value of the object in question. The relative divergence of offers from optimal in the two experiments gives us a basis of assessing biases given subjects of both games suffer from a degree of confusion or game form misconception.

The model formulations I assess use the random utility model of Luce-McFadden with choices consistent with either optimal offers with a degree of noise or consistent with choices generated from a first price game form misconception. The degree of offer sensitivity between the two game types and the implied object valuation are estimated and compared to assess biases due to the subject's role in each type of experiment.

II. Literature Review

In experimental settings, several different factors may influence the subject's valuation of the object in question. Perhaps the subject has an emotional attachment to the item he or she is holding, the subject is swayed by the range of possible payoffs, or they don't understand the rules as presented. In this section, I provide a brief background on some of the well-studied cognitive biases theorized to effect decision making. I also provide background on game form misconceptions.

a. The Endowment Effect

The endowment effect posits people place an excess value on items merely because they own them. This leads to the phenomena where individuals add excess value to items due to some psychological attachment to the item. It is easy to think of real life situations where an endowment effect may be present. For example, an individual may refuse to sell an old car of his, even at a more than fair price, because he inherited the car from his father. The endowment effect is also prevalent in the stock market where investors are reluctant to divest certain inherited stocks due to intangible reasons such as familiarity or comfort, even though these assets are having an adverse effect on their portfolio (Hayes, 2015). The endowment effect has also been shown to have an effect on the housing market (Genovese & Mayer, 2001.

The endowment effect is a violation of the utility maximization theory. In a competitive market, consumers' willingness-to-pay (WTP) for an item should be equal to consumers' willingness-to-accept (WTA). The endowment effect is usually defined by the gap in the measure of an item's WTA valuation and an item's WTP valuation. Kahneman, Knetsch & Thaler (1990) observed an endowment effect in multiple experiments where measures of willingness-to-accept greatly exceeded measures of willingness-to-pay. The authors found this effect persisted even in settings where individuals had the opportunity to learn.

The endowment effect has been extensively studied with mixed results. Horowitz & McConnell (2002) surveys this literature and finding that this effect is more pronounced in experiments using incentive-compatible devices, the highest for "non-ordinary goods" and the lowest for money. Shogren, et al. (2001) found evidence of an endowment effect in an initial trial, but found that the effect did not persist across multiple trails. Knetsch, et al (2001) found evidence suggesting the endowment effect remains robust over time; however, the valuations may be dependent on the context of the valuation. Beggan (1992) found evidence to support the existence of an ownership effect, when an individual's ownership of an object causes the owner to treat the object as a social entity, due to a possible psychological connection. Samuelson & Zeckhauser (1988) found a related status quo bias by researching heath/retirement plan activity of faculty members--doing nothing is disproportionately preferred to beneficial alternatives.

Perhaps the most prominent explanation for the existence of the endowment effect, is the theory of loss aversion found in Tversky & Kahneman (1991) in which the disadvantage of a loss impacts an individual more than the advantages of a gain. In the world of sports, the endowment effect, as driven by loss aversion has been shown to have a significant effect on the decisions of managers in major league baseball (Pedace, 2013).

b. The Framing Effect

The framing effect is a common bias wherein ones preference for particular decision depends on how that decision is described, even though the underlying rational choice is the same (Tversky & Kahneman, 1981). Frame dependence is a subjective evaluation of an individual's attachment or avoidance of certain information or numbers.

Levin, Gaeth, Schreiber and Lauriola (2002) identified three distinct forms of the framing effect; attribute framing, goal framing, and risky choice framing. They find an individual's decision frame has a significant effect on choices involving risk. The authors also suggested that the effects of framing should be judged on an individual basis, rather between subjects, in order to avoid errors due to aggregation, wherein a significant effect appears via combining several individuals with minimal effects, or a significant effect does not appear due to several individuals with significant effects cancelling each other out. As opposed to between subjects analysis, this within subject analysis allows the ability to examine framing effects individual subject basis.

Experimental economics has long been used to test for framing effects for both buyers and sellers. Price frame manipulation has been shown at times to significantly alter an individual's valuation process. Bohm, Lindén, and Sonnegård (1997) test for framing effects in a WTA (seller) study and found individuals' whose possible payoff frames had higher maximum values had significantly higher WTA valuations. The framing of information has been shown to impact valuations in either side of a transaction. Kamins, et al. (2004) found that in auctions the price individuals are willing to pay is lower when a reserve price is listed rather than not listed. Gilkeson (2003) and Stern (2006) studied internet auction behavior and found that the relative opening price of two similar items (which is not inherently tied to the item's actual value) had a significant effect on the items closing price.

The earliest studies of the framing effect include Tversky & Kahneman (1974) and Lichtenstein and Slovic (1971), who find evidence that an individual's place a certain value on an item and are likely to adjust that valuation based on the range of the prices being offered. Recently, Urbancic (2011) finds evidence of an attraction to the maximum, or a psychological affinity towards the maximum price an individual can receive which affects one's evaluation process. This leads to mass-seeking bias, in which an individual's valuation is pulled toward the mean of a price distribution.

Urbancic provides possible explanations for this bias such as thrill-seeking, avoidance of extremes, or misunderstanding implications.

c. Game Form Misconceptions

Charles Plott & Kathryn Zeiler (2005) questioned whether the WTA/WTP gap is caused by true individual preferences or a subject's misconception. Using a modified version of the Becker, DeGroot, Marschak (BDM) valuation method they found that after installing a system of tight controls, and providing extensive training, the researchers were able to eliminate the gap between WTA and WTP. These findings are similar to those of Shogren, et al. (2001) whose tests showed an initial presence of a WTA-WTP gap, but also show that the gap disappears after repeated trials, which calls into question the fundamental existence of an endowment effect.

Cason & Plott (2014) questioned whether experimental results which showed support for non-standard preference theories were caused by an individual's true preferences, or by a disconnect between an individual's choices and their possible outcomes. They argue that when the consequences of actions are not completely known to the individual, that action can not necessarily be equated with a desired preference. These misconceptions of game form can lead to confusion being interpreted as evidence of certain ideas which violate rational choice, such as the framing effect theory.

Cason & Plott's study shows consistent over-valuations of the objects involved. Since the known preference for subjects is to prefer monetary reward, decisions based on preference can be differentiated from decisions based on mistakes of comprehension. Therefore, the author's derive two behavior models and attempt to systematically explain these mistakes. In the author's study, the two reasons for divergence from optimal bidding are framing noise and first price auction misconceptions, where the subject believes he or she is in control of an item's transaction price. First price auction misconceptions are paramount to this dissertation, and are explained in detail in Part II – d (Experimental Design). The authors find that their model of misconception more accurately describes their subject's bidding pattern when compared to a model built around subjects bidding optimally with variability for framing effects. For this reason I need to be extremely careful when interpreting choice data to preference revelation, and also when evaluating the viability of non-standard preference theory.

d. Experimental Design

Experimental economics involves applying experimental methods in order to test the validity of economic theories as well as shed light on certain mechanisms in financial and economic markets. Data from individual choice elicited from experiments show they mimic certain real-world financial and economic patterns (Horowitz, 2002). The design of the experiment and the conditions under which the experiment take place are paramount, because the nature of individual choice is highly volatile. In this section, I cover the first price auction, the second price auction and the BDM elicitation mechanisms found in the literature.

In a first price auction, the individual who submits the highest bid is awarded the item being auctioned, the price he pays is equal to the highest amount he bid. Consider a first price auction for a used car. The price I'm willing to accept (WTA) is unknown to the buyer, but say the hidden reserve price for this car is $5,000. After a month of receiving bids from other potential buyers, the highest bid $6,000 and the second highest bid is $5,500. In this scenario, the buyer purchases the car for $6,000, the highest amount bid.

In a second price auction, the individual who submits the highest bid is again awarded the item being auctioned; however, the price he pays is equal to the second highest amount bid. Consider a second price auction for the same car and the same bidding behavior. In this instance, the purchase price will be the $5,500, or the second highest bid.

A Vickrey auction is a special instance type of sealed-bid second price auction. The individuals involved in the auction submit written bids with no prior knowledge of the bids of others involved. Vickrey auctions have many applications in today's markets[2], across several industries. The most cited example is likely Google, who utilized Vickrey auctions to generate over $32 billion in advertising revenue via Google AdWords in 2011. In their auction, the winning advertiser pays an amount equal to a penny more than the second highest advertiser's bid. These auctions attempt to guarantee that subjects will provide honest valuations of the object or service in question, since they do not control final price, but only control whether or not the transaction takes place.

In a first price auction, the individual bidder controls the final sales price of the transaction. The bidder is therefore incentivized to bid some value less than the item's worth and it becomes difficult to determine an individual's true assessment of the value of an item. The benefit of a second price auction is that individuals have the incentive to bid the items true value because the winning bidder only controls whether or not the transaction occurs; not the price paid. Researchers can glean more information from individual choice data in a second price auction setting because bidding one's true value is the dominant strategy therefore one's choices are more likely to reflect their preferences in a second price auction. First price auctions are more common place in day to activities,

[2] 2nd Price (Vickrey) Auctions also tend to occur with high stake transactions such as privatization, see Cornelli (1997) or Bortolotti (2001).

as many individuals purchase vehicles through first price auctions, and recently TV shows like Storage Wars have increased the visibility of such auctions. This real world familiarity may bias an individual's understanding of the particular experiment, as stated earlier a first price misconception occurs when an individual believes that they determine the final price.

The Becker, DeGroot, and Marschak (1964) method attempts to measure individual preferences through experimental response by creating an incentive compatible elicitation. The term incentive compatibility means all participants achieve their maximum outcome by adhering to their true preferences. The most common variation of the method involves comparing a subjects bid to a price generated by a random number generator. In the present study, the BDM device is no different than a second price action. The subjects bid has to be large enough (WTP) game), or small enough (WTA) for a transaction to occur, in which they receive the randomly selected payoff price.

Bohm (1997) found that the BDM mechanism is sensitive to the choice of the upper bound of a subject's possible payoff frame, and therefore the BDM cannot be truly incentive-compatible in practice. However, Irwin, (1998) tested the BDM and their experiment verified its incentive-compatible nature in a pure induced-value setting. Induced value theory (Smith, 76) depends on the postulate of non-satiation, where any autonomous individual's utility function is increasing monotonously with the monetary reward. The referenced authors also found that the optimality of the bidding behavior is a function of the information provided. The accuracy of the BDM method is not a subject in this dissertation, since I utilize the same elicitation device for both games, the measurements should be comparable. I will, however, test how the subjects' offers are affected by the upper and lower bounds of their payoff possibility frames, as well as the role of feedback information and repeated trials.

III. The Experiment

The design of my experiments is borrowed from the Cason & Plott (2014) game performed at Purdue University. In their experiment, the subject takes the role of a seller and is given a card, shown in Figure 1A, worth $2.00 cash. The subject is then asked how much he is willing to accept (WTA) in order to sell his card given information that the sales price is determined randomly between two values stated on the card, a sale will occur only if his offer is lower or equal to the sale price. After declaring an offer, the subject turns the card over and removes a piece of tape revealing the sales price. The sales price, or posted price, is drawn from a uniform distribution in the interval given by one of five possible ranges stated on the front of the card, $P = U[P_l \, , P_u]$, where $P_l \; = 0$, and $P_u = \{4,5,6,7,8\}$. The optimal offer is always the card value, as subjects will potentially miss out on a sale if their offers are greater than the card value. If no sale occurs they receive the card value of $2.00.

{Insert Figure 1A here}

Symmetric to the Cason and Plott (2014) seller game, I also create a buyers game with the set of payoffs (shown in the modelling section) designed to elicit how much a buyer would be willing to pay (WTP) for the card shown in Figure 1B. With the same setup, the subject is given a card worth $6.00 cash for anyone who purchases it. The subject is told the purchase price is determined randomly between two prices stated on the card and a purchase will occur if his offer is above the purchase price. They receive $2.00 in addition to any profit (or loss) on the purchase. Similarly, the subject turns the card over after declaring his offer and removes a piece of tape revealing the purchase price. . The purchase price, or the posted price, is drawn from a uniform distribution in the interval given by one of five possible ranges stated on the front of the card, $P =$

$U[P_l, P_u]$, where $P_l = \{0,1,2,3,4\}$ and $P_u = 8$. Likewise, the optimal offer is always the card value as subjects will potentially miss out on a purchase if their offers are lower than the card value. If no purchase occurs they simply receive $2.00.

{Insert Figure 1B here}

I conducted my experiment with 194 subjects at the University of New Orleans during the spring 2016 semester. In eight class sessions over two weeks, 97 subjects took part as sellers (WTA game), and 97 subjects took part as buyers (WTP game)[3]. Two cards in Round sequential order were placed in an envelope. The round 1 card was either white (WTA) or yellow (WTP), and the round 2 card was green in both cases. Subjects were asked to choose envelopes from a bin and then take their seats. Envelops contained round 1 cards allocated so that each of the five frame sizes, $P_u - P_l + 1$, were equally represented. Envelop round 2 cards were allocated so that subjects faced a 1/3 chance of an upward, downward, or no-change in frame when compared to the round 1 card.

The game scripts I followed for each game are contained in Appendix A-1 and A-2. Once seated, I read through the instructions as printed on their cards. I told subjects not talk to their fellow classmates and not to ask me any questions, as their individual understanding of the instructions was a primary concern of my study. I then told the subjects to reach into their envelope and remove the white (WTA) or yellow (WTP) cards depending on the game.

[3]While 97 subjects were given a card for the buyer game (WTP), 93 completed the Round 1 cards and 94 completed the Round 2 cards leaving 90 subjects completing. All seller (WTA) game cards were completed. Students attending multiple sections where the experiment was conducted only took part in during the first section attended.

After the subject wrote down their offer price, I asked then to turn the card over and remove the tape to reveal the posted price. They were then instructed to fill in the blank on the back and circle the correct answer as to what they should be paid. Subjects were also asked to write their name at the bottom of the back of the card so payment could be arranged. No payments were made at this point.

After I collected the round one cards, the subjects were told to reach into their envelope and take out the green card. I then repeated the experiment instructions on their 2nd round card. After envelops were collected, I told them they would be able to claim their earnings at an office in the College of Business Administration. Individual sealed envelopes were then prepared with their earnings and distributed to the subjects. Earnings ranged between $1.60 and $13.75 with an average of $5.98 per subject, total earnings amounted to $1159.80[4].

IV. Initial Results

a. Symmetry of Games

The two games are as identical as possible with simple instructions and the same set of payoffs in order to isolate the subject's role as a seller or as a buyer. As shown in Table 1 the payoffs and expected payoffs are the same for each game for each frame size.

[4] 51% of the total earnings were collected by the subjects.

Table 1. Payoffs of Seller and Buyer Games and Expected Profit Given Optimal Offer

	P_u	V_r	V_c	P_l	$P_u - V_c$	$P[p > b]$	$E[p\|p > b]$	$E[p\|p > b] - V_c$	$E[\pi^*]$
	4	-	2	0	2	.500	3.0	1.0	2.50
	5	-	2	0	3	.600	3.5	1.5	2.90
Seller	6	-	2	0	4	.667	4.0	2.0	3.33
	7	-	2	0	5	.714	4.5	2.5	3.78
	8	-	2	0	6	.750	5.0	3.0	4.25
	Avg					.646	4.0	2.0	3.35

	P_u	V_r	V_c	P_l	$V_c - P_l$	$P[p < b]$	$E[p\|p < b]$	$V_c - E[p\|p < b]$	$E[\pi^*]$
	8	2	6	0	6	.750	3.00	3.00	4.25
	8	2	6	1	5	.714	2.50	3.50	3.78
Buyer	8	2	6	2	4	.667	2.00	4.00	3.33
	8	2	6	3	3	.600	1.50	4.50	2.90
	8	2	6	4	2	.500	1.00	5.00	2.50
	Avg					.646	2.00	4.00	3.35

Table Notes*: Table depicts symmetry of payoffs and expected payoffs given optional offer of WTA and WTP games The game setup variables are defined as; P_u= value of upper frame, P_l =lower frame, V_r= rebate value, V_c = card value, b = offer. Table assumes optimal offer $b = V_c$. In the seller game [WTA$[p > b]$] a sale occurs when posted price exceeds offer price. The probability of a sale is $[p > b] = 1 - \frac{b-P_l}{P_u-P_l} = 1 - \frac{2}{P_u}$, Expected offer price given a sale is $E[p|p > b] = \frac{P_u+b}{2} = \frac{P_u+2}{2}$, and Expected profit is $E[\pi_A^*] = V_c + \frac{(P_u-V_c)^2}{2(P_u-P_l)} = 2 + \frac{(P_u-2)^2}{2P_u}$. In the buyer game [WTP$[p < b]$] a sale occurs when offer price exceeds posted price. The probability of a sale is $P[p < b] = \frac{b-P_l}{P_u-P_l} = \frac{6-P_l}{8-P_l}$, Expected offer price given a sale is $E[p|p < b] = \frac{P_l+b}{2} = \frac{P_l+6}{2}$, and expected profit is $E[\pi_P^*] = V_r + \frac{(V_c-P_l)^2}{2(P_u-P_l)} = 2 + \frac{(6-P_l)^2}{2(8-P_l)}$.*

There are five rows for each game because there are five possible frame sizes $P_u - P_l$ for a particular game. The card value $V_c = \{\$2.00, or\ \$6.00\}$ is fixed. The V_r= rebate value is fixed a \$2.00 for the buyers game in which they are rebated \$2.00 plus any game profits and b_i is the subjects offer. The table shows that subjects facing a fame range in either game have the same game payoff.

Cason and Plot (2014) refer to subjects that form expectations according to game rules as using the optimal model. The expected profit for the seller's game is,

$$E[\tilde{\pi}|b_i(opt)] = \quad V_c + (E[P|P > b_i) - V_c) * Pr(P > b_i), \tag{1}$$

given by card value plus expected profit from the sale with probabilities given by a conditional uniform distribution. The probability of a sale is $Pr[P > b] = 1 - \frac{b-P_l}{P_u-P_l}$. The expected price given a sale is, $E[p|p > b] = \frac{P_u+b}{2}$. Expected profit then becomes,

$$E[\tilde{\pi}|b_i(opt)] = \frac{1}{P_u}\left[2b_i + \frac{(P_u^2 - b_i^2)}{2}\right]. \tag{2}$$

when $V_c = 2$ and $P_l = 0$. Table 1 assumes optimal offer $b = V_c$.

In the buyers game, the buyer is awarded \$2.00 plus game profits. The expected value is,

$$E[\tilde{\pi}|b_i(opt)] = V_r + \left(V_c - E[P|P < b_i]\right) * Pr(P < b_i), \tag{3}$$

where the probability, $P[p < b] = \frac{b-P_l}{P_u-P_l}$, is the same as before and the expected offer price given a purchase is $E[p|p < b] = \frac{P_l+b}{2}$. Expected profit becomes,

$$E[\tilde{\pi}|b_i(opt)] = 2 + \frac{P_l^2 - b_i^2 + 12(b - P_l)}{16 - 2\,P_l} \tag{4}$$

when $V_r = 2$, $V_c = 6$, and $P_u = 8$. Table 1 assumes optimal offer, $b = V_c$.

The table reveals that the buyer's game may be mapped into an equivalent seller game by,

$$b(seller) = 8 - b(buyer), \tag{5a}$$

$$P(seller) = 8 - P(buyer), \text{ and} \tag{5b}$$

$$P_u(seller) = P_u(buyer) - P_l(buyer). \tag{5c}$$

The transformation requires the offer, the posted price and upper frame to change. The simplest case is first seller entry and the last buyer entry where there is a 50/50 chance of a sale or a purchase given each offers optimally (i.e., $V_c = \{\$2.00, or\ \$6.00\}$). Now the bid is transformed \$8.00 - \$6.00 = \$2.00. Say the realized price in the buyer game is \$1.00 under card value or \$5.00. This translates to \$8.00 - \$5.00 =\$3.00 over card value yielding the same \$1.00 profit, the same expected profit, and the same actual payoff. Lastly the frame range reflects the new interval for the realized price (note: $P_l = 0$).

b. The Endowment Effect

As an initial test of bidder behavior, I look at the properties of earnings of sellers and buyers. Table 2 provides the average earnings and average valuation errors for the full sample. While the average earnings for sellers were higher than those of buyers (6.22 vs. 5.96) the two-tail T-Test does not reject that null hypothesis [p-value = 0.44], that the average earnings between roles are equal. Because the two experiments were designed to have equal payoffs and there is no significant difference between the earnings of buyers and sellers, I can make an initial inference that the experiment performed as designed on an aggregate level.

Table 2. Average Bidding Earnings, Errors & Optimality

Panel A. Seller Game			*Panel B. Buyer Game*		
Round	Stat	Avg. Offer	Round	Stat	Avg. Offer
1st	N	97	1st	N	90
	Avg. Bid	3.99		Avg. Bid	4.22
	Std. err	0.15		Std. err	0.19
	Val. Error	1.99		Val. Error	1.78
	% Val. Error	99.5%		% Val. Error	24.33%
	% Optimal	11.34%		% Optimal	10.00%
2nd	Avg. Bid	3.74	2nd	Avg. Bid	4.54
	Std. err	0.21		Std. err	0.19
	Val. Error	1.74		Val. Error	1.46
	% Val. Error	87.0%		% Val. Error	27.0%
	% Optimal	15.5%		% Optimal	3.3%
Average	Avg. Bid	3.86	Average	Avg. Bid	4.38
	Std. err	0.18		Std. err	0.19
	Earnings	6.22		Earnings	5.96
	Std. Err	0.23		Std. Err	0.24

Table Notes: *Table displays statistics for all subjects who completed both rounds of the experiment. Sellers were bidding their willingness-to-accept (WTA) values for a $2.00 card, buyers were bidding their willingness-to-pay (WTP) values for a $6.00 card.* μb_i *denotes average bid. Val. Error =* $|b_i - V_c|$, *%Val. Error =* $\frac{|b_i - V_c|}{V_c}$, *%Optimal is the percentage of students who bid within 0.25 of the card value*.

One facet of the BDM mechanism which will be expounded upon later is the fact that not all valuation mistakes are punished. A seller may overvalue their object and still make a profit depending on the bids he or she receives. The first result showed no significant difference in the earnings of the two roles, next, I test to see if the valuation errors (judged in dollar value) made by the subjects of the experiment is conditional on their role in the experiment. I define a dollar valuation error as the difference between a subjects' bid and the true value of the item involved in the game.

$$\$Valuation\ Error = \ |B_i - V_c| \tag{6}$$

The lack of significant difference in average earnings should coincide with a lack of significant difference in the valuation errors made by the sellers and buyers. Here, the average dollar valuation error for sellers (\$1.86) was greater than the average dollar valuation error for buyers (\$1.62), but the two-tail t-test does not reject the null hypothesis that the valuation errors, judged on a dollar basis, are equal among transaction roles.

$$\%Valuation\ Error = \frac{|B_i - V_c|}{V_c} \tag{7}$$

Lastly, I examine test for differences in the magnitude of these of valuation errors for each role. It is important to note the differences in the values of the objects involved in the two games. In the seller game, the subject places his willingness-to-accept valuation on a card with a true value of \$2.00 while in the buyer game; the subject places his willingness-to-pay valuation on a card with a true value of \$6.00. When accounting for the difference in the objects underlying value, the disparity in valuation errors becomes much more pronounced. Now, the average % valuation error for sellers (93.25%) was much greater than the average %valuation for buyers (27%), the two tail t-test strongly rejects the null hypothesis [p-value = 0.00], which provides strong evidence that sellers' errors, as judged on percent of item value basis, were significantly greater than those of buyers.

The fact that the dollar valuation errors are not different, yet the errors as judged as a percentage of the items' value are significantly different calls into question whether or not the true value of the object involved in these type of experiment has a significant effect on the subject's valuation methodology. I take the time to note the differences in the value of the objects involved in each game, however, it is important to note that the objects true value should not matter. The strategy to maximize the expected payoff is always for the subject to value the object at its true value, whether that value is $2.00 (WTA game) or $6.00 (WTP game), and whether the subject is a buyer or a seller. Therefore, the results in Table 2 provide evidence of the possible existence of an ownership effect as evidenced by the much larger relative valuation errors appearing on the seller side (Beggan 1992). Per Horowitz (2002), differing valuations may be caused by factors such as the uniqueness or scarcity of a good, as well as any transaction costs involved, neither factor should have an effect in this study.

This preliminary analysis also supports the part-whole bias theory as referenced by Bateman (1997) where in incentive compatible procedures, valuations of parts of objects consistently exceed the valuation of the whole. Another explanation is that subjects are systematically drawn towards $2.00 valuation errors. The role of the $2.00 error will be explored in further detail later, but it should be noted that both buyers and sellers start out receiving $2.00 per round, so this may influence their bidding behavior. For the sellers, $2.00 represents the value of the card, and for buyers, $2.00 represents the redemption amount for participating in a single round of the experiment.

The analysis thus far shows the danger in the straightforward judgment of individual choice data. Any assertions made from the sample of buyers and sellers would be based on the condition that each party in the transaction fully understood their role and the implications of their choices, or at the least, each role understood their transactional implications at the same level. In the following analysis, I will utilize the concept of game form misconceptions to quantify the level of transactional understanding. The results will show how game form misconceptions can drastically alter one's interpretation of individual choice data, and should progress the understanding of such data going forward.

For sellers, the average subject offer fell from $3.99 in round 1 to $3.74 (Table 2) in round 2, suggesting that repetition did, in fact, lead to a more optimal pattern on bids. The magnitude of this valuation learning effect for sellers amounts to $0.25 or 12.5% of the item's true value. I also see a 3.1% increase in the proportion of optimal bids, which is indicative of the subjects learning and improving their bidding patterns from round 1 to round 2.

$$\%Valuation\ Learning\ Effect = \frac{(\mu B_i|R2 - \mu B_i|R1)}{V_c} \tag{8}$$

For buyers, the average subject offer increased from $4.22 to $4.54 (Table 2) from round 1 to round 2, again suggesting that repetition leads to more optimal bidding pattern. The magnitude of this valuation learning effect for buyers amounts to $0.32 or 5.3% of the items true value. I also see a 5.4% decrease in the proportion of optimal bids, this finding represents the initial sign of confusion by the buyers, as some of the subjects who offered optimal bids in round 1 deviated from optimal in round 2.

In the next section, I further the analysis by testing the findings of Cason & Plott on the samples of data. I don't aim to challenge the findings of the authors but attempt to utilize their framework to analyze individual choice decisions on either side of a transaction. Cason & Plott state that the BDM mechanism does not provide accurate measurements of preferences, but that statement may be too definitive in the face of mixed evidence. The BDM provides an assessment, which indicates a preference, but the exact magnitude of the preference is likely exaggerated by the presence of some form of misunderstanding on the part of the subjects, of the implications of their decisions within the experiment.

{Insert Figures 2A & 2B here}

A graphical representation of the subjects bidding behavior appears above in Figures 2A and 2B. The data, like Cason & Plott (2014), show that a greater proportion of subjects chose offers close to other dollar figures. For the sellers, the 10 percent of the subjects valued the card at $2.00 (its true value), while 18 percent valued the card at $3.00 and 23 percent at $4.00. For the buyers, 9 percent of the subjects valued the card at $6.00 (its true value, while 10 percent valued the card at $5.00 and 22 percent at $4.00. One explanation for these valuation errors is the minimal information theory presented by Irwin (1998) where the author finds that subjects make optimal decisions via the BDM when they are provided with the necessary information, but minimal information was not enough to deduce the optimal strategy. Although the subjects were given all of the information necessary to determine the optimal bid, the results show that they did not appear to fully process and understand the information provided to them.

The initial evaluation of the subjects bidding patterns through graphical representation show no significant difference. Both roles show a tendency towards a $2.00 valuation error, which may be tied to the true value of the card (seller game) or the initial payoff (buyer game), or perhaps an alternate explanation. These results showing a consistent trend of valuation errors provide support for the overall presence of some form of misconception on both sides of the transaction.

c. Optimality Effect

Now that I have seen signs of misconception in both experiments, I next look for signs of understanding within in the two games. I begin with the role of optimality, a subject who bids optimally in the first round appears to understand the implications of this mechanism[5]. I would expect that given another attempt at this game, more subjects would bid optimally as the second attempt should increase the subjects understanding.

[5] Optimality is defined by bids which are within $0.25 of the card's true value.

Table 3. Round 1 to Round 2 Offer Price Movements of Those Choosing Incorrectly

Panel A. Seller Game

	Seller	%Total	Buyer	%Total
Total	81	(100%)	86	(100%)
Move Onto Optimum	2	(2%)	5	(6%)
Move Towards Optimum	30	(37%)	33	(38%)
Move Away from Optimum	22	(27%)	29	(34%)
No Change	19	(23%)	27	(31%)

	χ^2	df	$pval$
Pearson Chi-Square	3.634	3	.304
Likelihood Ratio	3.684	3	.298

Panel B. Buyer Game

	Exposed	%Total	Not Exposed	%Total
Total	55	(100%)	112	(100%)
Move Onto Optimum	2	(4%)	5	(4%)
Move Towards Optimum	29	(53%)	34	(30%)
Move Away from Optimum	14	(25%)	37	(33%)
No Change	36	(65%)	10	(9%)

Tests	χ^2	df	$pval$
Pearson Chi-Square	8.258	3	.041
Likelihood Ratio	8.230	3	.041

Panel C. Offer Ratios- Move Toward Optimum

Type	Exposed?	0ffer1 Ratio > Offer2 Ratio	total	%
Buyer	N	29	61	48%
	Y	18	25	72%
Seller	N	19	51	37%
	Y	14	30	47%

***Table notes**: Exposure occurs when an individuals' non-optimal bid, ends up reducing their payoff. Optimal bids are those within 0.25 of the card's value. Offer ratio is calculated as $(b - V_c)/(P^* - V_c)$, a quotient of 0 represents the optimum. Pearson Chi-Square / Likelihood Ratio tests for independence between columns (i.e. Sellers vs. Buyers, and Exposed vs. Not Exposed).*

I test this assertion of round to round optimality independence by running Fisher's exact test on the data. Price movement data for those subjects who did not bid optimally in round 1 appears above in Table 3. Part of the data, like Cason & Plott show an optimal bid learning effect, as the subjects bid patterns become more optimal after completing the first round. Of the sellers, the number of sellers bidding optimally in round 2 jumped from 11.3 percent (11 subjects) to 15.4 percent (15 subjects), for an optimal bid learning effect of 4.1%. This is consistent with Noussair (2004) who found that bias in the BDM tended to decrease over time.

$$Optimal\ Bid\ Learning\ Effect = \quad \%Opt|R2 - \%Opt|R1 \qquad (9)$$

The buyer game told a different story, as the proportion of optimal bidding decreased from 10 percent (9 subjects) to 3.3 percent (3 subjects) or an optimal bid learning effect of negative 6.7%. This result runs counter to intuition, as well as Cason & Plott (2014) and the seller version of this experiment. The only plausible explanation for the 6 subjects who deviated from their round 1 optimal bid is confusion, (although 2 out of 6 were not rewarded for his optimal bid which may lead one to be more prone to change their bid, even though the initial bid was optimal). The apparent confusion in the bidding pattern provides possible evidence of a high level of game form misconception in the buyer game. In both cases, the data rejects the null hypothesis [p|seller <.01, p| buyer <.01] that the rate of optimality in round 2 is independent of the rate of optimality in round 1, but for opposite reasons.

The last result showed that subject's second round behavior, namely their likelihood of bidding optimally in round 2 was dependent on their likelihood of bidding optimally in round 1. In this section, I delve further into the effects of round 1 optimal bidding and expand the conversation into choice stability. In theory, subjects who bid optimally in round 1 should be more likely to stay with their optimal choice, and therefore less likely to change their bid from round 1 to round 2.

Of the 97 sellers, 86 did not choose optimally during round 1. Of those 86, 67 (78 percent) chose a different offer price in the second round while 19 (22 percent) chose the same offer price. 11 sellers did make offers near $2.00 in round 1. Of those 11, 10 (91 percent) chose the same offer price and 1 (9 percent) chose a different price on the second card. The data strongly rejects the null hypothesis of independence and supports the theory that for sellers, round 1 optimality leads to more stability of choice.

Of the 90 buyers, 81 did not choose optimally during round 1. Of those 81, 54 (67 percent) chose a different offer price in the second round while 27 (33 percent) chose the same offer price. 9 buyers did chose optimally in round 1. Of those 9, 3 (33 percent) chose the same offer price and 6 (66 percent) chose a different price on the second card. The data does not reject the null hypothesis that buyer's stability of choice is independent of Round 1 optimality.

These results run counter to Cason & Plott (2014) as well as the seller side of the same experiment. In Cason & Plott, 15 percent of the subjects who bid optimally in round 1 of the experiment bid optimally in round 2, for the seller side of the experiment, the probability of round 1 optimal subjects changing bids was 9 percent whereas on the buyer side, the probability of changing bids after round 1 optimality is a staggering 66 percent. This result again points towards relatively more misconception on the buyer side of the experiment, as there is little in the way of rationale explaining a subject deviating from his initial optimal bid.

d. The Framing Effect

The next step in the analysis is to test for possible signs of framing effects. Since the optimal strategy is always to value the card at its true value, the subject's bids should be independent of payoff frame. Therefore, there should be no correlation between an individuals' change in bid and the change in their payoff frame.

Table 4. Offer Descriptives by Posted Price Range Max Excluding Offers $\pm$25cents.

Panel A. Seller (WTA)

Round	Stat	Range					
		[0,$4]	[0,$5]	[0,$6]	[0,$7]	[0,$8]	Total
1^{st}	N	16	23	17	14	16	86
	mean	4.24	3.78	4.06	4.11	5.19	4.24
	Std err	0.49	0.18	0.17	0.45	0.34	0.15
	Median	4.00	3.75	4.00	4.00	5.00	4.00
	% optimal	16%	4%	6%	26%	6%	11%
2^{nd}	N	14	16	18	17	17	82
	Mean	4.27	3.47	3.53	4.41	4.61	4.05
	Std err	1.01	0.36	0.23	0.38	0.48	0.23
	Median	3.25	3.13	4.00	4.50	4.00	4.00
	% optimal	33%	11%	10%	6%	15%	15%

Panel B. Buyer (WTP)

Round	Stat	Range					
		[4,$8]	[3,$8]	[2,$8]	[1,$8]	[0,$8]	Total
1^{st}	N	12	14	18	19	18	81
	Mean	5.42	4.26	4.48	3.33	3.18	4.02
	Std err	0.40	0.51	0.44	0.34	0.30	0.19
	Median	5.00	4.00	4.00	3.00	3.38	4.00
	% optimal	0%	18%	5%	10%	14%	10%
2^{nd}	N	20	22	15	19	9	85
	mean	4.83	4.08	4.35	4.68	4.29	4.46
	Std err	0.28	0.32	0.49	0.50	0.86	0.20
	Median	5.00	4.00	4.00	4.50	4.50	4.50
	%Optimal	9%	4%	12%	0%	0%	6%

***Table notes**: Table shows average bid for each available payoff frame for subjects who did not bid optimally (within 25 cents of card value). Subjects' payoff frames are known before subject places bid. %Optimal is the percentage of students who bid within 0.25 of the card value.*

Table 4 – Panel A summarizes the mean price offer for each of the 5 upper bounds for the full sample of sellers. When the bids are categorized by their upper bounds, there is weak evidence of a framing effect, the majority (6 out of 8) of the sequential average bids are within the standard error,

however, those that fall outside the standard error (2 out of 2) all move in concert with the upper bound.

Table 4 – Panel B summarizes the mean price offer for each of the 5 lower bounds for the full sample of buyers. The trend here is similar to the buyer results again the majority of the sequential average bids fall within the standard error, but those that do not (3 out of 3) move downwards as the lower bound decreases.

The two tables above two show how the average bids on aggregate are tied to the frame of randomized posted price. Next, I utilize a Mann–Whitney U test in order to analyze the relationship between the bids placed and the upper (seller) or lower (buyer) bounds of the subject's subjects payoff ranges.

Table 5. Offer Similarity and Posted Price Range - P-Values Excluding Optimal Offers $\pm$25cents

Panel A. Seller

Round		Range			
		[0,$5]	[0,$6]	[0,$7]	[0,$8]
1^{st}	Range [0,$4]	0.861	0.483	0.768	*0.026*
	Range [0,$5]		0.167	0.358	*0.001*
	Range [0,$6]			0.824	*0.012*
	Range [0,$7]				0.099
2^{nd}	Range [0,$4]	0.736	0.405	0.044	0.138
	Range [0,$5]		0.861	*0.045*	0.106
	Range [0,$6]			*0.017*	0.121
	Range [0,$7]				0.958

Panel B. Buyer

Round		Range			
		[3,$8]	[2,$8]	[1,$8]	[0,$8]
1^{st}	Range [4,$8]	*0.041*	*0.034*	*0.000*	*0.000*
	Range [3,$8]		0.535	0.151	0.159
	Range [2,$8]			*0.020*	*0.032*
	Range [1,$8]				0.916
2^{nd}	Range [4,$8]	0.069	0.233	0.799	0.583
	Range [3,$8]		0.827	0.342	0.740
	Range [2,$8]			0.651	0.976
	Range [1,$8]				0.674

Table notes: *Table shows p-values from Mann-Whitney U Test, excluding offers within $\pm$25 cents of optimal value, between offers with posted price ranges for each game round. Values significant at 10% are in italics. Panel A depicts the seller (WTA) game and Panel B depicts the buyer game (WTP). The sample includes all UNO students who completed both rounds of the experiment. Seller p-values range from 0.001 to 0.958. Buyer p-values range from 0.000 to 0.976.*

In Cason & Plott (2014) 75 percent of the pairwise tests show a significant difference in offers based on the subject's payoff ranges, which appears to be evidence of a framing effect. The data (Table 5, above) does not show the same level of distributional dependence, for the full sample of data 35 percent of the pairwise tests show a significant difference in the subjects bid based on the payoff range. The sellers (35 percent of pairs) and the buyers (35 percent of pairs) show the similar amounts of distributional dependence, and this dependence decreases in both games from round 1 to round 2.

Although the Mann-Whitney test did not show a significant difference between the distributional dependence of seller and buyer bids, table 4 does provide evidence that the minimum amount that buyers have to pay may have more effect on an individual's valuation than the maximum payoff available does for sellers. This is consistent with a form of endowment effect, as anchoring will tend to reduce offer price flexibility Bokhari (2011). The anchoring effect as well as the ownership effect (Beggan, 1992) and loss aversion (Tversky, 1991) are amongst the most commonly referenced theories on the roots of the appearance of an endowment effect, in an effort to disentangle these biases I extend the analysis in order to further understand the role of other types of information on the subjects bidding behavior.

Table 6. Within Sample Framing Analysis

Sub-Sample	Stat	Seller	Buyer
	N	70	67
	μb_i	3.50	4.68
	μP_j	5.96	2.39
$\Delta Frame$	$\mu(Midpt_i)$	2.93	4.81
	$\mu(b_i - Midpt_i)$	0.57	0.13
	SE	(0.225)	(0.206)
	$r_{\Delta \mathrm{b_i}, \Delta p}$	0.262	0.180
	P-val	[0.029]	[.145]
	N	63	59
	μb_i	3.70	4.57
	μP_j	6.00	2.25
$\Delta Frame \vert NoOpt_1$	$\mu(Midpt_i)$	2.90	4.87
	$\mu(b_i - Midpt_i)$	0.80	0.30
	SE	(0.229)	(0.221)
	$r_{\Delta \mathrm{b_i}, \Delta p}$	0.280	0.229
	P-val	[0.026]	[0.088]

Table Notes: *statistics are based off round 2 bidding data for subjects whose frame changed from round 1 to round 2 ($\Delta Frame$). $NoOpt_1$ are those subjects who did not bid optimally (within 0.25) in round 1. μb_i denotes an individual's average bid. p^*denotes the upper payoff bound for sellers and the lower payoff bound for buyers. $Mdpt_i$ is the midpoint of an individual's payoff frame. r is the Pearson correlation coefficient.*

Lastly, I turn to the within subject framework suggested by Levin (2002), this method of analysis allows me to look for framing effects on an individual basis, and avoids errors of aggregation. Table 6 (above) presents statistics for the individual subjects average offer distance from the mean of their payoff distribution $\mu(b_i - Midpt_i)$ as well as the correlation between an individual's bid change and the change of their payoff frame. The subjects showed a shorter distance from midpoint than the sellers did, which suggests that on an individual subject level, buyers were more attracted to the minimum price of their payoff distribution than sellers were attracted to their maximum.

e. The Role of Feedback

In the next section of the analysis, I attempt to determine the role of feedback in the BDM mechanism. In the case of many individuals, a non-optimal bid may still result in the individual earning profit, or the non-optimal bid may have no effect at all. Exposure, as defined here, occurs when an individuals' non-optimal bid, ends up reducing their payoff, for example, a seller who set their WTA at $4.00 would be exposed if the randomized sales price was anything amount greater than $2.00 and less than $4.00. If the sales price was $3.95 the individual could have earned an extra $1.95 by setting their valuation at $2.00 (objects true value). Theoretically, a mistake that costs an individual money in round 1 should have a pronounced effect on their round 2 bidding behavior.

{Insert Figures 3A & 3B here}

Figure 3A illustrates the pattern of bidder movements towards and away from the optimal offer ratio[6] by those subjects who were not exposed to their error, Figure 3B displays the same for those subjects who were exposed to their errors. Seller activity is depicted by diamonds and buyer activity is depicted by "X's". Marks on the 45-degree line represent subjects who maintained a consistent offer ratio from round 1 to round 2. Marks below the 45-degree line represent movements toward the optimal offer ratio of 0, while marks above the 45-degre line represent movements away from optimal, detailed analysis of these bidding patterns appears below.

I first look to assess the overall effect of a subject being exposed to his first round error. Of the sample of UNO subjects who did not bid optimally in the first round, a total of 55 subjects were

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[6] *Optimal Offer Ratio [0.00] is defined by (b_i – $2) / ($P_u$ - $2), where b_i is the individual's bid and P_u is the upper bound of the payoff frame.*

exposed to their error, of those 55 subjects, 31 (56 percent) improved their offer ratio. A total of 112 subjects were not exposed to their round 1 error, and 39 (35 percent) of those subjects improved their offer ratio. I can define the samples overall exposure effect as the difference between the percentage of subjects who improved their bids after being exposed and the percentage of subjects who improved their bids without being exposed. In the sample the overall exposure effect is 21 percent.

Of the 86 sellers who did not bid optimally in the first round, 25 were exposed to their error (see Table 3), of those 25, 18 subjects (72 percent) improved their offer ratio from round 1 to round 2. Of the 61 subjects who were not exposed to their mistake in round 1, 29 subjects (47.5 percent) improved their offer ratio, so it could be said that subjects being exposed to their, or the seller side exposure effect, increased their propensity to improve his bid by 24.5 percent.

$$Exposure\ Effect = \quad \%Improve\ Ratio|Exposed - \%Improved\ Ratio|Not\ Exposed \quad (10)$$

Of the 86 sellers who did not bid optimally in the first round, 25 were exposed to their error (see Table 3), of those 25, 18 subjects (72 percent) improved their offer ratio from round 1 to round 2. Of the 61 subjects who were not exposed to their mistake in round 1, 29 subjects (47.5 percent) improved their offer ratio, so it could be said that subjects being exposed to their, or the seller side exposure effect, increased their propensity to improve his bid by 24.5 percent.

Of the 81 buyers who did not bid optimally in the first round, 30 were exposed to their error, of those 30, 14 subjects (47 percent) improved their offer ratio from round 1 to round 2. Of the 51 subjects who were not exposed to their mistake in round 1, 19 subjects (37 percent) improved their offer ratio, so it could be said that subjects being exposed to their, or the buyer seller side exposure effect, increased their propensity to improve his bid by 10 percent.

$$\Delta Exposure\ Effect = \quad Exposure\ Effect|Seller - Exposure\ Effect|Buyer \qquad (11)$$

When evaluating both games, the evidence here suggests feedback, namely being exposed to a round 1 mistake, was 14.5 percent more likely to improve bidder behavior for sellers rather than buyers [ΔExposure Effect = .145]. Feedback having more of an effect of on sellers than buyers is inconsistent with the ownership and anchoring aspects endowment effect theory. For a seller, the endowment effect causes the individual to set their valuation at a certain monetary value, plus an intangible value. Extra information and feedback will do less to shift the sellers' valuation than the buyers' valuation, this is due to the ownership effect explanation of endowment effect theory, the intangible attachment is only considered on the seller side, and therefore, information has less sway. Consider the stock market and divestiture aversion, bad news is more likely to dissuade one from purchasing a stock than it is likely to cause one to sell a stock they own, especially one that they may have inherited or attached an intangible value to for any reason.

f. Summary of Initial Findings

So far the analysis has shown us that valuation errors between the two transactional roles were about equal in dollar values, but much higher for sellers when considering the error as a percentage of the items' value, this showed possible evidence of an endowment effect, but also lead us to ponder whether the subjects considered the value of the item when determining their valuation.

When considering the effect of optimality, I saw that the sellers bid pattern became more optimal over time, while several buyers who bid optimally in round 1 adjusted to a sub-optimal pattern in the second round, this is a sign of high levels of confusion or purely random behavior in the seller game. Excess confusion on the buyer side of an experiment could be due to an alternate explanation of the endowment effect, namely rational inattention (Matejka, 2014) which will be discussed later.

The framing analysis also provided evidence in support of the endowment effect, as I saw that manipulating the framing of the payoffs had slightly more effect on the buyers than it did the sellers, which supports endowment effect theory. However, when evaluating the role of subject exposure, I see that financial feedback (exposure) has a much stronger effect on changing seller behavior than it does on changing buyer behavior. This exposure analysis presents evidence against the prominent explanations of the endowment effect.

The analysis thus far has provided us with very mixed results, there are valuation errors, but there is also evidence of confusion, there is evidence in support of, and against the endowment effect. I have learned from Cason & Plott (2014) that I should not view the individual choice data as a true indication of their pure preferences. The initial results presented earlier provide strong evidence that many of the subjects who took part in this experiment were not clear about the implications of their valuations, therefore, I follow the model presented in Cason & Plott to evaluate how the data fit the two choice models which they present.

V. The Models

My empirical work compares models of optimal bidding and first-price misconception. Cason & Plott (2014) find that sub-optimal choices made their experimental setting do not reveal an individual's preference, but rather a misconception of game rules. I adapt the Cason & Plott methodology by estimating random utility choice models of subjects forming expectations using optimal bids or a first-price misconception bids. A mixed choice model is also considered to assess which of the two models provides a better fit to their experimental data.

a. Optimal Model with Noise

It's possible for a subject to understand the implications of the BDM mechanism, and make mistakes. These mistakes are often not penalized by the mechanism. In the experiments, 29% of the sellers and 37% of the buyers who did not bid optimally in round 1 were exposed to their mistake. The model derivation is in terms of the seller's game, but the buyer's game can be easily transformed into to the seller's game using equations (5). The subject, who understands the implications of second price Vickrey auction, will formulate his/her expected profit as in equations (1) and (2). Cason and Plott (2014) characterize subjects using computing these expectations as following a model that is optimal with noise. According to equation (2) the expected profit is a function of the distance between the upper frame and the individuals bid. This represents framing noise in individual choice behavior.

I derive a new semi-closed form expression based on Cason and Plott (2014) who assume and estimate only discrete versions of the model. Here, the upper frame can be any value, $P_l = 0$ and the card value is \$2.00 as in Cason and Plott.[7] They base probability that offer will be any bid value is derived from a quantal choice framework in which individuals make Luce-McFadden logit errors (McFadden, 1976). The probability of any offer equally to the subjects bid is:

$$P[offer = b_i(opt)] = \frac{e^{\lambda\left[\tilde{\pi}\middle|b_i(opt)\right]}}{\sum_j e^{\lambda\left[\tilde{\pi}\middle|b_j(opt)\right]}} = \frac{e^{\lambda\left[\tilde{\pi}\middle|b_i(opt)\right]}}{\int_l^u e^{\lambda\left[\tilde{\pi}\middle|b(opt)\right]}db}. \tag{12}$$

[7] More general expressions can be calculated. I concentrate on specific values to simplify the exposition.

If bids are continuous on the interval $[l, u]$ then the denominator becomes,

$$\int_l^u e^{\lambda[\tilde{\pi}|b(opt)]}db = \frac{1}{\sqrt{\lambda}}2e^{\frac{2\lambda}{P_u}+\frac{P_u\lambda}{2}}\sqrt{\frac{P_u\pi}{2}}[\Phi[\mathrm{x(u)}] - \Phi[\mathrm{x(l)}]]; x(j) = \sqrt{\frac{\lambda}{P_u}}(P_j - 2). \tag{13}$$

$\Phi[.]$ is the cumulative normal. The log-likelihood (i.e, $\ln(P[offer = b_i])$) of the i^{th} subject is,

$$Logl_i(opt, u) = \tag{14}$$

So the grand likelihood for each game is,

$$Logl(opt) = \sum_i \sum_u d_{u,i} Logl_i(opt, u) \tag{15}$$

where $d_{u,i}$ is from a set of five range dummies. For each round of a game , $d_{u,i} = 1$ for subject i only for the frame she faces on the front of the card, $P_u = \{4,5,6,7,8\}$.

b. First Price Misconception Model

Cason & Plott (2014) also develop an alternative bidding behavior model patterned after subject incorrectly believing that the auction experiment is a first price auction. In a first price action, subjects believe that their profit is based on the price they offered instead of the price on the back of the card. For the sample, 45 percent of sellers and 43 percent of buyers showed signs of this misconception, either directly by circling the incorrect payoff box (where is this documented), or indirectly by twice bidding above (seller) or below (buyer) the random payoff price[8].

Now the bid value replaces the conditional expected value of the randomly drawn price:

$$E[\tilde{\pi}|b_i(1^{st})] = 2 * Pr(b_i > P) + b * Pr(P > b_i),. \tag{16}$$

[8] Of the sellers, 10 directly displayed misconception through their card feedback, 34 showed possible misconception through their bids (44/97 = 45%). Of the buyers, 15 directly displayed misconception through their card feedback, 24 showed possible misconception through their bids (39/90 = 43%).

Assuming a uniform distribution the expression becomes,

$$E[\tilde{\pi}|b_i(1^{st})] = \frac{1}{P_u}[2b_i + b_i(P_u - b_i)]. \tag{17}$$

The optimal bid is the conditional expectation of the posted price greater than the card value of \$2, $b_{1^{st}} = E[P|P > 2] = \frac{2+P_u}{2}$. The probability of the offer equal to bid is,

$$P[offer = b_i(1^{st})] = \frac{e^{\lambda[\tilde{\pi}|b_i(1^{st})]}}{\sum_j e^{\lambda[\tilde{\pi}|b_j(1^{st})]}} = \frac{e^{\lambda[\tilde{\pi}|b_i(1^{st})]}}{\int_l^u e^{\lambda[\tilde{\pi}|b(1^{st})]} db}. \tag{18}$$

If bids are continuous on the interval $[l, u]$ then the denominator becomes,

$$\int_l^u e^{\lambda[\tilde{\pi}|b(1^{st})]} db = \frac{1}{\sqrt{\lambda}} e^{\lambda\left(1+\frac{1}{P_u}+\frac{P_u}{4}\right)} \sqrt{P_u \pi}[\Phi[\mathrm{x(u)}] - \Phi[\mathrm{x(l)}]]; x(j) = \frac{1}{2}\sqrt{\frac{2\lambda}{P_u}}[2P_j - 2 - P_u] \tag{19}$$

The log-likelihood (i.e., $\ln(P[offer = b_i])$) of the i^{th} subject is,

$$Logl_i(1^{st}, u) = \frac{-1}{4\mathrm{P_u}}\left[(2 - 2b + \mathrm{P_u})^2\lambda + 2\mathrm{P_u}\ln[\pi/\lambda] + 4\mathrm{P_u} ln[\sqrt{P_u}\Phi[x(u)] - \sqrt{P_u}\Phi[x(l)]]) \right] \tag{20}$$

where the cumulative normal term is slightly different: $x(j) = \sqrt{\frac{\lambda}{2P_u}}\left[2P_j - 2 - P_u\right]$. The game likelihood is,

$$Logl(1^{st}) = \sum_i \sum_u d_{u,i} Logl_i(1^{st}, u) \tag{21}$$

Again, $d_{u,i}$ is a dummy variable which equals 1 only for the upper frame $\mathrm{P_u}$ the individual faces in that round.

c. Model Comparison

{Insert Figure 4 here}

Figure 4 displays the expected profit of each of the two previously discussed models, given their payoff ranges. The optimal model is designated by two solid lines, an optimal bid of $2.00 given the smallest available payoff range ($0.00 to $4.00), the model accounts for framing noise and leads to an expected profit of $2.50, as the payoff range increases the probability of receiving a random price of over $2.00 increases and therefore so does the expected profit. Increases of the payoff range will also increase the likelihood of subject bidding error and the more one deviates from the optimal bid, the lower his expected profit.

The first price model is designated by the two dashed lines, the subject believes that he is in competition with the upper frame, and therefore he formulates his optimal bid = $(2 + P_u)/2$. The graphs display this behavior as the misconceived optimal bid increases as the payoff range expands. The two overlapped expected payoff models displayed in Figure 4 provide a possible explanation for the differences in bid behavior amongst subjects taking part in the experiment.

VI. Experimental Results

The task of creating a behavior model based on misconceptions, as well as testing that model against an optimal behavior model has already been completed in Cason & Plott (2014). The primary aim of this paper is to add to the literature by assessing whether the model fits are a function of the subjects' role in the experiment.

a. Lambda Analysis

From the earlier equations, I know that the λ parameter represents the sensitivity of bidding behavior to each model, λ_o represents the samples sensitivity to the optimal model with noise, and λ_m represents to the sensitivity to the first price model. As lambda approaches infinity the model fits the bidding behavior perfectly with no errors, as lambda approaches zero, the subjects are completely insensitive to the model of choice and choose bids with equal probability, and as lambda approaches negative infinity the bidding behavior represents the inverse of the bidding pattern predicted by the model.

{Insert Figure 5 here}

Figure 5 displays a probability density function for both choice models, given a range of posted prices, and assuming a λ value of 3.0[9]. In the optimal model, I see the bidding behavior condensed near the true value of the card $2.00, a higher lambda estimate would lead to a thinner and steeper curve, representing an increased probability of bids around $2.00, a lower lambda estimate would lead to a wide and flatter distribution of bids spread across the payoff range. I also observe that the probability of bidding optimally decreases as the upper bound of the payoff range increases, which is due to the framing noise included in the model.

In the first price model, I see that the optimal bid under this model is directly related to the upper frame P_u. This is consistent with the maximization of the incorrect payoff expression, which yields $\tilde{b} = 1 + .5P_u$. So when P_u=4, the optimal bid is calculated as $3.00 and when the P_u=8, the optimal bid is calculated as $5.00 as depicted, the bidding probabilities based given payoff ranges appear in Figure 5.

[9] Lambda is set at 3.0 for illustrative purposes only.

I begin my analysis with the examination of the payoff sensitivity parameters obtained from the maximum likelihood estimation. Table 7 reports estimates for the sensitivity to the optimal model, denoted as λ_o, well as estimates for the sensitivity to the first price model, λ_m for each of three sub-samples, broken down by the different data sources for both sellers and buyers.

Table 7. Sensitivity Estimates of Optimal and First Price Misconception Models by Subject Type/Game and Data Source

Subjects	Rnd	N	λ_o	SE_o		$Logl(o)$	λ_m	SE_m		$Logl(m)$	$\frac{Logl(m)}{Logl(o)}$
				UNO-ALL							
All	1	187	-0.370	(0.156)	**	-329.5	0.957	(0.160)	***	-306.5	93%
	2	187	-0.306	(0.170)	*	-322.6	0.530	(0.129)	***	-314.1	97%
ShwMis	1	83	-0.826	(0.224)	***	-139.5	1.117	(0.261)	***	-131.9	95%
	2	83	-0.922	(0.244)	***	-134.8	0.888	(0.234)	***	-131.5	98%
NoOpt	1	169	-0.588	(0.159)	***	-293.4	1.177	(0.189)	***	-269.2	92%
	2	170	-0.485	(0.171)	***	-292.1	0.570	(0.138)	***	-285.5	98%
				UNO-WTA							
All	1	97	-0.327	(0.229)		-168.6	1.611	(0.307)	***	-144.4	86%
	2	97	-0.093	(0.235)		-170.5	0.853	(0.211)	***	-159.3	93%
ShwMis	1	44	-0.951	(0.327)	***	-70.9	1.570	(0.448)	***	-63.9	90%

	2	44	-0.650	(0.319)	*	-74.2	1.611	(0.455)	***	-64.7	87%
NoOpt	1	87	-0.556	(0.233)	**	-149.5	2.164	(0.407)	***	-121.7	81%
	2	84	-0.345	(0.236)		-147.8	1.018	(0.247)	***	-136.3	92%
				UNO-WTP							
All	1	90	-0.408	(0.214)	*	-160.9	0.551	(0.185)	***	-157.2	98%
	2	90	-0.569	(0.249)	**	-151.2	0.264	(0.164)		-152.3	101%
ShwMis	1	39	-0.716	(0.309)	**	-68.5	0.780	(0.318)	**	-66.9	98%
	2	39	-1.338	(0.390)	***	-59.7	0.421	(0.272)		-64.0	107%
NoOpt	1	82	-0.617	(0.219)	***	-143.9	0.665	(0.206)	***	-141.0	98%
	2	86	-0.650	(0.250)	**	-143.9	0.263	(0.168)		-145.7	101%
				PLOTT							
All	1	244	0.963	(0.210)	***	-416.2	1.158	(0.156)	***	-386.5	93%
	2	244	1.109	(0.219)	***	-414.3	0.581	(0.115)	***	-415.5	100%
ShwMis	1	110	0.425	(0.261)		-190.8	2.985	(0.473)	***	-141.5	74%
	2	110	-0.009	(0.228)		-192.7	1.742	(0.305)	***	-161.5	84%
NoOpt	1	203	0.531	(0.198)	**	-352.1	1.795	(0.229)	***	-296.8	84%
	2	168	0.281	(0.198)		-296.1	1.029	(0.175)	***	-271.8	92%
				JOINT							
All	1	431	0.237	(0.122)	*	-759.6	1.066	(0.112)	***	-693.4	91%
	2	431	0.376	(0.131)	***	-750.9	0.559	(0.086)	***	-729.6	97%
ShwMis	1	193	-0.209	(0.163)		-337.3	1.840	(0.240)	***	-280.2	83%
	2	193	-0.400	(0.162)	**	-331.2	1.290	(0.187)	***	-295.6	89%
NoOpt	1	372	-0.068	(0.121)		-655.8	1.470	(0.147)	***	-568.2	87%
	2	338	-0.120	(0.127)		-592.7	0.772	(0.109)	***	-559.5	94%

Table Notes: λ_o denotes sensitivity to optimal model. λ_m denotes sensitivity to first price model. Log Likelihood Ratios ($\frac{Logl(m)}{Logl(o)}$) less than 100 percent indicate the first price model provides a better fit for the data.

Based off of the experimental design, there are two patterns that I look to observe in the data. The first is sub-sample to model fit correlation, the second is possible learning effects. There are 3 sub-samples involved in the overall estimation. Sub-sample 1 is the full sample of data from a given source, within that source, sub-sample 2 represents the subjects who did not bid optimally in either round and, sub-sample 3 is made up of the subjects who appeared to show a misconception, either through the feedback they provided on their game card or via their bid pattern.

As I move from sub-sample 1 to sub-sample I expect the sub-samples to become less sensitive to optimal model λ_o, and more sensitive to the first price model λ_m. The estimation done by Cason & Plott (2014) follows this pattern in the majority of their sub-samples (see Table 7, PLOTT). The second pattern is learning effects, which would be represented by an increase in optimal model sensitivity λ_o after one round, or a decrease in first price model sensitivity λ_m after 1 round. Cason & Plott's data do not show an increase in optimal model of sensitivity, but do in fact show first price model sensitivity significantly decreasing in all 3 sub-samples, after round 1. This combination gives us mixed evidence as to whether or not repetition of the game lead to learning amongst subjects.

1. Combined UNO Sample

The initial analysis starts with the sample of subjects who took part in the experiments at the University of New Orleans (UNO), in this sample there were 97 sellers and 90 buyers for a full sample of 187 subjects.

As I move from sub-sample 1 to sub-sample 3 (Table 6), in the UNO sample I expect subjects to begin to show more signs of possible confusion denoted by a decrease in λ_o. The data loosely fit this behavior pattern, in round 1, the λ_o parameter decreases from -0.37 to -0.59 to -0.83, however, none of these changes in λ_o are significantly different. In round 2 I again show a significant decrease in λ_o only when I move from sub-sample 2 to sub-sample (-.49 to -0.92). Following this same pattern from sub-sample 1 to sub-sample 3, I would expect the parameter λ_m to increase as I move to sub-samples with less optimal behavior. In both round 1 and round 2, there is no significant difference in the three λ_m parameters from sub-sample to sub-sample.

Several studies, including Plott & Zeiler (2005) have shown that optimal behavior in an experiments utilizing the BDM mechanism can increase as subjects have more opportunities at the game. Since I expect subjects bid accuracy to increase with repeated trials I expect the parameter λ_o to increase within sub-samples from round 1 to round 2. While the λ_o parameter increases after 1 round in all 3 sub-samples, none of the increases are of significant magnitude, and therefore there is no evidence of a learning effect when defined as an increase in optimal behavior after 1 opportunity.

Another interpretation of a learning effect would be a decrease in confusion, sub-samples 1 and 2 of the data do in fact show sharp declines in the sensitivity parameter to the first price model λ_m. While it is interesting to note this decrease λ_m, I must evaluate this trend in context, while the subjects appear to become less confused after 1 round, they do not become more optimal. This observations suggests that the UNO sample of data may be bidding under a model not discussed in this paper, or simply at random. When evaluating the results of evaluating the lambda estimation results for individual games, I see that this decrease in λ_m sensitivity is primarily driven by the WTA subjects, whose results showed significantly less confusion in both sub-sample 1 and sub-sample 2.

2. Evaluation of Model Fit

The estimates presented in Table 7 also provide us with the opportunity to evaluate whether the optimal model or first price model provides more accurate estimations of the data. I do this by observing the ratio of log likelihoods, where a $logl(o)$ represents the log likelihood of the λ_o estimation, while $logl(m)$ provides the same for the estimation of λ_m. The UNO-ALL panel provides log likelihood ratios that are all less than 100% indicating that in all of the estimations the first price model provided a more accurate estimation. This finding is consistent with the results from Cason & Plott (2014) (see PLOTT panel), whose estimates were also more accurate using the first price model. The only estimation which didn't follow this trend was the UNO-WTP estimations, where the bid behavior was extremely erratic. This result, combined with the fact that all of the UNO-WTP estimates for λ_o were negative suggests that buyer behavior may be driven by some confusion other than a first price auction misconception.

3. Lambda Sensitivity Equivalence

I have estimated data to suggest that, based on the ratio of log likelihoods, the first price model provides a more accurate estimation. The final test of this parameter is designed to assess whether the sensitivity estimates are significantly different between seller and buyer. Table 8 shows the results of a constrained estimation, wherein λ_s, the seller's model fit sensitivity, is equal to λ_b, which is the model sensitivity parameter for the buyers.

Table 8. Sensitivity Equivalence of buyers and sellers, $\lambda_s = \lambda_b$

Panel A. Optimal Model

Rnd	N	λ_p		λ_s		λ_b		$logl_u$	λ_p		λ_u		$logl_c$	$pval$
						All								
1	431	0.963	***	-0.327		-0.408	*	-745.59	0.963	***	-0.370	**	-745.62	0.796
		(0.21)		(0.229)		(0.214)			(0.21)		(0.156)			
2	431	1.109	***	-0.093		-0.569	**	-736.01	1.109	***	-0.306	*	-736.98	0.164
		(0.219)		(0.235)		(0.249)			(0.219)		(0.17)			
						ShwMis								
1	193	0.425		-0.951	***	-0.716	**	-330.15	0.425		-0.826	***	-330.29	0.600
		(0.261)		(0.327)		(0.309)			(0.261)		(0.224)			
2	193	-0.009		-0.650	*	-1.338	***	-326.49	-0.009		-0.922	***	-327.43	0.170
		(0.228)		(0.319)		(0.39)			(0.228)		(0.244)			
						NoOpt								
1	372	0.531	**	-0.556	**	-0.617	***	-645.49	0.531	**	-0.588	***	-645.51	0.847
		(0.198)		(0.233)		(0.219)			(0.198)		(0.159)			
2	338	0.281		-0.345		-0.650	**	-587.86	0.281		-0.485	***	-588.26	0.374
		(0.198)		(0.236)		(0.25)			(0.198)		(0.171)			

Panel B. First Price Model

Rnd	N	λ_p		λ_s		λ_b		$logl_u$	λ_p		λ_u		$logl_c$	$pval$
						All								
1	431	1.158	***	1.611	***	0.551	***	-688.11	1.158	***	0.957	***	-693.00	0.002
		(0.156)		(0.307)		(0.185)			(0.156)		(0.16)			
2	431	0.581	***	0.853	***	0.264		-727.09	0.581	***	0.530	***	-729.60	0.025
		(0.115)		(0.211)		(0.164)			(0.115)		(0.129)			
						ShwMis								
1	193	2.985	***	1.570	***	0.780	**	-272.25	2.985	***	1.117	***	-273.34	0.139
		(0.473)		(0.448)		(0.318)			(0.473)		(0.261)			
2	193	1.742	***	1.611	***	0.421		-290.17	1.742	***	0.888	***	-293.05	0.016
		(0.305)		(0.455)		(0.272)			(0.305)		(0.234)			
						NoOpt								
1	372	1.795	***	2.164	***	0.665	***	-559.53	1.795	***	1.177	***	-566.04	0.000
		(0.229)		(0.407)		(0.206)			(0.229)		(0.189)			
2	338	1.029	***	1.018	***	0.263		-553.86	1.029	***	0.570	***	-557.31	0.009
		(0.175)		(0.247)		(0.168)			(0.175)		(0.138)			

Table Notes: $\lambda = (1 - src)\lambda_p + src * (\lambda_s(1 - game) + \lambda_b\, game)$ $H_0: \lambda_s = \lambda_b$. *The null hypothesis is tested under a Chi Squared distribution with 1 degree of freedom.* $\lambda_j, j = \{p, s, b\}$ *denotes model sensitivity for University of Purdue subjects (p),UNO sellers (s), and UNO buyers (b).* λ_u *is model sensitivity for all UNO subjects.*

When utilizing the optimal model to in estimating λ under these constraints, the p-value does not reject the null hypothesis that that the lambda parameters may be equal. This is dues to the significant level of divergence from the optimal model prevalent in both games, and that the optimal model does a poor job of estimating these results for both games.

When testing this constraint under the first price model, the five of the six sub-sample to round combinations strongly reject the null hypothesis. In all cases, the λ estimate for the buyers was higher than that of the sellers, and in 5 of 6 cases it was significantly so. These estimation results fall in line with the idea that the first price model does a much more accurate job of predicting the behavior of the subjects involved in the experiment.

4. Mixed Model Analysis

The next step in the analysis is to utilize both behavior models in order to estimate the grand likelihood, which is constructed as a probability weighted average of each conditional likelihoods. Table 9 reports estimates for a pooled payoff sensitivity parameter λ as well as the probability that the first price misconception model best describes the data pattern, Θ_m. This estimation procedure assumes that all bidding behavior was driven by either optimal model or the first price auction misconception model.

$$Logl(\lambda, \Theta_m, y_i) = \sum_i Logl[(1 - \Theta_m) l_i^{OPT} + \Theta_m l_i^{1st}] \tag{19}$$

I start with Panel A of Table 9, which utilizes the full sample of 187 UNO students who completed the experiment. Similarly to the analysis from Table 9, I expect to find a sub-sample to theta correlation, where the probability of misconception parameter is directly correlated with the designed probability of misconception in each sub-sample. I will also look for a learning effects, or a decrease in misconception after a round of the experiment familiarizes the subjects with the games' rules.

Table 9. Mixed Model Analysis

Panel A. University of New Orleans

Rnd	N	λ		SE_{λ}	Θ_m		SE_{Θ_m}	Θ_1		SE_{Θ_1}	$logl$
					All						
1	187	1.151	***	(0.354)	0.935	***	(0.090)				-306.26
2	187	0.711	**	(0.711)	0.870	***	(0.165)				-313.91
					NoOpt						
1	187	2.086	***	(0.390)				0.908	***	(0.038)	-292.40
2	187	1.193	***	(0.355)				0.814	***	(0.074)	-309.63
					ShwMis						
1	187	1.219	***	(0.359)				0.215	***	(0.106)	-304.20
2	187	0.926	**	(0.351)				0.450	**	(0.172)	-310.03

Panel B. Purdue University (from Cason &Plott, 2014)

Rnd	N	λ	SE_{λ}	Θ_m	SE_{Θ_m}	Θ_1	SE_{Θ_1}	$logl$
				All				
1	245	4.49	(0.839)	0.65	(0.046)			-932.4
2	244	2.65	(0.824)	0.42	(0.059)			-962.5
				NoOpt				
1	245	5.59	(0.735)			0.85	(0.033)	-884.9
2	244	4.39	(0.948)			0.76	(0.052)	-913.9
				ShwMis				
1	245	5.06	(0.787)			0.50	(0.078)	-913.1
2	244	2.40	(0.699)			0.99	(0.096)	-927.8

Table Notes: *λ represents the pooled payoff sensitivity to mixed model. Θ is the probability that subjects bid using the first price auction misconception model. $\Theta_m = \Theta_0 + \Theta_1 d$. Θ_1 denotes the coefficient on a dummy variable those subjects did not bid optimally (NoOpt) or separately showed signs of misconception (ShwMis). The equation for the dummy variable estimation is $\Theta_m = \Theta_0 + \Theta_1 d$. Panel B is taken directly from Cason & Plott (2014) Table 5.*

For the full sample of UNO subjects, the theta value of 0.93 shows the bidding behavior is significantly more likely to follow the first price auction model than the optimal model. Θ_m of .93 indicates and 93% probability that subjects' bids are driven by the first price misconception model and a 7% chance that their biding behavior is more heavily influenced by the optimal model.

In this estimation procedure, Heading 2 and Heading 3 utilize the dummy variable Θ_1 in order to test for changes Θ_m when subjects did not bid optimally (heading 2, $NoOpt$) or showed a possible misconception through their bidding pattern or card feedback (heading 3, $ShwMis$). Therefore, the misconception likelihood is captured by the equation:

$$\Theta_m = \Theta_0 + \Theta_1 d. \tag{21}$$

Cason & Plott utilized the same methodology and observed an uptick an uptick in the probability of misconception for those in heading 2 and heading 3, with one exception. The data does now show the same pattern, the non-optimal dummy variable ($NoOpt$) produces a Θ_1 parameter that is not significantly different from the Θ_m estimated in heading 1, this is likely due to the very high Θ_m parameter estimated in panel 1, which leaves little room to increase. The likely misconception dummy variable ($ShwMis$) produces a Θ_1 estimate which is significantly less than the Θ_1 originally estimated. Along with earlier results, this suggests that those subjects who shows the most signs of confusion were likely bidding randomly, confused, or not paying attention to the rules stated on the card and during the experiment.

When observing the Purdue data (Table 9, Panel B), I see that the Θ_1 parameter in round 1, is also significantly less than their original Θ_m estimates. This result indicates a misconception in that sub-sample of Purdue subjects other than a first price auction misconception. In round 2, however, that estimate significantly increases to 0.99, this indicates that the Purdue subjects who showed the most signs of confusion, originally bid under an undetermined pattern, but after 1 round, those subjects behavior fell strongly in line with the first price misconception model. The data shows no such significant increase in Θ_1 for those with likely misconceptions and provides evidence that the while the confused Purdue subjects appeared to learn the incorrect (first price) behavior model after one round, the confused UNO subjects did not adapt in the same fashion, and continued to bid using an undefined pattern or no pattern at all. When described as a significant decrease in probability of misconception Θ_m after round 1, the UNO subjects showed no signs of learning.

5. Summary of Model Fit

The mixed model analysis provides strong evidence in favor of the first price model, however, this analysis assumes that all behavior is driven by one of two patterns. The analysis of the theta parameters suggests that perhaps a significant proportion of the subjects in the UNO sample may have been bidding randomly.

When comparing the lambda estimation results from the both the buyer and seller perspectives, I see that both the optimal and the first price auction misconception models fit better when the subject is the seller, this difference in model fit is significantly pronounced when utilizing the first price model. This is consistent with a pattern of anchoring and adjustment, where the seller anchors his valuation around the true value of the card, and then uses some methodology to adjust his/her bid based on the rest of the information available to him (Tversky & Kahneman, 1974). The lack of a clear reference point, inherit from the ownership of the object may lead to buyer bidding patterns which are scattered indiscriminately. Other theories which may help explain these divergent behavior patterns are discussed in the conclusion.

VII. Tests of the Endowment Effect

a. Univariate Analysis

For the initial test of the endowment effect, I must first consider the differing value of the objects involved and convert the valuations to an equivalent scale. Consider the seller who over-values his $2.00 card by $1.50, or places a round 1 bid of $3.50. Next consider the buyer who makes an equivalent error, meaning he undervalues the \$6.00 card by \$1.50, or places a round 1 bid at \$4.50. Conveniently, the bid equivalence is a function of the static \$8.00 upper frame in the seller game.

$$Bid\ Equivalency: Bid|Seller(WTA) = \quad \$8.00 - Bid|Buyer(WTP) \qquad (22)$$

In the previous example, I can see that \$4.50 buyer bid is the equivalent valuation of the \$3.50 seller bid (\$8.00 - \$4.50 = \$3.50). With this information, I can calculate the average valuation of the buyers and sellers. I know that for the full sample of UNO information, the average WTA amount over 194 bids by the sellers was \$3.87 for their \$2.00 card. For the buyers, I have a 187 bids with an average WTP amount of \$4.38, using the bid conversion formula, I calculate a transformed average buyer bid amount of \$3.62.

This initial endowment effect test shows us that in terms of subject bid equivalency, the sellers valued their objects at a higher amount than did the buyers (\$3.87 vs. \$3.63), however, this is negligible difference which falls within the standard error. Therefore, when defined strictly by the average bids of sellers and buyers, there is no evidence of an endowment effect.

This method of analysis assumes that the subjects' bid is a completely accurate portrayal of their internal card valuation preferences. The earlier analysis shows an existing level of misconception amongst both sellers and buyers, such that the subjects' valuations may not match their true preferences. Therefore, I require a more sophisticated measure in order to more accurately assess the subjects' valuations.

b. Maximum Likelihood Estimation

Maximum likelihood analysis allows us the ability to estimate the more accurately estimate the subjects' bidding behavior in non-linear fashion. I run a pooled maximum likelihood estimation in order to elucidate the subject's true card valuations for both the optimal and the first price auction misconception model.

I start by estimating the parameter α, which estimates the card value for the optimally bidding subjects. I also utilize dummy variables to account for changes in game (δ_s = WTA or δ_b = WTP) or source (δ_p Purdue), the results are displayed in Table 10.

Table 10. Card Valuation

Panel A. Optimal Model

#	α_0	δ_s	δ_b	δ_p	λ_s	λ_b	λ_p	$logl$
			NoOpt					
1	1.903 ***	4.488 ***	5.698 ***	3.582 ***	3.917 ***	0.791 **	5.536 ***	-588.44
	(0.162)	(0.203)	(1.19)	(0.083)	(0.763)	(0.384)	(0.593)	
2	1.815 ***	4.408 ***	6.612 **	3.538 ***	1.855 ***	0.493	3.599 ***	-650.99
	(0.168)	(0.354)	(2.873)	(0.118)	(0.481)	(0.397)	(0.439)	
			ShwMis					
1	3.096 ***	5.117 ***	7.387 ***	3.842 ***	2.569 ***	0.659	4.539 ***	-627.63
	(0.105)	(0.441)	(2.416)	(0.132)	(0.597)	(0.399)	(0.515)	
2	2.403 ***	5.914 ***	20.608	3.874 ***	1.162 ***	0.172	3.442 ***	-656.81
	(0.128)	(1.022)	(37.533)	(0.158)	(0.425)	(0.372)	(0.421)	

Panel B. First Price Model

#	α_0	δ_s	δ_b	δ_p	λ_s	λ_b	λ_p	$logl$
			NoOpt					
1	-2.078 ***	2.975 ***	4.408 **	1.361 ***	1.973 ***	0.481 *	2.547 ***	-620.20
	(0.344)	(0.4)	(2.046)	(0.162)	(0.437)	(0.249)	(0.283)	
2	-2.009 ***	2.674 ***	-3.884	1.125 ***	0.974 ***	-0.378	1.896 ***	-661.79
	(0.325)	(0.697)	(2.882)	(0.214)	(0.283)	(0.231)	(0.232)	
			ShwMis					
1	0.375 *	4.231 ***	7.768	1.864 ***	1.362 ***	0.363	2.064 ***	-655.62
	(0.208)	(0.861)	(4.862)	(0.263)	(0.352)	(0.248)	(0.248)	
2	-1.028 ***	5.116 ***	-5.773 *	1.769 ***	0.704 **	-0.440 **	1.914 ***	-660.09
	(0.231)	(1.752)	(3.433)	(0.275)	(0.271)	(0.206)	(0.231)	

Table Notes: *α represents card value for optimal students, δ_s card value for sellers, δ_b card value for buyers and δ_{bp} card value Purdue subjects. λ_0 represents optimal subject sensitivity, . λ_1 seller sensitivity and λ_2 buyer sensitivity.*

Under the optimal model, I estimate the initial α parameter values for the non-optimal sub-sample and observe that the subjects' card valuations are not different from $2.00 in either round, the sub-sample of subjects who show misconceptions produce a card valuation of $3.10 in the first round 1, α drops to $2.40 in round 2. Under the first price model, the α parameter produces estimates that are either negative or less than $2.00, this is due to the first price model correcting for misconceptions and noise that are not existent in the subset of optimal bidders.

I next analyze the card valuation parameters for the two games, δ_s represents the card valuation for those who took part as sellers (WTA) and δ_b represents the card valuation for those subjects who took part as buyers (WTP). While estimating the card values utilizing the optimal model, I see that the δ parameter values are consistently higher for the WTP game (δ_b), but due large standard errors, I see no significant difference in the card values between the two games. While estimating the card values using the first price model, I see no significant difference in card values in round 1, in the second round I see higher valuations for the WTA parameter (δ_s) due to several negative card valuations in the WTP sample.

This estimation procedure takes into account the level of misconception evident in the subjects' bidding behavior. Therefore, when combined with the previous analysis, I can ascertain that these valuations are due to the level of error (or non-model conforming bids) evident in the WTP game relative to the WTA game. When looking at the complete set of card value estimations for the two games, I see no significant evidence of the endowment effect when defined as the gap between WTA and WTP valuations.

c. Summary

The analysis has consistently shown us that the bidding behavior of the subjects more closely followed the first price model than it did the optimal model. Furthermore, the first price model provides significantly better estimates as for sellers than it does for buyers. I also see consistently larger estimates when utilizing dummy variables to estimate the card valuations from the WTP game. The presence of excess noisy behavior in the WTP game leads us to conclude that the games are not symmetrical in practice, although they were in design. This leads us to the question of why these games performed differently in practice. The only relevant differences between the two games are is the role of the subject involved, and the process by which the subjects calculate their payoff.

So then, why would seller's behavior appear follow a specific models, but buyer's behavior appear to be random?

One explanation is the economic theory of rational ignorance which occurs when an individual views marginal cost of acquiring information (or learning rules in this case) as higher than the potential marginal benefit of that knowledge. This theory is widely cited, and is often listed as the primary cause for low voter turnout amongst certain groups of people or in certain geographic locations (Arnold, 2016 and Martinelli, 2007).

While rational ignorance is a known theory, it has not been explicitly linked to the endowment effect in published works. One theory is that while the games are designed symmetrically, the buyers start the game owning nothing while the sellers are endowed with a $2.00 card. This lack of ownership by the buyers leads to a pattern of rational ignorance, as they don't believe the time it will take to pay attention is worth the expected payoff. Those subjects who begin the game endowed with a card, believe they have more incentive acquire information (in this case, read and comprehend the instructions on the card) and therefore their bidding behavior more closely falls in line with both the optimal model, and the first price model.

Another explanation that has recently been presented is the concept of rational inattention. Matejka (2014) models a rational inattention approach in discrete choice analysis, he finds that that the decision maker's optimal strategy results in choosing probabilistically in line with a generalized multinomial logit model, which depends both on the actions' true payoffs as well as on prior belief. Sims (2015) defines states that rational inattention models introduce the idea that people's abilities to translate external da into action are constrained by their capacity to process information. While the expected payoffs for both games are the same, the buyers are tasked with one additional step in calculating their payoff, this combined with the subjects prior beliefs, leads to rational inattention on the buyer side which causes their noisy behavior. Whether this rational inattention is a primary cause for results that indicate an endowment effect is left for future work.

VIII. Conclusion

Decades of research has been done in an effort to more completely understand the reasons for the possible existence, as well as the magnitude of the endowment effect. While the concept is understandable on a psychological level, scholars in finance and economics have looked to gain a greater understanding of why this behavior exists and how it effects economic policy decisions, investor portfolio behavior, the housing market, as well as a myriad of other applications. The work of Plott and Cason (2014) provided us with the ability to evaluate such behavior using non-linear estimation, and introduced the variable of subject comprehension into these discussions.

The results herein may further the conversation on the possible driving forces behind the endowment effect, namely the effect of rational inattention. Marzilli (2014) recently questioned the relationship between loss aversion and attention. By utilizing a sophisticated framework while evaluating subject behavior on both sides of the transaction, I was able to make intriguing inferences on how a subject's transactional role affects his bidding behavior. Evaluating the endowment effect under the lens of rational inattention may lead to increased understanding of how to evaluate an individual's financial decision making, how to shape economic policy, and further supplement the conversation on one of economics longest running quandaries.

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Figure 1A. Seller - WTA Game Card Example

FRONT OF CARD	*BACK OF CARD*
This ticket is worth $2.00 to you. You can sell it. Name your offer price. __________________________.	Posted price is under the tape. To be viewed only after you have named your offer price on the other side. $ 1.55
Located under the tape on the other side of this card is a posted price.	Circle the appropriate amount and print your name so we can pay you.
The posted price was drawn randomly between: [$ ____0.00____ and $ ____4.00_____]	My offer price is **below** the posted price. Pay me the posted price of $________________.
If your offer price is below the posted price on the back of the card then you sell your ticket at the posted price.	My offer price is **above** the posted price. Pay me $ 2.00.
If your offer price is above the posted price on the back of the card then you do not sell your ticket but you do collect the $2.00 value of the ticket. You can view the posted price after you have named your price.	Name ____

Card notes: *Each subject takes part in the game twice. The lower bound of payoff frame is constant at $0.00, lower frame takes the value* $P_l = \{4,5,6,7,8\}$*, the randomized payoff price is uniformly distributed about the payoff range. Price on back of card is unknown to subject until they declare their offer price. Possible misconceptions occur if the subject circles the incorrect box, or if the subject's offer price is below the randomly generated price in both rounds.*

Figure 1B. Buyer - WTP Game Card Example

FRONT OF CARD This ticket is worth $6.00 to the one who purchases it. You can buy it. Name your bid price. __________________________. Located under the tape on the other side of this card is a posted price. The posted price was drawn randomly between: [$ ____4.00____ and $ ___8.00_____] If the price you bid is above the posted price on the back of the card then you buy this ticket at the posted price, you receive $2.00 in addition to any gain/loss on the purchase. If the price you bid is below the posted price on the back of the card then you do not buy your ticket but you do collect $2.00. You can view the posted price after you have named your price.	*BACK OF CARD* Posted price is under the tape. To be viewed only after you have named your bid price on the other side. $ 5.20 Circle the appropriate amount and print your name so we can pay you. My bid price is **above** the posted price. Pay me $2.00 plus the value of this card minus the posted price of $________________. My bid price is **below** the posted price. Pay me $ 2.00. Name _______________________________________

Card notes: Each subject takes part in the game twice. The upper bound of payoff frame is constant at $8.00, lower frame takes the value $P_l = \{0,1,2,3,4\}$, the randomized payoff price is uniformly distributed about the payoff range. Price on back of card is unknown to subject until they declare their offer price. Possible misconceptions occur if the subject circles the incorrect box, or if the subject's offer price is below the randomly generated price in both rounds.

Figure 2A. Student Offer (WTA) All Rounds

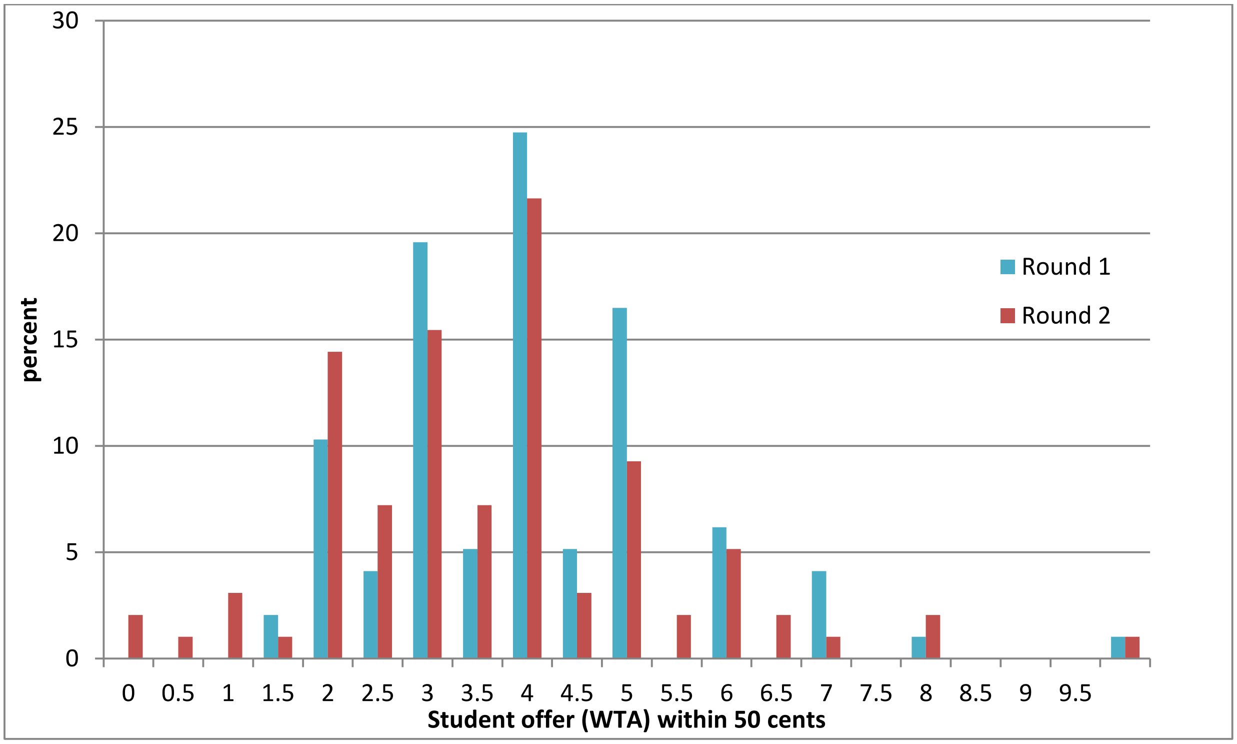
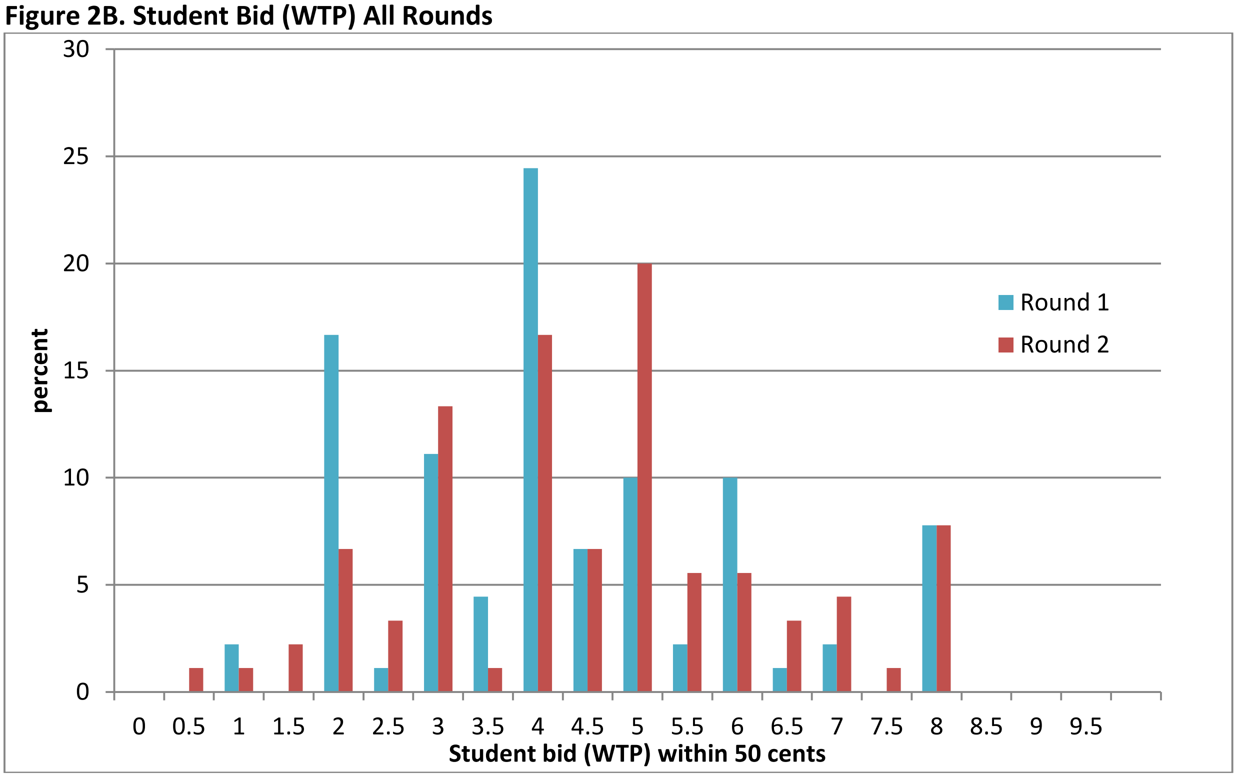


Figure 2B. Student Bid (WTP) All Rounds



Notes: Figures represents histograms of offers by game round within 50 cents on a total of 374 bids on the 97 WTA subjects and the 90 WTP subjects who completed both game rounds.

Figure 3A. Offer Ratios of Subjects Not Exposed to Round 1 Error- Both Games

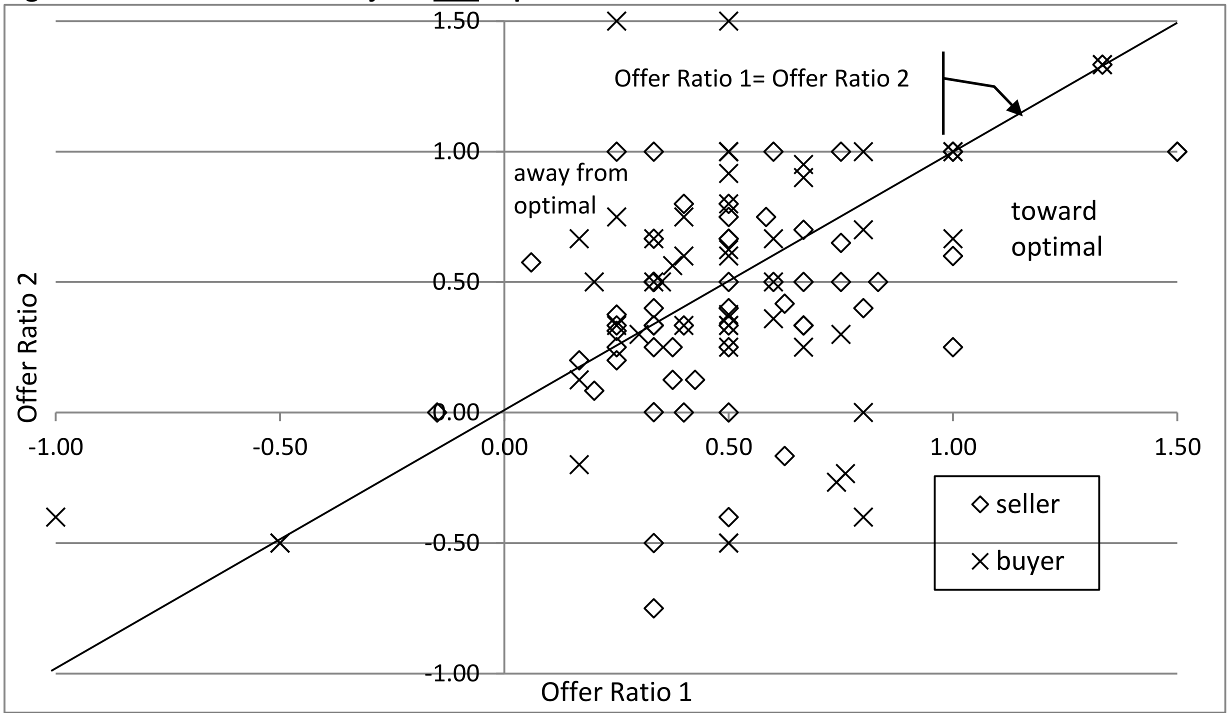
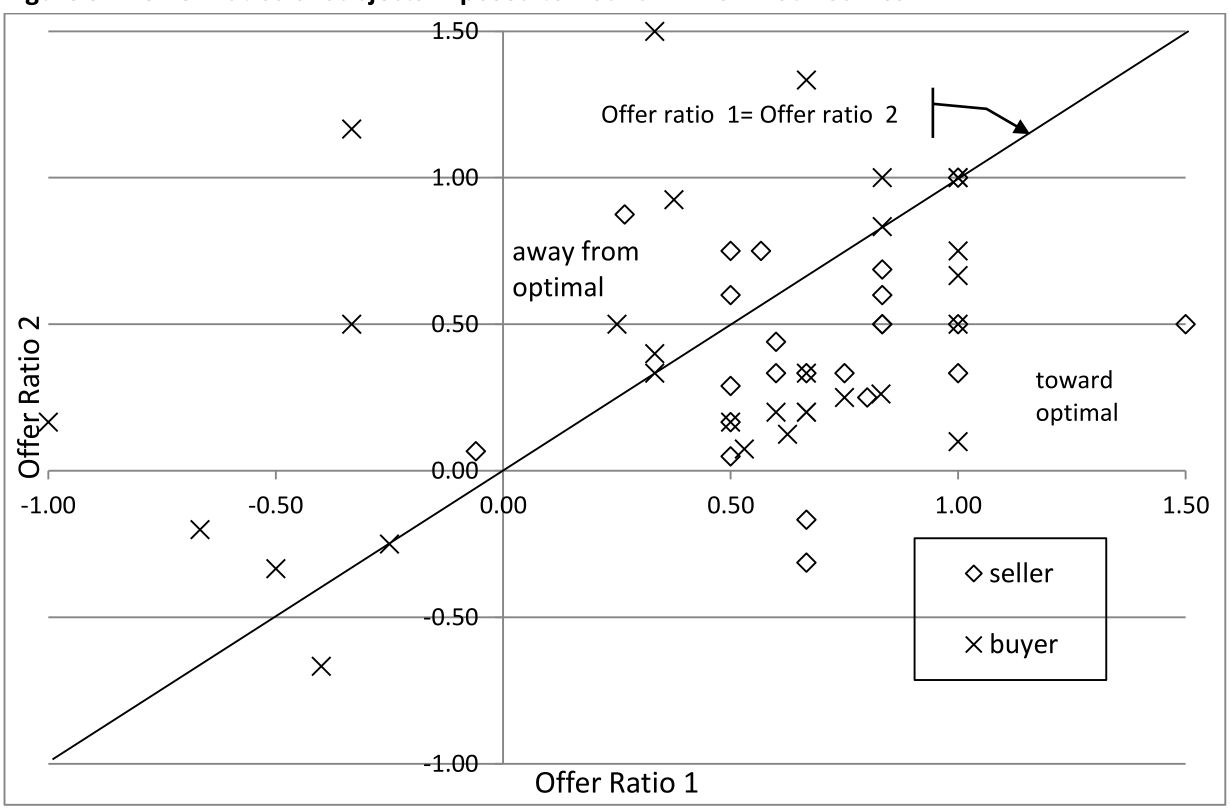


Figure 3B. Offer Ratios of Subjects Exposed to Round 1 Error- Both Games



Notes: Offer ratio is calculated as $(b - V_c)/(P^* - V_c)$, a quotient of 0 represents the optimum.

Figure 4. Expected Profit Given Optimal and Misconception Models w/ Range of Posted Prices [4,8]

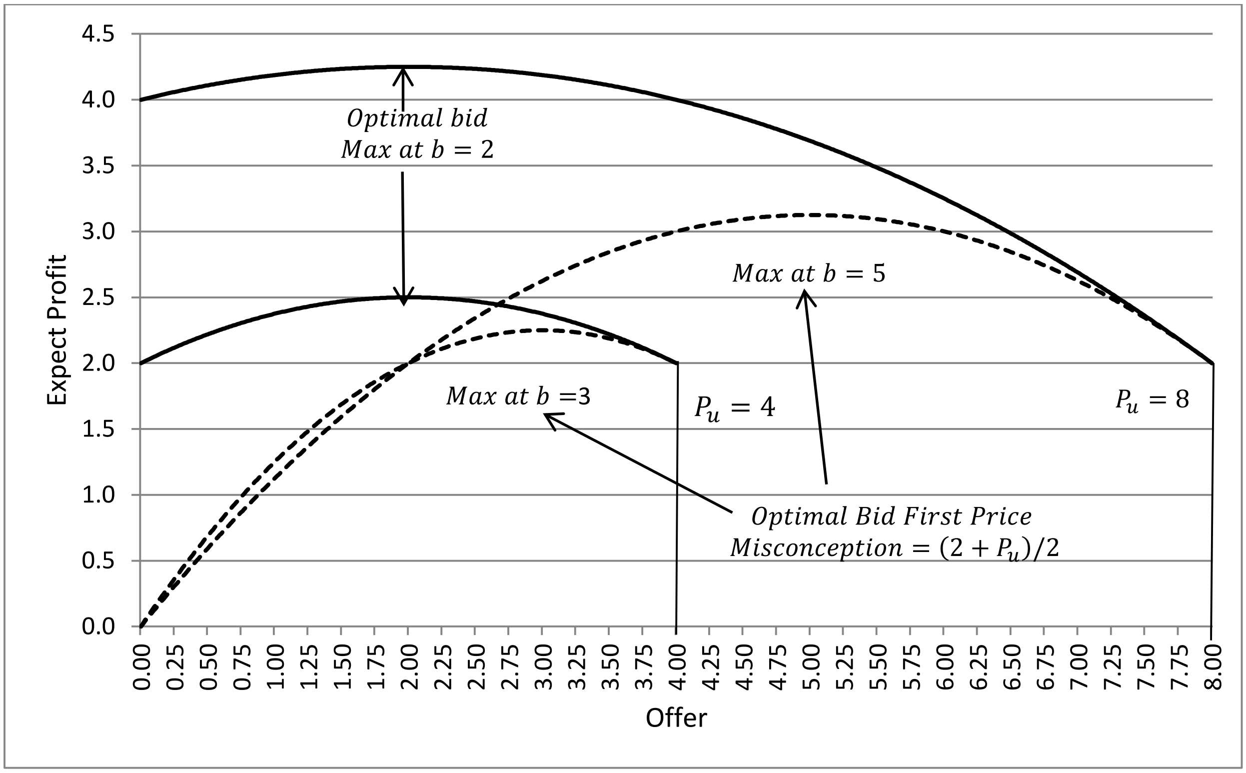


Figure Notes: Expected profit given optimal model is defined by, $E[\tilde{\pi}|b_i(opt)] = \frac{1}{P_u}\left[2b_i + \frac{(P_u^2 - b_i^2)}{2}\right]$. Expected profit given misconception model is defined by, $E[\tilde{\pi}|b_i(1^{st})] = \frac{1}{P_u}[2b_i + b_i(P_u - b_i)]$.

Figure 5. P[Offer=b] $\lambda = 3.0$, Optimal and Misconception Choice Models w/ Range of Posted Prices

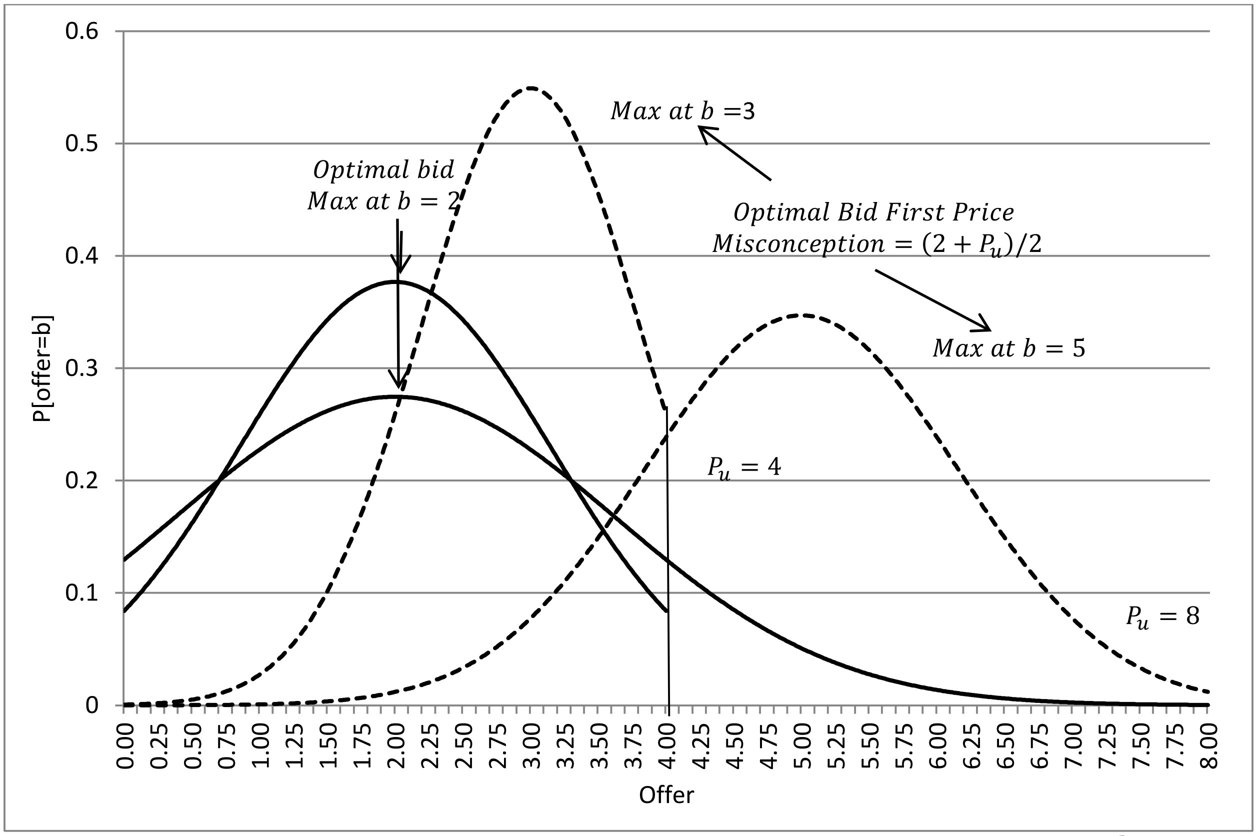


Figure Notes: The probability of a subject's offer is defined by $Prob(offer = b_j) = \frac{e^{\lambda E}[\pi|b_j]}{\sum_{k=1}^{n} e^{\wedge}\lambda E[\pi|b_k\}}$

Appendix A-1. Seller (WTA) Experiment Detail

1. Today I'll be conducting an experiment on Financial Decision Making. This experiment relies on a controlled environment with no outside feedback, each of you should act as if you are in isolation as your individual interpretation of the game is extremely important, therefore I ask that you not talk to your classmates.
2. After I have completed reading the instructions for the second time, please do not ask me any questions. *(This is so that one subject's question doesn't affect another's strategy.)*
3. At this point is where I read the instructions to the game. These instructions are printed on the subjects' cards, but I will first read the instructions to them, in order for them to have some semblance of the type of experiment I am conducting [See Game Cards below Tables A-1 and A-2].
4. In this game, you will be paid the card value ($2.00) in addition to any gain or loss you achieve during the transaction. That is, if you are able to sell the $2.00 card for $5.00, you will be paid $2.00 plus the $3.00 of profit for a total payoff of $5.00, if no transaction occurs, you will still receive the $2.00 card value. It's very important to state the Randomized Sales Price represents the price I'm willing to purchase your card for,, and has an already been determined by a Random Draw from a Uniform Distribution, so basically, the Random Price on the back of the card, is equally likely to be any number between the Upper and Lower Bounds of the Payoff Range you see on the Front Side of the Card.
5. At this point, the subjects come to the front of the classroom and select any individual envelope
6. After subjects have been seated, they are asked to take out the White (Round 1) Card.
7. Next, I re-read the instructions verbatim from the front of the card.
8. Please name your offer price, which represents the amount you are Willing-To-Accept for your card, which has a value of 2.00.[]
9. Please turn the card over and remove the tab. The price underneath the tab represents the amount that I am Willing-To-Pay to purchase your card.
10. Based on your offer price (your WTA), and my Sales Price (WTP), please circle the appropriate option. (Transaction or No Transaction, Payoff Calculation)
11. Make sure you have written your name in the appropriate space.
12. I collect all of the Round 1 Cards.
13. Please reach into your envelope, and remove the Green (Round 2 Card)
14. Repeat Steps 6 through 11.
15. Data Collection & Analysis.
16. Results will be tabulated, and subjects (during their next class period) will receive a voucher for the amount they earned.
17. Subjects will need to present their voucher and their Student ID Card in order to redeem their Experiment payments. A detailed log consisting of each subject's name, ID#, Class, and Earnings will be kept.

Appendix A-2. Buyer (WTP) Experiment Detail

1. Today I'll be conducting an experiment on Financial Decision Making. This experiment relies on a controlled environment with no outside feedback, each of you should act as if you are in isolation as your individual interpretation of the game is extremely important, therefore I ask that you not talk to your classmates.
2. After I have completed reading the instructions for the second time, please do not ask me any questions. *(This is so that one subject's question doesn't affect another's strategy.)*
3. At this point is where I read the instructions to the game. These instructions are printed on the subjects' cards, but I will first read the instructions to them, in order for them to have some semblance of the type of experiment I am conducting [See Game Cards below Tables A-1 and A-2].
4. In this game, you will be paid $2.00 in addition to any gain or loss you achieve during the transaction. That is, if you are able to purchase the $6.00 card for $5.00, you will be paid $2.00 plus the $1.00 of profit for a total payoff of $3.00. It's very important to state the Randomized Sales Price represents the price I'm willing to sell the card for, and has an already been determined by a Random Draw from a Uniform Distribution, so basically, the Random Price on the back of the card, is equally likely to be any number between the Upper and Lower Bounds of the Payoff Range you see on the Front Side of the Card.
5. At this point, the subjects come to the front of the classroom and select any individual envelope
6. After subjects have been seated, they are asked to take out the Yellow (Round 1) Card.
7. Next, I re-read the instructions verbatim from the front of the card.
8. Please name your offer price, which represents the amount you are willing to pay for this $6.00 Card.[]
9. Please turn the card over and remove the tab. The price underneath the tab represents the amount that I am Willing-To-Accept or the amount that I will sell the card for.
10. Based on your offer price (your WTP), and my Sales Price (WTA), please circle the appropriate option. (Transaction or No Transaction, Payoff Calculation)
11. Make sure you have written your name in the appropriate space.
12. I collect all of the Round 1 Cards.
13. Please reach into your envelope, and remove the Green (Round 2 Card)
14. Repeat Steps 6 through 11.
15. Data Collection & Analysis.
16. Results will be tabulated, and subjects (during their next class period) will receive a voucher for the amount they earned.
17. Subjects will need to present their voucher and their Student ID Card in order to redeem their Experiment payments. A detailed log consisting of each subject's name, ID#, Class, and Earnings will be kept.

VITA

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He joined the University of New Orleans graduate program to pursue a PhD in financial economics in 2012. He received his Master's of Science degree in Financial Economics in 2016 and hopes to receive his PhD in Financial Economics 2017. He plans to spend his future as a college professor.