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MISCONCEPTIONS AND GAME FORM RECOGNITION OF THE BDM METHOD: CHALLENGES TO THEORIES OF REVEALED PREFERENCE AND FRAMING

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Misconceptions and Game Form Recognition of the BDM Method: Challenges to Theories of Revealed Preference and Framing

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Abstract

This study reports a simple experiment using induced-value items to assess the accuracy of the Becker, DeGroot, Marschak (BDM) method (1964 *Behavioral Science*) for measuring preferences. Although the BDM mechanism is incentive compatible the data indicate that it can be empirically unreliable due to susceptibility to subject misconceptions about the game form. The resulting choices appear to reflect preferences constructed through a framing process, but further analysis reveals types of misconceptions through specific patterns of behavior. The data are more consistent with a hypothesis that the choices represent mistakes, such as a misconception that the BDM is a first-price auction mechanism. This highlights that preferences should be considered as distinct from choices unless misconceptions are eliminated. Neglecting misconceptions and related mistakes can lead the theory of framing and the theory of revealed preference to result in incorrect interpretations of data.

Keywords: Preference Elicitation; Misconceptions; Reference Dependence; Endowment Effect

JEL codes: C8, C9

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Section 1. Introduction

The important and growing literature about the nature of preferences often uses the Becker, DeGroot and Marschak (1964) method of eliciting and measuring preferences (hereafter, BDM). While the BDM is a very powerful tool, inconsistencies of preference measurement across different versions of the method and other techniques for eliciting preferences suggest that the methodology itself should be examined. The reliability and use of the BDM is closely related to a fundamental controversy about the properties of preferences, which is the focus of this paper. The controversy has on the one hand the theory of revealed preference, which rests on the hypothesis that individuals have preferences over outcomes and those preferences are independent of the feasible set of outcomes. On the other hand, the theory of framing holds that preferences are dependent on and perhaps even constructed from the context faced by the individual and might have no particular existence outside that context.[1] This study provides evidence that the widely-used BDM mechanism is a problematic measurement tool, leading to a reinterpretation of this controversy because many choices reflect mistakes rather than preferences.

Any pattern of choices can be described as having been produced by some form of preference if the set of admissible preferences is sufficiently rich. For any choice, one can imagine a preference that could have produced it, suggesting that the theory of preference is not falsifiable. The theory of revealed preference was created to explore this issue. Over the decades, this theory has evolved to isolate various features of preference consistency together with tests that can logically lead to its rejection. The weak axiom of revealed preference is an example. The "integrability" problem in the theory of market demand is another example. A natural question presents itself about whether framing theory lends itself to a similar testing process, including questions about how framing theory might be rejected.[2] Specifically, what form might such tests take and under what circumstances might they be used?

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[1] See Lichtenstein and Slovic (2006). The contrast of ideas is revealed by their summary of the issue: "If different elicitation procedures produce different orderings of options, how can preferences be defined and in what sense do they exist?"

[2] Some may consider framing as an unstructured catch-all for context dependence, but without structure it is difficult to envision how it could be rejectable. If that is the case then it may be premature to take seriously proposals to modify policy and law to reflect properties of preferences derived from framing theory.

Two possible challenges immediately present themselves as difficulties at a foundational level. First, framing theory often suggests that preferences are built on reference points but the general theory does not say exactly what values the reference point parameters take or how such parameters might be limited or constrained. However, the literature contains special cases that will become useful in the sections that follow. Second, the preference, which the theory seeks to explain, is determined by the context of the measurement including the methods used to measure it. All features of the context are part of the preference-determining frame. It is a classical observer effect: that what is to be measured is influenced by the attempt to measure it.

To solve the problem, we study commodities for which subjects have clearly identifiable preferences. The focus is on commodities, a fundamental building block in economics, as opposed to the more abstract concept of "prospects" developed in prospect theory, which can differ from person to person and thus reflect personal gains and losses. The focus on commodity spaces in economics stems from their central role in connecting preferences to scarce resources, the laws of supply and demand (including the need for a common unit of measurement that can be summed across agents), market price, equilibrium and efficient allocations. We use a preference for those commodities that will not be influenced by the measurement process.

The exercise is based on an uncontroversial preference, with no risk or uncertainty to bring expected- or non-expected utility theories into play. We can therefore use that preference to assess the accuracy produced by the BDM measurement method often used in applications of framing theory. The particular preference used is consistent with the classical theory of preference found in economics so any tests apply equally to classical preference theory. An accurate theory and method of measurement should accurately return the measurements of things for which accurate measurements are known. The method is like using a known weight to test the accuracy of a scale.

The preference is for dollars and for a card that is directly translated into two dollars with certainty. As emphasized by Kahneman et al. (1990, page 1328), this implies that the subjects should value the card at its induced value. The rate of substitution for the card and money is "two" just like the rate of substitution of two five dollar bills for one ten dollar bill is "two", which should be uncontroversial as it is demonstrated in market transactions every day. Indeed, the experiment itself has an internal consistency check on the rate of substitution.[3] We pose an experiment that is widely used in the classical economics and in studies of framing theory, the willingness to accept as measured by the BDM We also perform the experiment in an environment which minimizes the influence of the experimenter and training, which have both been implicated in affecting measurements in earlier scientific analysis.

The choices produced by the BDM procedure reflect neither the known preference nor a preference with properties postulated by framing theory, and an immediate source of difficulty surfaces. Both the theory of revealed preference and the theory of framing tend to apply a labeling convention in which a choice is automatically defined as a preference. The convention of calling choices preferences obscures what the preferences really are. The data suggest that choices do not reflect the known preference but instead reflect systematic misconceptions due to a "failure of game form recognition (FGFR)". Detection of the misconception is subtle because the choices have properties that masquerade as coming from the preferences of framing theory. That is, major features of the choices are consistent with the properties frequently attributed to framing, such as dependence on "reference points." Indeed, at first glance the experiment provides substantial support for framing theories but a complete study yields the opposite conclusion. Subject misconceptions and a failure of game form recognition provide an alternative and better explanation of the data. Indeed, once the failure of game form recognition is identified and the choices filtered through that theory, the choices are substantially explained by the classical preference theory of economics.

Our focus on economic environments dictates that important features be present: (i) well specified commodities are available, (ii) the rules governing the relationships between choices and allocations are clearly specified, and (iii) are understood by decision makers.[4] Clearly,

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[3] The card was a thick piece of paper. The subject could keep the card if she wanted. Unless it was valued as some sort of trophy or work of art it had no more value other than scraps of paper. Its only possible value was from giving it back to the experimenter and collecting the $2. The subject could keep the card if she placed a value on it that exceeded the $2 so the choice to exchange it was value revealing. Of the 264 cases in which subjects faced the decision to keep the card or to turn it in for the $2.00 in all 264 cases they took the $2.00, including 217 cases when subjects stated a BDM willingness-to-accept value greater than $2.00. Logic, theory, and data reveal that the subjective value of the card was the objectively known and uncontroversial $2.00.

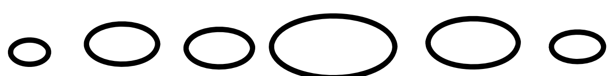
[4] Our discussion rests on the convention that preferences, decisions and choices can be separate, but related, phenomena. Furthermore, our focus on issues of preference measurement is distinct from theories of decision processes. Both revealed preference theory and framing theory have been criticized as being inadequate theories of processes (Berg and Gigerenzer, 2010). This issue involves substantially different theories from those addressed here. Our analysis is restricted to theories about the forms of preferences as opposed to the process that brings them into being or the possible relationships between preferences and the process of decision that produces choices.

incorrect conclusions will result if an individual is mistaken about the commodity in the sense that she thinks the purchase is for an X when she is actually buying a Y, the terms of trade or how her choice affects whether she buys or sells. This will be called a failure of game form recognition, a failure to recognize the connections between acts and their consequences.[5] The mistaken choice should not be interpreted as a preference for Y and the subject's adjustment of choice due to a suspected or realized mistake should not be considered a failure of rationality, but rather a misunderstanding/misconception of the task. This is why a preference need not be defined by a choice and why the two concepts, preference and choice, should be recognized as different and kept separate. The view is that a theory of mistakes is an alternative to non-standard preferences, a view that can be found expressed by others (Kőszegi and Rabin, 2008).

A simple hypothetical example illustrates some of the delicate issues among the concepts of preference, framing and misconceptions. Consider the task represented in Figure 1 in which the subject is given a monetary incentive to choose a specific oval. As a subject you are asked to follow the instructions and chose one of the ovals as directed. You are paid if you choose exactly as directed.

Figure 1

Consider the following task. Study the ovals below. You will earn $20 if you mark an X through the correct one.



Study them carefully. Now, to earn the $20 you must choose

[redacted].

If you are like many people you will not see that your maximum payoff occurs if and only if you choose the small oval on the left. You will be misled by a well-known optical

[5] The concept reflects the traditional tools of game theory in which distinctions are made among acts, outcomes, and game structure that connects acts to outcomes, preferences over outcomes, and decisions that are the choices from among acts. Much economic theory proceeds on the assumption that these elements are known. When the elements are not known information and information sets are key concepts that might be extended to deal with the lack of information about the game form but is not be part of the analysis here.

illusion and your choice might be one of the other ovals. (In order to see that your preference is to choose the smallest oval on the left, do not look at the black puzzle-looking pieces. Instead look at the white areas between the black parts. You might be able to see the word "LEFT".)

The subject's underlying preference is clear. The subject wants to choose the oval that produces the most money. However, the subject's understanding of the relationship between the acts (the choice of oval) and the consequences of the acts (the money received) may not be correct. The subject may misunderstand the instructions and have a misconception of the game form. The application of revealed preference theory to the choice would produce an incorrect account of the subject's underlying preference over the ovals.

The issues from a preference measurement perspective stem from the fact that the experimenter does not know what the subject perceives as the game form, the relationship between the choice of an oval and what the subject wants (the money). In one sense, the subject is given all of the information—e.g. the word LEFT is correctly spelled—but in another sense the subject lacks key information. Basically, the experimenter has lost control and theory can be misleading about where to look for explanations of the choice. Revealed preference theory would just treat the preference as random. By contrast, framing theory instructs us to look to features of the decision task that can be embodied in the construction of the preference. What are the possibilities? Is there a preference across oval size such as a bias against small ovals? Location presents a possibility that the construction reflects a bias against extremes such as the far left or right. Other possibilities exist such as a focus on the most prominent oval followed by adjustment to others.

The thesis developed in the paper is that neither revealed preference theory nor framing theory are appropriate to interpret choices made in certain contexts. Choice cannot be equated to preference without filtering the theory through models of subject's understanding. The example illustrates a mistake –a failure of game form recognition - a misconception of the task. The misconception can be revealed by adding innocuous appearing information to the context –a pair of thick black lines used to "emphasize" a key word. With the thick lines added the key instruction is to choose

Adding the additional information of the lines to the context helps the subject clearly understand the task, and the choice may change even though the task and incentives were not changed. A context effect would be observed but the underlying preference would not have changed. The point is that an actual preference for ovals was not observed when the task was misunderstood.

Adding the thick lines above and below the puzzle pieces could be interpreted as changing the frame, and thus according to framing theory it could change the preference and reflect a violation of a "principle of procedural invariance".[6] But in this example, as in our experiment with an induced value object worth $2, it is nonsensical to think of the frame change leading to a preference change. This is a task where subjects (if they understand the game form) have an unambiguous preference for the left oval. Any choice other than that must indicate a misconception of the game form/task.

Of course, a proper perception of the game form is assumed by the theory of revealed preference and is closely tied to the context of choice, including the actions used to produce choices. There would seem to be little disagreement that choices based on mistakes do not reflect revealed preferences over commodities any more than would be the case if the context included a magician's "sleight of hand", fraud or print too small to read. Yet, the sources of mistakes can be subtle and the evolution of perception is complex. The substance of this paper concerns how mistakes can arise, be identified and be documented.

Failures of game form recognition have been documented in the experimental literature (e.g., Rydval et al., 2009; Chou et al., 2009). Indeed systematic mistakes by economic decision makers are an integral part of the theory itself.[7] The data presented here show that the failure can occur in the simple BDM task where it might not be recognized by researchers and instead be interpreted as something else, such as a preference based on reference points or other framing effects. Researchers understand the truthful revelation incentives of the BDM, but to many subjects the BDM may appear as confusing as the initial instruction to choose the left oval.

[6] Procedural invariance says that the preference order should be invariant regardless of what procedure is used to elicit the preferences.

[7] Many economic theories rely on a systematic failure of game form recognition. Examples include price taking behavior in the competitive model, price adjustments in partial equilibrium settings, temporary equilibria, Nash responses in dynamic settings, and monopoly in general equilibrium. Occasionally, this property of the theory to incorporate mistakes as an integral part of the theory is not recognized. Patterns of mistakes can be systematically characterized and incorporated into the models in ways that maintain the basic principles and parsimony across applications (see the discussion at Plott, 1996).

Our interest in the issue is motivated by a sequence of questions. (1) Is the BDM reliable as a tool for measuring preferences? When applying the method do the data reveal a preference that we know exists? (2) What is the source of any unreliability detected and how can we measure it? In particular, can the lack of reliability be traced to systematic mistakes? (3) Can the data be misinterpreted as support for theories based on the existence of preferences affected by framing effects? (4) What are the implications of the experiment for the theory of revealed preference and the theory of framing together with patterns of experiments that suggest preferences are labile?

We emphasize that our interest is *not* in exploring how more elaborate instructions and training of subjects in the use of the BDM can "improve" its ability to reveal preferences more accurately. While such a task might be very useful for some purposes, it is an aside to the issue we pose. Furthermore, a problem resides in the fact that such training can be interpreted as changes of the framing of the BDM elicitation method and thus according to framing theory, training can change the preference that the BDM is supposed to measure. Thus, whether "improved BDM measurement" can lead to the possibility of rejecting framing theory is questionable. A similar issue arises for other preference measurement methods, such as the multiple price list method used in some versions of the BDM.

The outline of the paper is as follows. An underlying theme is that the object we wish to measure, subject preferences over well-defined commodities, need not be reflected in subject choice from among available actions. This theme is well known in economics and decision theory but can be overlooked in the world of experiments where a presumption of experimental control exists. Section 2 provides a brief introduction to the BDM method of preference measurement as applied to our experiments. We describe the preference over alternatives if the subject is fully informed about the relationship between the choice from among alternatives and the consequences of those choices. The analysis relies on an assumption that this preference is not controversial and that any successful measurement should produce this preference as the measurement. Any measurement that produces some other preference is flawed.

Section 3 explains our experimental environment (procedures, subjects and instructions). The procedures were designed to minimize the presence of the experimenter so theories about experimenter influence cannot surface to confound the results. Section 4 presents an initial look at the empirical results and shows that the objective, induced preference described in Section 2 is not consistent with the choice data. Section 5 explores why the choice data do not reflect the known preference. In particular, the section examines some popular models in the context of the experimental data (e.g., reference points, anchoring and adjustment, mistakes) and finds that some patterns of choices reflect properties suggested by these framing theories. By construction, however, we know that these theories cannot be a proper explanation since the preference is induced and known. This section presents additional examination of the data and demonstrates that the choices reflect a misconception about the task—a mistake about the BDM process. Estimates of a simple structural model of errors lead to the conclusion that a majority of subjects initially misunderstand the BDM rules. Section 6 contains conclusions and final observations.

Section 2. The BDM, Preferences and Possible Mistakes

The BDM mechanism has a long history of use as a tool for measuring preferences. The subject is required to state a dollar value for an object, such as a mug or a lottery. The stated dollar value is compared to a randomly drawn price. If the measurement is a buying exercise, the subject buys at the randomly determined price if it is less than the subject's stated value. If the measurement is a selling exercise, then the subject receives the randomly drawn price if it is above the subject's stated value. Because the subject does not determine the price paid or received, only whether it is paid or received, she has a dominant strategy to state her true value. The subject cannot lose by accurately stating her preferences for the objects and might gain. The mechanism is popular because unmotivated expressions of preferences for objects that are collected by alternative methods need not be (theoretically) accurately expressed.

The basic theory of the mechanism finds application to wide areas of economics that focus on policy and institutional design including auctions and public goods. For example, it shares the same (dominant strategy) incentive properties as the second-price Vickrey auction. It is also widely used as a tool for preference measurement in growing and important new subfields of economics such as behavioral economics and neuroeconomics.

The reliability of the BDM has been the subject of considerable research and our experimental design is extremely simple relative to the applications found in the literature.[8] In

[8] E.g., Bohm et al., 1997; Irwin et al., 1998; Grether et al. 2007; James, 2007; Urbancic, 2011; Kagel and Levin (indirectly through the study of second-price auctions). While the results have been mixed it survives as a useful tool, and researchers have employed it in various ways. Its performance appears better when buying or selling prices

part, the simplicity of our design is dictated by a need to strip the experiment from other potential explanatory variables that can be found in the more complex applications. Our approach is a bit "upside down" from the usual applications of BDM where the preference for the object is not known and is sought through the application of BDM. By contrast we use an object for which the preference is known and clearly defined: money. The objective of our experiment is to determine if the application of BDM to measure the preference, as if we did not know what the

Front Side of Card

This ticket is worth $2.00 to you.

You can sell it.

Name your offer price ___________________________.

Located under the tape on the other side of this card is a posted price.

The posted price was drawn randomly between:

[$ ___________ and $ ___________]

If your offer price is **below** the posted price on the back of the card then you sell your ticket at the posted price.

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.

Back Side of Card

Posted price is under the tape. To be viewed only after you have named your offer price on the other side.

Circle the appropriate amount and print your name so we can pay you.

My offer price is **below** the posted price.

Pay me the posted price of $________________.

My offer price is **above** the posted price.

Pay me $ 2.00.

Name ____

Figure 2: Decision Form Used in Both Rounds

are chosen from a price list (Vossler and McKee, 2006; Murphy et al., 2010), although the use of a coarse grid of possible valuations does not provide narrowly-defined valuation estimates and thus a relatively weak test. Some studies have "trained" subjects on its revelation incentives using objects of known, objective value before using it to value things of interest (e.g., lotteries, products), e.g., Noussair et al. (2004a; 2004b). Others have trained subjects using different lotteries before eliciting values of objects (Plott and Zeiler, 2005; later comments by Isoni et al. (2011) put these training procedures at the center of the discussion). Researchers have also used examples and explained the strategy of the process and why it is theoretically incentive compatible.

preference is, returns an accurate measure of the preference that we know exists. It is a test of measurement accuracy and reliability since people prefer more money to less. In essence, our experiment amounts to giving subjects an opportunity to express a preference for money stated in the context of a BDM method of preference measurement. The opportunity given the subjects is shown in Figure 2. Subjects are handed the card exactly as displayed, with the left half of the figure on the front side of the card and the right half on the back. The first sentence explains that card is worth $2.00. Subjects are instructed to state an offer price that amounts to a minimal selling price for the card. A posted price is randomly drawn from the interval [0, $\$\bar{p}$] where the lower and upper limits is clearly printed on the card and the upper limit differs across subjects. If the posted price is above the subject's offer price the subject is paid the posted price and if not the subject is paid the $2.00 for the card. After the subject states an offer price, the opaque tag on the back can be removed.[9] After she reveals the posted price the subject computes the amount received for the card as determined by her offer price and the randomly determined posted price.

In this choice situation, a subject who prefers more money to less has a dominant strategy of stating $2.00 as an offer price. Failure to state $2.00 reflects a mistake. A subject offering a price higher than $2.00 will never receive more and can receive less for the card than a subject offering $2.00. If the subject offers $2.00 for the card, he receives $2.00 if the random posted price is less than or equal to $2.00 but he receives the posted price whenever the posted price is above $2.00. For example, if the subject offers $2.00 and if the posted price is $2.00+X he will receive the $2.00+X and will never receive less than the $2.00 offer price. But if the subject offers more than $2.00, say $2.00+Y, she receives the posted price whenever the posted price is greater than or equal $2.00+Y and if the posted price is less than $2.00+Y she is paid $2.00 for the card. Thus, subjects who offer the card at values strictly greater than $2.00 redeem the card at $2.00 when the posted price is above $2.00 but below the subject's offer price. Basically, a failure to offer $2.00 means that subject simply failed to take the opportunity to receive money when available and we know that is something that the subjects do not want to do. The decision must rest on a misconception, mistake or confusion.

To verify that the failure to take money when available was a mistake the experiment included a repeat decision in which subjects are given the opportunity to correct the mistake

[9] Notice that the procedure removes the possibility that the posted price might depend on the subject's offer price. It also largely removes the experimenter from personal contact with the subject. Thus, concerns based on how the behavior of the experimenter might influence the subjects do not apply.

when faced with a nearly identical choice. After the subject completes the question on the back of the card, which reinforces attention on the rules and the possible outcomes, the subject turns the card in. After the first cards are collected the subjects are given another card exactly like the first, except the $\$\bar{p}$ on the second card is usually different from the $\$\bar{p}$ on the first card but due to the randomness they are sometimes the same. Again, the correct response if the subject understands the options correctly is to offer a price of $2.00.

The application of BDM in this environment differs from typical applications along four dimensions. First, unlike the typical application of BDM we know the preference that should be revealed. The card has a clear cash value stated in the first sentence which is further explained on the front of the card, and it has no other outside value. It has no intrinsic value. The subject is acting in isolation so there is no value associated with a social context. The card has no enhancement values that might be created by using words like "gift". As mentioned in the introduction, the difference between the card and cash is no different than the difference between two five dollar bills and one ten dollar bill, an indifference that is expressed daily in transactions. Thus, the analysis proceeds on the proposition that the value of the card to the subject is objectively known to be $2.00, allowing a test of whether or not the BDM produced an accurate preference measurement. Second, the choice is repeated with the same structure of preference, an object valued at $2, only with a randomly determined different upper limit of the posted price – basically a repeated measurement of the same preference using the same instructions. Third, the answers to the questions on the back of the card provide evidence of how the subject perceived the task.

The fourth dimension is important. The nature of the questions answered at the completion of the first card could expose the subject to evidence that the subject made a mistake. If the posted price was above $2.00 and below the subject's offer price he can see that by stating a lower price he would have received more money. Thus the subject is exposed to evidence of a possible mistake. If the choice was indeed a mistake as opposed to an accurate statement of preference, and the subject perceives this as a mistake, then the subject would change behavior in the direction of a stated price of $2.00. Thus, the experimental design can produce evidence of failure of game form recognition. With the data in hand we then ask if the choice is better explained as mistake due to a failure of game form recognition or by a theory of constructed preference based on a process of framing. That examination is contained in Section 5.

Section 3. Experimental Task and Procedures

Data were collected from 245 subjects during the first 10 minutes of seven sections of Purdue University microeconomics principles classes that were not taught by the experimenters. One of the experimenters, assisted by 2 or 3 research assistants, simply passed out (face up, shown on the left side of the figure) the decision cards shown in Figure 2. Although all cards indicated an induced and known "face value" of $2.00, it was not common knowledge that all cards had the same face value. The experimenter orally described this classroom activity as a "simple exercise to understand how people make decisions." He asked subjects not to talk, and to read the front of the card and indicate their offer price carefully since the money they receive can depend on their answer. They were told to turn over the card after indicating this price, look under the taped tab, and write the amount they should be paid. The class sizes were relatively small (30 to 40 students) in arena-style seating, and the experimenter and assistants observed subjects carefully and none were seen violating the experiment rules.

Once all cards were collected, a second card was passed out. This second decision round was not announced in advance. The card was identical to the first, except that it was a different color and the maximum posted price varied randomly across subjects. Subjects were paid for both card answers, using sealed envelopes of cash distributed when class was dismissed. Earnings ranged between $3.05 and $13.66, with an average of $6.11 per subject.

The cards were identical except for the range for the uniformly-distributed random posted price. The minimum posted price was always $0, but the maximum posted price was $4, $5, $6, $7, or $8. Each of these ranges was assigned one-fifth of the cards. While the range does not affect the theoretical incentive-compatibility of the BDM mechanism, as discussed in Section 5 it does influence the expected payoff consequences of suboptimal offer prices.

Section 4 Results: Data Patterns

The prominent patterns of the data are reviewed here and stated as a series of results. The first two results indicate that the proportion of optimal choices ($2.00) is not high but increases substantially on the second choice. The third, fourth, and fifth results summarize the relationship between the pattern of "optimal" choices, experience and subsequent choice.

Result 1: With simple instructions and no training or feedback, the BDM does not provide reliable measures of preferences for the induced-value object.

Support: Figure 3A displays the distribution of offer prices chosen by the 245 subjects during the first round, pooling across the maximum offer price treatments. Only 41 out of the 245 (16.7 percent) subjects chose offers within 5 cents of the $2 true value. A greater fraction of subjects chose offers near $3 and near $4 than near the optimal offer.

Figure 3A: Offer Price Distribution on First Choice

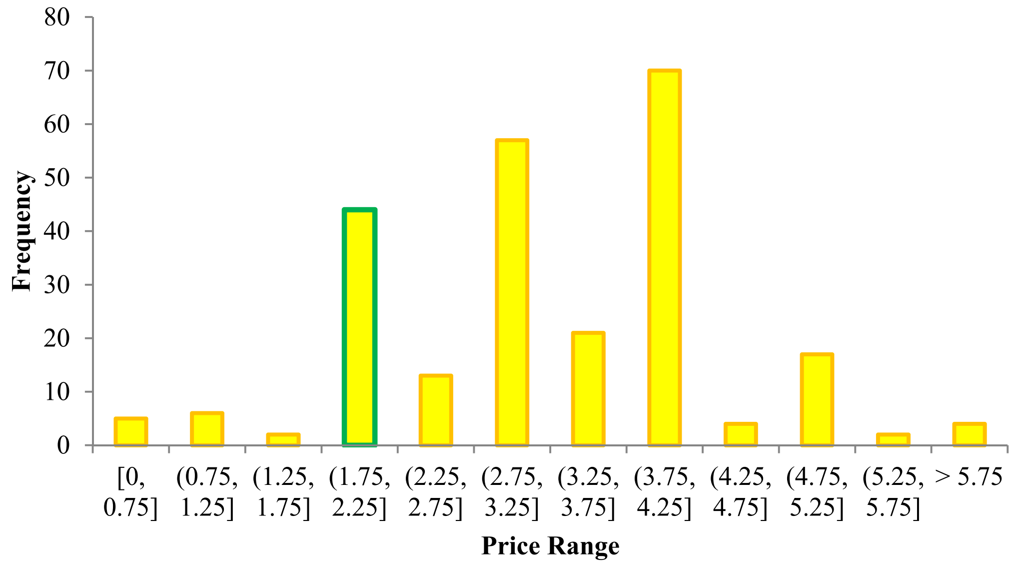
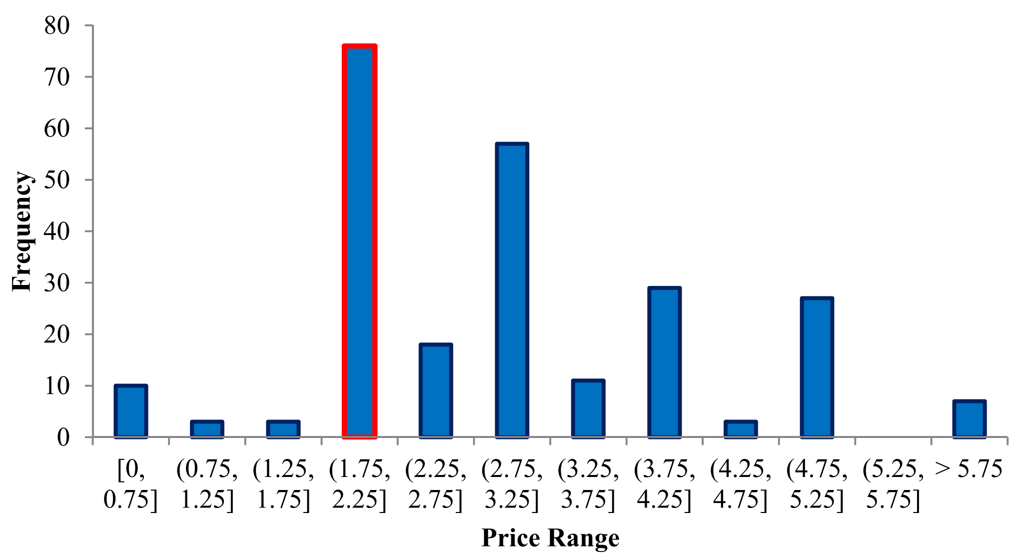


Figure 3B: Offer Price Distribution on Second Choice



Result 2: A second round of decisions (including subjects re-reading the instructions and after receiving feedback) nearly doubles the number of subjects stating the correct valuation.

Support: Figure 3B shows that the number of subjects indicating an offer price within 5 cents of the $2 true value increases to 76 out of 244 (31.1 percent) on the second, repeat decision.[10] The data strongly reject the null hypothesis that the rate that subjects state an offer price within 5 cents of $2 is equal on the first and second decisions (Fisher's exact test p-value<0.01).

Result 3: Subjects that chose the theoretically optimal offer price (near $2) on the first card also usually choose the theoretically optimal offer price on the second card. Subjects who did not choose optimally on the first card tend to choose a different offer price on the second card.

Support: Of the 244 subjects, 203 did not choose the theoretical optimum (within 5 cents of $2) on the first card. Of these 203, 159 (78%) chose a different offer price on the second card and 44 (22%) indicated the same offer price. Of 244 subjects, 41 chose near $2 on the first card. Of these 41, 35 (85%) chose the same offer price and 6 (15%) chose a different offer price on the second card. The hypothesis that the stability of choice is the same for those who chose optimally and those who did not choose optimally on the first card is strongly rejected (Fisher's exact test p-value<0.01).

These results demonstrate that the misconceptions subjects apparently have about the BDM procedure are distinct from framing effects. A natural interpretation is that the frame changes when subjects observe different upper limits of the posted price. However, many subjects who received the exact same upper limit in the two rounds and did not choose optimally in the first round changed their offer price in the second round. In particular, 26 of the 46 subjects (57%) who observed the same upper bound (and thus the exact same frame) in rounds 1 and 2 but who did not offer within 5 cents of $2 in the first round changed their offer in the second round. While non-optimal subjects who received a different upper limit in the two rounds changed their offer price more frequently (133 out of 157, 85%), framing theory cannot explain the frequent change in behavior even when the frame stayed the same across rounds. Moreover, those subjects who chose optimal responses (presumably those with no misconceptions) tend to have stable choices, even when the frame (interpreted as the random price upper bound) changes.

[10] The number of observations decreases to 244 on the second decision because one subject did not write his offer price on his second card.

Result 4 illustrates data patterns that could be attributed to a theory of framing based on this interpretation that the random price upper bound determines the frame. Result 5 below provides more direct evidence that subjects learn across rounds and how the feedback subjects receive at the end of round 1 affects how they adjust their offer price in round 2. These two features of the data will play an important role in determining the nature of game form misconceptions.

Result 4: For both the first and second round choices the pattern of non-optimal price offers are related to the maximum of the posted price range.

Support: Table 1 summarizes the mean price offers for each of the 5 upper bounds in the two rounds for offers not within 5 cents of $2. The trend is for offers and standard errors to increase in the upper bound, with only a couple of exceptions. Median offers (not shown) also generally increase with the upper bound. Table 2 indicates that the differences in offers for different upper bounds is statistically significant in most pairwise tests, similar to findings in Bohm et al. (1997). The frequency that subjects offer near $2 is not systematically related to the upper bound.

Table 1: Mean Price Offers for Each Posted Price Range Maximum, Excluding Offers within 5 Cents of $2

Panel A: Round 1

	Range [0, $4]	Range [0, $5]	Range [0, $6]	Range [0, $7]	Range [0, $8]
Mean Offer	2.98	3.35	3.50	3.93	3.80
(Std. Error)	(0.11)	(0.13)	(0.18)	(0.14)	(0.21)
Observations	45	39	39	40	41
Percent Offer $2±0.05	10%	19%	22%	17%	16%

Panel B: Round 2

	Range [0, $4]	Range [0, $5]	Range [0, $6]	Range [0, $7]	Range [0, $8]
Mean Offer	2.73	3.08	3.37	3.85	4.16
(Std. Error)	(0.13)	(0.20)	(0.25)	(0.19)	(0.36)
Observations	32	35	28	41	32
Percent Offer $2±0.05	32%	27%	44%	18%	35%

Result 5: Subjects who were “exposed” to their mistake (in the sense that a different offer amount would have increased their payoff) were more likely to choose a correct offer in round 2.

Support: One problem with the BDM is that incorrect offer prices are financially punished infrequently (Harrison, 1992). In the present context, for example, if a subject states an offer price for the card that is greater than \$2 but the random posted price exceeds this offer price, then this subject could not have increased her payment by choosing any other offer. We define a subject as "exposed" to her mistake if an alternative offer could have increased her payment. This occurs when the posted price is greater than \$2 but less than the subject's offer price, or when the posted price is less than \$2 but greater than the subject's offer. Only 57 of the 204 subjects (28 percent) who incorrectly offered an amount more than 5 cents away from \$2 in round 1 were exposed to their mistake. Table 3 displays the directional shift in offers from round 1 to round 2 for those subjects who were exposed to their mistake and those who were not exposed. Fisher's exact tests reveal that those who were exposed were significantly more likely to jump to \$2 (p-value=0.049) and significantly less likely to move even further away from \$2 (p-value=0.024) on round 2.[11]

Table 2: Wilcoxon Rank-Sum Tests Comparing Offers for Different Posted Price Ranges

Panel A: Round 1

	Range [0, \$4]	Range [0, \$5]	Range [0, \$6]	Range [0, \$7]
Range [0, \$5]	**0.013**			
Range [0, \$6]	**0.001**	0.176		
Range [0, \$7]	**0.000**	**0.007**	0.135	
Range [0, \$8]	**0.000**	**0.003**	*0.076*	0.784

Panel B: Round 2

	Range [0, \$4]	Range [0, \$5]	Range [0, \$6]	Range [0, \$7]
Range [0, \$5]	**0.007**			
Range [0, \$6]	**0.001**	0.474		
Range [0, \$7]	**0.000**	**0.005**	*0.056*	
Range [0, \$8]	**0.000**	**0.007**	**0.040**	0.423

Note: Tests exclude offers within 5 cents of \$2. Table entries denote p-values for two-tailed Wilcoxon tests.

[11] These figures are based on a transformation of the offers to the ratio (offer-\$2)/($\bar{p}$ -\$2), where $\bar{p}$ is the maximum random posted price draw, since subjects might have faced two different upper bounds and the adjustment relative to the optimum can be sensitive to this maximum possible price. Results are similar when defining movements using the raw offers, rather than with this normalization, although the p-value for the difference in propensity to move away from \$2 becomes 0.082.

Table 3: Adjustment of Round 1 to Round 2 Offer Prices for Subjects Choosing Incorrectly on Round 1

	Exposed to Round 1 Error	Not Exposed to Round 1 Error
Total Subjects	57 (100%)	146 (100%)
Move Onto Optimum ($2)	16 (28%)	24 (16%)
Move Towards Optimum	24 (42%)	57 (39%)
Choose Same Offer Ratio	9 (16%)	24 (16%)
Move Away From Optimum	8 (14%)	41 (28%)

Note: Movements are based on offer ratio=(offer-$2)/($\bar{p}$ -$2), where $\bar{p}$ is the maximum random posted price draw.

Figure 4 illustrates the movements toward and away from the optimal $2 offer using the ratio=(offer-$2)/($\bar{p}$ -$2), where $\bar{p}$ is the maximum random posted price draw. By construction of this ratio, 0 is the optimum. No "bubbles" are on the vertical axis because this figure excludes the 41 subjects who chose the optimal offer in round 1. (As already noted, those subjects nearly always chose optimally in round 2 as well.) Bubbles on the 45-degree line indicate subjects who chose offers to maintain a consistent ratio in both rounds. (The largest bubble representing the most subjects is at (0.5, 0.5), and 62 subjects chose offers that led to a ratio of 0.5 on at least one of the rounds. This is a significant incorrect ratio discussed in the next section.) Bubbles below the 45-degree line usually indicate movements toward the optimal ratio of 0, and bubbles above the 45-degree line indicate movements away from the optimal offer. Panel A shows how offers change among subjects who were not exposed to their error, and they are scattered both above and below the 45-degree line. By contrast, Panel B indicates a more systematic movement among subjects exposed to their error, below the 45-degree line and towards or onto the optimal ratio of 0.

Section 5. Results: Models

Three classes of general theories can be tested and compared for analysis of our experimental results: A. theories based on framing; B. theories based on random choice; C. theories based on game form misconceptions. Theories within a class tend to rest on the same or similar basic principles but the basic principles differ across classes. As will be demonstrated our data exhibit support for prominent features of framing theories, which appears to be inconsistent with the claim (originally offered in Kahneman et al. 1990) that the preference for the card is objective,

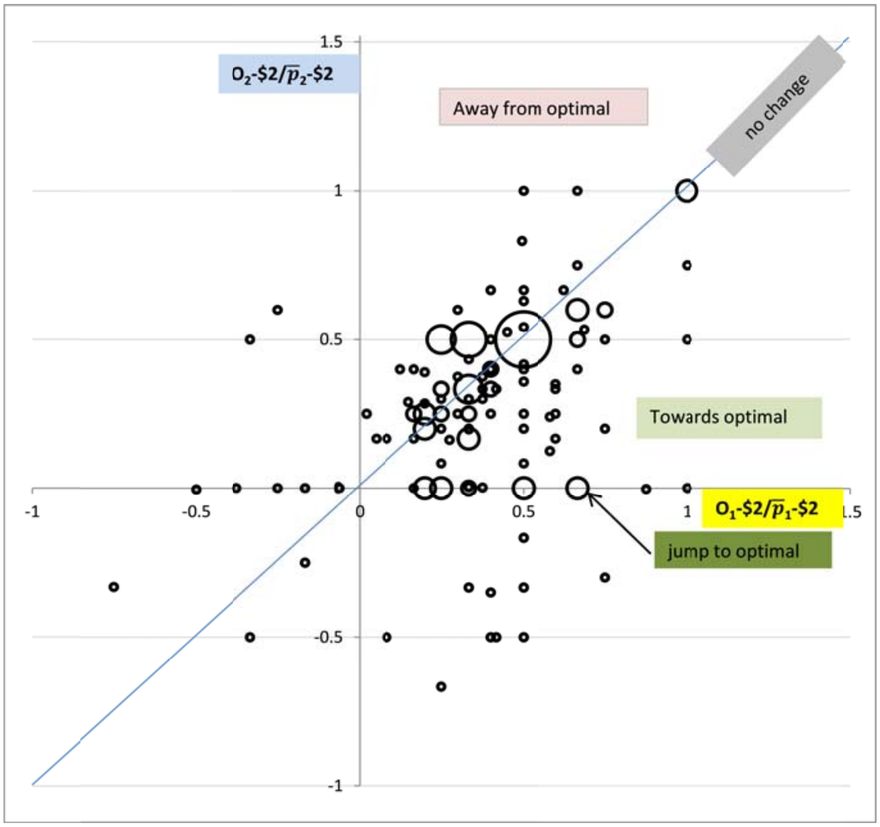


Figure 4, Panel A: Offer Ratios and Changes for Subjects Not Exposed to Round 1 Error

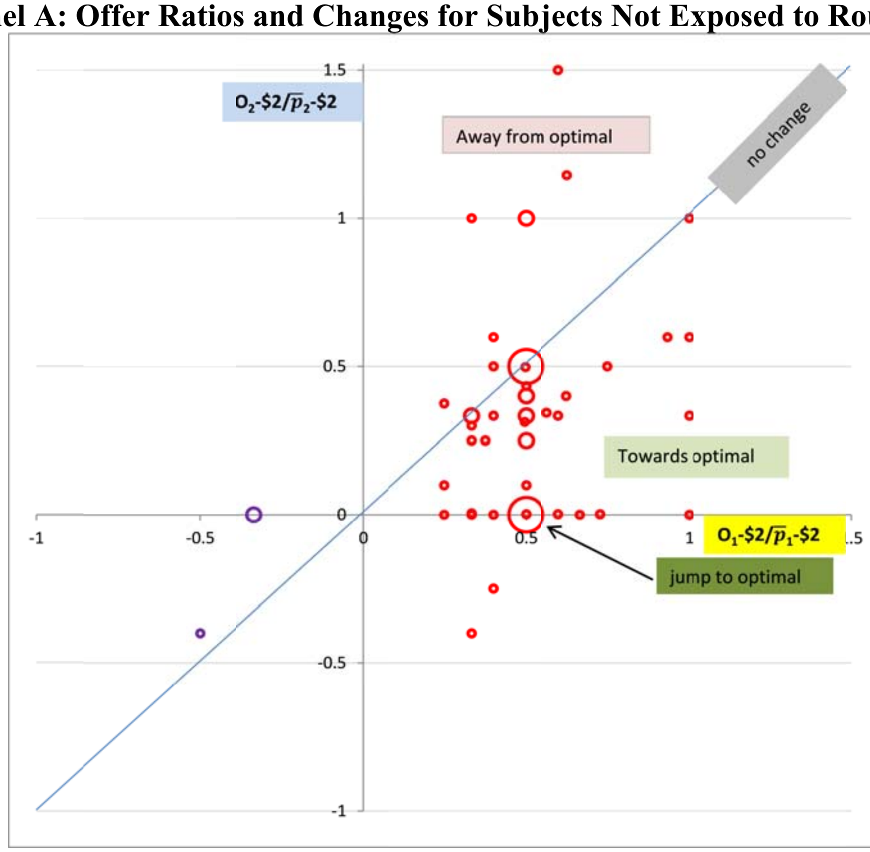


Figure 4, Panel B: Offer Ratios and Changes for Subjects Exposed to Round 1 Error constant and known. If the preference was not known, one could easily conclude that the preference for the commodities resulted from framing. However, a close examination of the choices demonstrates that a case for framing is not convincing. The data are better and more completely explained by a specific type of game form misconception. A discussion of the general theory of framing is reserved for Section 6.

A. THEORIES OF FRAMING.

Four theories derived from the theory of framing are applicable in our experiment, and the data exhibit patterns often interpreted as confirming evidence for them. We shall argue below, however, that a completely different assessment emerges when comparing these patterns to theories of mistakes stemming from game form misconceptions, Before turning to that assessment, consider first the four theories based on framing listed below.

- **Endowment effect/reference points:** Those names suggest that the data reflect a special factor such as the "endowment" or a "reference point" from which utility losses loom greater than gains. This leads to a "kink" in the utility function at the endowment, the reference point in this frame, so the asking price for the item (willingness to accept) is greater than the buying price (willingness to pay). According to framing theory, possession (ownership) of the object creates a sense of loss should the object be sold or given up in exchange. Since the object is a card worth $2 some might question whether the necessary "sense of ownership" will develop, and whether or not an "endowment effect" will be observed. However, the data clearly show BDM measurements of willingness to accept that are substantially more than $2, which we can confidently conjecture is more than the willingness the pay for a $2 card. These patterns are reported in Results 1, 2, and 4. Thus, since the WTA greater than the WTP an "endowment effect" is observed, just as the theory would predict (Kahneman et al., 1990, 2008; Tversky and Kahneman, 1991). Furthermore, one might conclude that sellers require compensation for the consumption value of the ticket plus additional value for the loss of the ticket, creating a positive relationship between the value of the ticket and the upper bound of the draw. Indeed, these data are consistent with what some would describe as a "widely observed" pattern in the literature.[12] Thus, whether or not an endowment effect applies can be debated but there can be no debate about the fact that the data have properties that are predicted by the theory.

- **Anchor and adjustment:** This theory holds that the frame centers the subject's focus on the prominent feature of the good and assesses the value, and then creates a value of the good by adjusting for other features (Lichtenstein and Slovic, 1971; Tversky and Kahneman, 1974). A reasonable assumption is that the prominent feature of the BDM in our application is the upper bound of the posted price range. Subjects could focus attention on the maximum possible value and then construct their preference through an adjustment downward based on probabilities or characteristics of the card, but with an incomplete adjustment that might not consider the strategic issues. The result would tend to be a value above \$2 as is observed and the positive relationship between the upper bound and the offers reported in Result 4 could be interpreted as further support.
- **Attraction to the maximum:** Similar to anchoring, this theory holds that a psychological "pull" to the maximum payoff (posted price range) draws decisions to it (Urbancic, 2011). The maximum serves as a reference point used for the construction of a preference that depends on the distribution governing the outcomes in the BDM. Presumably this preference is accurately measured by the BDM mechanism. The preference will be influenced by the location of the maximum, which is consistent with Result 4.
- **Expectations of a trade (Kőszegi and Rabin, 2006):** Anticipating selling the item means losing the item for a gain in money. Depending on the anticipated selling price losses loom greater than gains, which motivates an offer price that is above the buying price of the item. It is a form of endowment effect and the theoretical mechanism applies directly through lotteries and the expectations of a trade. While the expectations of trading are not directly observed, Kőszegi and Rabin's model makes predictions that depend on the assumptions made about expectations for trades. In particular they note that if the subject does not expect to trade then a loss aversion effect will be observed. However if the subject does expect to trade then the effect would depend on the subject expectations. Since the WTA is greater than the (presumed) WTP in our experiments,

[12] For example, Knetsch et al. (2001, page 257) state that "The endowment effect and loss aversion have been among the most robust findings of the psychology of decision making. People commonly value losses much more than commensurate gains…"

without looking deeper into the data, a natural interpretation is that the subjects expect not to trade and that the predictions of the Kőszegi and Rabin model are supported. Results 1, 2 and 4 contain the appropriate data.

Theories of framing appear to be consistent with parts of the behavior observed in the experiment. Other results do not support framing theory. Result 3 demonstrates that subjects who choose according to classical theory tend to repeat this choice. But contrary to framing theory that means that they are not influenced by a change in frame (as the change in upper limit that many experienced could be interpreted). More importantly, based on the convention of defining choices as preferences, the theories are reporting to have identified and measured a preference contrary to what was induced. We know that the true preference for the card is $2 but framing theories fail to produce that preference measurement. Result 4 demonstrates that subjects who exhibit the features exhibited by theories of framing tend to be those that change their choice when given the same option again. Contrary to framing theory, however, part of Result 3 indicates that for many subjects the frame remains the same but the choice changes. Subjects exposed to their possible misconception tend to correct it in the direction predicted by classical theory (Result 5) onto or towards the optimal choice. The patterns of choices across rounds (Results 3 and 5) are more consistent with learning than framing.

B. FLAT PAYOFF-LACK OF INCENTIVES TO REVEAL

Over two decades ago Harrison (1992) highlighted the weak incentives provided by the BDM for truthful revelation of preferences, in the context of his well-known "flat payoff" critique of preference measurement; see also Irwin et al. (1998). Some subjects may understand the instructions and the BDM task but they could make errors, and a key observation is that errors are very "cheap" in the BDM because they often are not penalized through financial losses. As already documented, in the present dataset only 28 percent of subjects who bid more than 5 cents away from the correct offer of $2 suffered any monetary cost from their suboptimal bid. Moreover, the likelihood of being exposed to a mistake is lower as the upper range of the random price distribution increases, and the expected cost of an error of any given size is smaller as the range of random price draws increases.

In particular, the expected loss from a suboptimal bid can be calculated as follows: Denote the offer price chosen by the subject as b and the randomly-drawn posted price as $p \sim U[0, \bar{p}]$ with maximum $\bar{p} \in \{4, 5, 6, 7, 8\}$. The expected payoff is E[π] = 2*prob(b>p) + E(p|p>b)prob(p>b), which simplifies for the uniform distribution to

$$\mathrm{E}[\pi] = \frac{1}{\bar{p}}\left[2b + \frac{\bar{p}^2 - b^2}{2}\right] \tag{1}$$

This can be differenced from the payoff of optimal offer price b*=2 to calculate the expected loss for any offer price other than the optimal offer price of \$2, given $\bar{p}$.

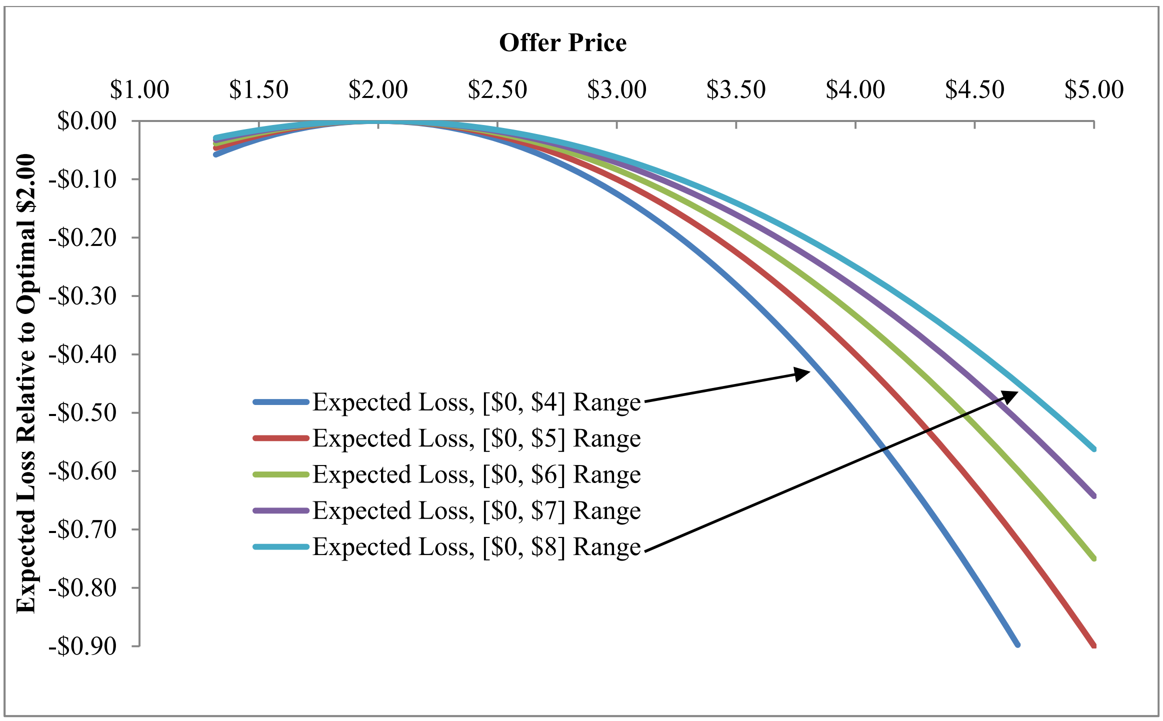


Figure 5: Expected Loss Relative to Optimal Price Offer for Different Maximum Prices

For example, the likelihood that a subject indicating a suboptimal offer price of \$3.00 will see a random draw between \$2 and \$3 indicating a loss relative to the correct offer price of \$2.00 is 1/8 when the range is [\$0, \$8] but is 1/4 when the range is [\$0, \$4]. Figure 5 illustrates the expected losses for the 5 different ranges employed in the experiment. The expected loss from a suboptimal offer price is quite small even for offers as much as \$1 away from the optimum, but note also that this loss is twice as great when the random posted price ranges between [\$0, \$4] rather than [\$0, \$8]. This suggests that more errors (and thus higher average offer prices) will occur for higher upper bounds for the random price draws, as already documented in the data (Result 4). Note that this is simply a model of random mistakes, which are more likely to occur when they are less costly. This is not an actual misconception of the BDM mechanism. In what follows we will refer to this as the "optimal" or "correct" model with noise.

C. FAILURE OF GAME FORM RECOGNITION

The theory of game form misconception in this context holds that the patterns of data are not due a preference that evolved from framing but are due to mistakes. Moreover, the mistakes are not simply random departures from a correct understanding of the experimental task, but rather arise from a systematic misconception of the rules of the BDM. In order to make a case that the choices reflect a systematic, fundamental mistake the mistake itself is described and stated in a form that yields testable predictions that are comparable to the predictions of other possible models.

A specific type of misconception was suggested by a particular type of error revealed on the cards filled out by some subjects. Recall that subjects were asked to write on the back side of their card the amount they should be paid after looking under an opaque tab covering their random offer price. Twenty-nine of the subjects indicated that they should be paid their offer price even when their offer price was less than the randomly-drawn posted price on their decision card.[13] It is as if the subjects believe the payment mechanism is similar to a first price procurement in which the lowest bid wins and is paid the bid price. An additional 82 subjects may have had this *first-price auction* misconception, but our data do not directly reveal it because on both of their cards their bid was above the drawn random price.[14]

This type of mistake suggests that some subjects believe that the buyer accepts the lower price, where the subject's offer price is in competition with the random posted price; and if they do not win this competition (i.e., if they do not have the lower price) then they are paid the $2 value on the retained card. In other words, they perceive their expected payoff to be

[13] We noted these mistakes when viewing their cards to prepare the money payment envelopes, and subjects were paid the correct amount—which was the higher drawn posted price in these cases.
[14] Two additional types of possible game form misconceptions are suggested by the data but were so sparse in the data that we do not pursue them. A few subjects seemed to think that they would be paid their bid independent of the posted price and thus stated asking prices equal to the maximum of the range. A few other subjects appeared to think that they only received a value if their asking price was below the posted price and thus stated an asking price below $2.00.

$$\mathrm{E}[\pi]' = 2\mathrm{prob}(b>p) + \mathrm{bprob}(p>b), \tag{2}$$

where again the offer price chosen by the subject is b and the randomly-drawn posted price is $p{\sim}U[0,\bar{p}]$. (The mistake here is that b replaces the correct $\mathrm{E}(p|p>b)$ in the second term of the expression.) For the uniform distribution this simplifies to

$$\mathrm{E}[\pi]' = \frac{1}{\bar{p}}[2b + b(\bar{p} - b)] \tag{3}$$

If the subject maximizes this incorrect expected payoff expression with respect to the offer b, then he will set $b' = 1 + 0.5\bar{p}$. Importantly, this incorrect offer depends positively on the maximum price drawn in the random offer distribution, similar to the random mistake in the optimal model with noise. Also, note that this offer function results in a constant ratio for (b'-\$2)/($\bar{p}$ -\$2)=0.5 displayed in the Figure 4 above, which appears prominently among those offers not near \$2.

To differentiate empirically between the simple "optimal model with noise" and the "first price misconception" explanations in the data, we turn to a familiar quantal choice framework in which agents seek to maximize their (perceived) expected payoff, but make (Luce-McFadden) logit errors:

$$Prob(offer = b_j) = \frac{e^{\lambda E[\pi|b_j]}}{\sum_{k=1}^{n} e^{\lambda E[\pi|b_k]}} \tag{4}$$

Less costly errors (in terms of perceived expected payoffs) are more likely than more costly errors. The λ term indicates how sensitive subjects are to differences in their expected payoffs. For λ=0 subjects are completely insensitive and choose all feasible offers with equal probability. As $\lambda\rightarrow\infty$ the choice model fits perfectly with no error. Of course, we do not claim that all subjects should be classified as making choices in one way or another; instead, we use standard maximum likelihood methods to fit the data pooled across subjects to the two models and estimate the λ that best approximates the aggregate behavior. Higher levels of λ indicate a better fit—requiring less noise to characterize subject choices according to that particular model. Below we also estimate a mixture model to determine what fraction of offers are best approximated by each model.

The log-likelihood, conditional on the first-price misconception (denoted with a 1st superscript), depends on the estimated payoff sensitivity λ^{1st} and the observed choices y_i:

$$\ln L^{1st}(\lambda^{1st}; y_i) = \sum_i \ln l_i^{1st} = \sum_i \ln\{y_i e^{\lambda^{1st} E[\pi|b_j]'} / \Sigma\, e^{\lambda^{1st} E[\pi|b_k]'}\} \tag{5}$$

where y_i is an indicator for offer i equal to b_j. Similarly, the conditional log-likelihood based on the assumption that the optimal and correct model is true (denoted with an OPT superscript) is

$$\ln L^{OPT}(\lambda^{OPT}; y_i) = \sum_i \ln l_i^{OPT} = \sum_i \ln\{y_i e^{\lambda^{OPT} E[\pi|b_j]} / \Sigma\, e^{\lambda^{OPT} E[\pi|b_k]}\} \tag{6}$$

Note that other than the different payoff sensitivity parameters, these log-likelihoods differ only in whether the correct expected payoff expression E[π] from eq. (1) or the misconceived expected payoff expression E[π]' from eq. (3) is used.[15]

Result 6 : Among the subjects who do not choose offers within 5 cents of the correct offer of $2, the first price misconception model provides a better overall fit than the optimal choice model augmented with logit errors, and a much higher fraction of these offers are more consistent with the first price misconception model.

Support: Table 4 presents the maximum likelihood estimates of the payoff sensitivity parameters λ along with bootstrapped standard errors and 90 percent confidence intervals. The first column is based on all the data and indicates some small differences in fit between the two models, but for the Round 1 bids the log-likelihood is considerably higher for the first price misconception model. The confidence intervals overlap in that first column, however, and subjects who offer the correct $2 clearly do not have the first price misconception nor do they make errors. The second column therefore excludes subjects who submitted offers within 5 cents of $2, and here the estimated payoff sensitivity λ terms diverge significantly. For both rounds the point estimates are more than three times higher for the misconception model than for the optimal model with noise, the confidence intervals are quite different, and the log-likelihood is substantially higher for the misconception model. This indicates that while the subjects who do not submit offers of $2 do not have the correct idea about the mechanism, they are not merely making random errors that are related to the economic cost of the errors. Their offers are better characterized by the first price misconception model augmented with a modest level of decision error. Finally, the rightmost column displays estimates for the 111 subjects who are most likely

[15] For tractability in the estimation, we first aggregate the offer data into 10-cent bins to reduce the dimension of the probability vector by one order of magnitude.

to have the misconception, either because they reveal it directly on their decision cards (*n*=29) or because on both of their cards their bid was above the drawn random price so we cannot rule out this type of misconception (*n*=82). Obviously the misconception model fits much better for this subset of subjects.

Table 4: Maximum Likelihood Estimates of Logit Choice Error Parameter λ for Optimal and First Price Auction Misconception Models

Model	All Data	Excluding Offers within 5 cents of $2	Subjects revealing misconception, or possibly holding it
Round 1			
Optimal Model λ^{OPT}	0.99	0.56	0.48
(standard error)	(0.149)	(0.130)	(0.141)
[90% confidence]	[0.81, 1.26]	[0.34, 0.73]	[0.25, 0.74]
observations	*n*=245	*n*=204	*n*=111
Log Likelihood	-985.4	-826.8	-449.4
First Price Auction Misconception Model λ^{1st}	1.18	1.83	3.05
(standard error)	(0.184)	(0.408)	(0.624)
[90% confidence]	[0.88, 1.49]	[1.30, 2.56]	[2.13, 4.20]
observations	*n*=245	*n*=204	*n*=111
Log Likelihood	-954.2	-769.3	-398.2
Round 2			
Optimal Model λ^{OPT}	1.12	0.30	0.01
(standard error)	(0.244)	(0.164)	(0.166)
[90% confidence]	[0.82, 1.51]	[0.09, 0.49]	[0, 0.41]
observations	*n*=244	*n*=168	*n*=111
Log Likelihood	-979.7	-685.7	-451.6
First Price Auction Misconception Model λ^{1st}	0.59	1.03	1.71
(standard error)	(0.115)	(0.239)	(0.273)
[90% confidence]	[0.39, 0.82]	[0.72, 1.53]	[1.34, 2.23]
observations	*n*=244	*n*=168	*n*=111
Log Likelihood	-980.5	-660.9	-420.0

Table 5 reports estimates for a two-parameter finite mixture model that estimates a pooled payoff sensitivity parameter λ and the probability θ^M that the optimal model or the first price misconception model applies to these same three samples (Harrison and Ruström, 2009). The grand likelihood that combines the two models is constructed as a probability weighted average of the conditional likelihoods, where θ^M denotes the probability that the (error-augmented) first price misconception model is correct:[16]

$$\ln L(\lambda, \theta^M; y_i) = \sum_i \ln\{(1-\theta^M)\, l_i^{OPT} + \theta^M l_i^{1st}\} \tag{7}$$

The results show that nearly two-thirds of all the offers are more consistent with the misconception in Round 1, and this fraction rises to 80 percent or more for the subsets of data in columns 2 and 3. The probability that an offer is more consistent with the misconception model is estimated reasonably accurately, and for Round 1 the 90% confidence interval never includes an equal likelihood of the two models (i.e., θ^M=0.5).

Table 5: Maximum Likelihood Estimates of Finite Mixture Model Logit Choice Error Parameter λ and Likelihood of First Price Auction Misconception Model π^M

Model	All Data	Excluding Offers within 5 cents of $2	Subjects revealing misconception, or possibly holding it
Round 1			
Payoff Sensitivity λ	4.49	4.19	5.14
(standard error)	(0.839)	(0.574)	(1.205)
[90% confidence]	[3.41, 6.08]	[3.29, 5.22]	[3.44, 7.52]
Misconception Prob θ^M	0.65	0.86	0.91
(standard error)	(0.046)	(0.0.38)	(0.045)
[90% confidence]	[0.59, 0.74]	[0.79, 0.91]	[0.83, 0.98]
observations	*n*=245	*n*=204	*n*=111
Log Likelihood	-932.4	-750.2	-394.4
Round 2			
Payoff Sensitivity λ	2.65	2.26	1.71
(standard error)	(0.824)	(0.437)	(0.333)
[90% confidence]	[1.68, 4.67]	[1.64, 3.04]	[1.28, 2.32]
Misconception Prob θ^M	0.42	0.80	1.00
(standard error)	(0.059)	(0.050)	(0.010)
[90% confidence]	[0.34, 0.54]	[0.71, 0.88]	[1.00, 1.00]
observations	*n*=244	*n*=168	*n*=111
Log Likelihood	-962.5	-652.4	-420.0

[16] This approach assumes that any offer can come from both models, but it includes the boundary case where one model or the other completely generates the offer. Alternative approaches and interpretations are possible (El-Gamal and Grether, 1995).

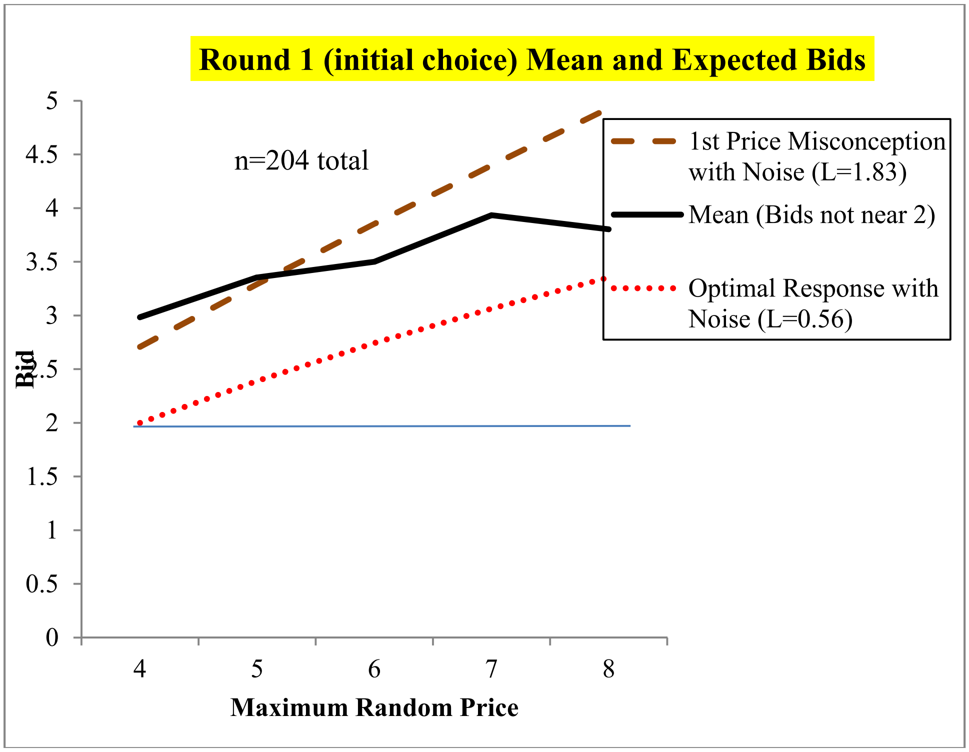


Figure 6, Panel A: Comparison of Fitted Correct (Optimal) and First Price Misconception Models with Noise, for Subjects Not Bidding within 5 cents of $2 (Round 1)

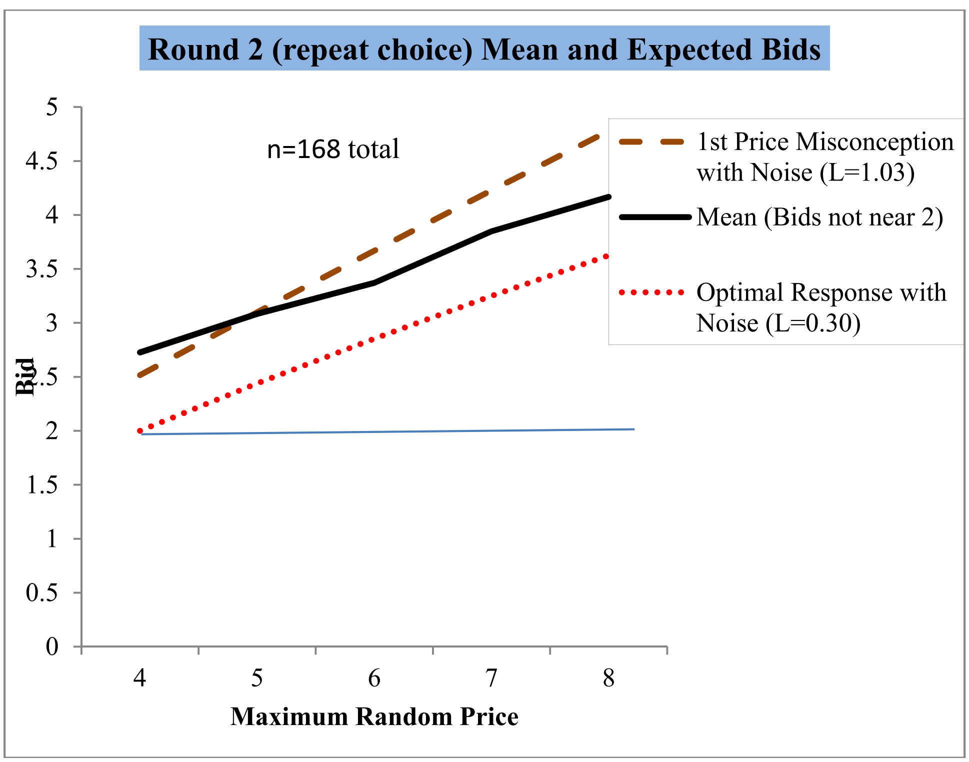


Figure 6, Panel B: Comparison of Fitted Correct (Optimal) and First Price Misconception Models with Noise, for Subjects Not Bidding within 5 cents of $2 (Round 2)

Figure 6 illustrates the fit of the correct and first price misconception models for the offers not within 5 cents of the true value of \$2 (i.e., based on the middle column of Table 4). Adding noise to the optimal model (the dotted red line) leads to higher mean expected offers because offers can be spread between zero and the maximum random price.[17] For λ near 0 (as in Panel B) the offers are nearly uniformly distributed over this range, so the mean is near the range midpoint (i.e., a mean offer of \$3 if the maximum random price is \$6). Increases in λ shift this predicted mean downwards towards the horizontal line at the correct offer of \$2. The higher dashed lines on this figure show the first price misconception model. For λ near 0 offers according to this model are similar to the optimal model, but increases in λ shift the mean offers upward towards $1 + 0.5\bar{p}$. This figure illustrates how the mean bids are better approximated by the first price misconception model, although this model over-predicts the level of the mean when the maximum random price takes on its highest values.

On one hand, the comparison of models yields a consistent pattern of failure of unmodified revealed preference theory and of framing theories. The BDM does not result in an accurate measure of the preference that is known to exist. A direct application of revealed preference theory does not suggest a reason why. Application of framing theories leads to a substantial misspecification of the preference. On the other hand, the theory of game form misconception proves helpful. Close examination of the data demonstrates that the problem resides with the BDM. The choices of many of these untrained subjects appear to be based on a misconception of the task. They think that it is a first price auction rather than a second price auction. That insight provides a key tool with which to apply the theory of game form misconception. The subjects consist of two groups. One group understands the game form as a second price auction and behaves substantially as game theory predicts. The other group has a misconception of the game form as a first price auction and under that model behaves substantially as game theory predicts. The classical "rational choice" models from auction theory give the best account. While repeated choice tends to alert some subjects about their misconception the most powerful correction comes with exposure to their mistake and its associated cost.

[17] Subjects were not actually restricted from making any offer, but they apparently viewed the maximum random price as a logical upper bound since only two of the 489 offers stated in the experiment were greater than this maximum random price.

Section 6. Concluding Summary and Observations

This experiment demonstrates the failure of game form recognition (FGFR) in the context of a very simple BDM preference measurement exercise. Two general points follow from the demonstration. First, misconceptions should be taken seriously as an explanatory theory of choice even in controlled laboratory experiments conducted using a simple BDM measurement. It is not the case that choices can be interpreted as revealing an unbiased preference. Second, the influence of context can be misinterpreted as reflecting the shape of a preference or even constructing a preference because the data from BDM can be mistakenly interpreted as support for framing theory. The experiment produces phenomena often cited as evidence of framing effects. In particular, the FGFR phenomenon can masquerade as support for the theory of framing such as through preferences constructed from reference points.

Our research strategy is to study commodities with such an obvious induced preference that there would seem to be nothing to test. A dollar is worth a dollar. Since we know the preference for the commodity, we can focus on the measurement method, its reliability and interpretations of the measurements through a comparison with the known preference. Does the method accurately measure what it is designed to measure or are other elements of the context incorporated in the measurement? Clearly, this experiment is only an example but it serves to demonstrate the existence of a mismeasurement problem that can accompany applications of the BDM.

The simplicity of the experiment avoids concerns raised in other contexts that controlling for misconceptions in tests of endowment effect theory might have confounding influences. Previous experiments demonstrate that when subjects are well trained on the features of the BDM a WTA/WTP gap for mugs does not exist but when subjects are not trained with the use of the BDM the WTA/WTP gap for mugs is observed. (Plott and Zeiler, 2005; Isoni et al., 2011). Kőszegi and Rabin question those experiments and presumably the replications, based on a concern that the training prevents the formation of appropriate reference points.[18] Kahneman suggests that the training subjects with the BDM leads them to choose according to the theory

[18] For instance, Kőszegi and Rabin (2006, page 1142) argue "One interpretation of the rare exceptions to laboratory findings of the [endowment] effect, such as Plott and Zeiler [2005], is that they have successfully decoupled subjects' expectations from their initial ownership status. Similarly, the field experiment by List [2003], which replicates the effect for inexperienced sports card collectors but finds that experienced collectors show a much smaller, insignificant effect, is consistent with our theory if more experienced traders come to expect a high probability of parting with items they have just acquired."

preferred by the experimenter.[19] Our experiments involve no extensive training with the BDM so those concerns do not apply. Moreover, there are no avenues for framing based theories of attachments, affiliations or enhancements to find their way to modify preferences: one dollar is worth one dollar.

Our results do have implications for theory. The simple existence of mistakes causes no particularly new problems for the theory of revealed preference. Many problems of mistakes and poor measurements are addressed in the literature in one form or another.[20] However, systematic mistakes can result in a misspecification of the revealed preference and thus present a challenge to the theory of choice, the theory of preference and the theory of decision processes, each of which is a separate development. The data from our experiments are examples and might benefit from a theory of "perception" to supplement the other context driven, individual characteristics used in economic theory (decision types, subjective probabilities, learning, temporary equilibria and even physiologically driven preferences such as hunger or sexual attraction). But the example with the word "LEFT" in Figure 1 suggests that additional theory might be useful. Clearly the choice from among the ovals does not reveal a fully informed preference until additional information is provided.[21] The implication is that "improving" the BDM method from the point of view of revealed preference theory may be considerably more complex than simply using different instructions or training procedures.

The phenomenon of misconceptions raises different problems for typical applications of framing theory, which attaches preference to choice as a matter of a definition. Framing is advanced as an alternative to a broad theory of "rational choice," which we assume means the

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[19] Kahneman (2011, p. 471) criticizes Plott and Zeiler (2005) because "they devised an elaborate training procedure in which participants experienced the roles of both buyers and sellers, and were explicitly taught to assess their true values… Psychologists would consider the method severely deficient, because it communicates to the participants a message of what the experimenters consider appropriate behavior, which happens to coincide with the experimenter's theory." We find this claim by Kahneman puzzling. The training process used by Plott and Zeiler concerns the method of measurement in order to reduce game form misconceptions, and not the preference for the objects being measured which is the focus of the research. Plott and Zeiler also included experiments in which training was absent but were overlooked by Kahneman

[20] For decades economic models have added random variables to account for the fact that choices found in field environments and in experimental environments reveal inexplicable changes. Therefore addition of the randomness produces extremely powerful models when applied at both the field level (e.g., Echenique et al., 2011) and experiments as is exhibited by the first price auction model used above.

[21] Gul and Pesendorfer (2008) suggest that "information" is the theoretical tool that can account for mistakes while maintaining the classical theory of preference. However, how information is presented can be a central issue. Information, when accompanied by "helpful hints" can be even more effective. For example, the black lines added to Figure 1 can be interpreted as information, as can the helpful hint to look at the white parts and not the black puzzle looking figures.

existence of an exogenous preference, even though the term is typically not defined by framing theory. According to framing theory as developed by Kahneman and Tversky a preference is constructed from a "frame" instead of being exogenously determined.

The frame is interpreted very broadly and includes both the game form and perceptions of the game form. Departing from economic theory, Tversky and Kahneman (1981) incorporate the perception of the game form within the frame. They make the point clearly; "We use the term 'decision frame' to refer to the decision-makers conception of the acts, outcomes and contingencies associated with a particular choice" (page 453). This incorporation merges concepts and distinctions that economics traditionally keeps separate, namely, the preferences over outcomes and the perceived relationship between outcomes and the instruments of choice (the game form).

A change in the frame therefore becomes associated with a change of preference. Thus, according to framing theory the preference for the card in our experiment is defined to be the measurement provided by the BDM, typically above $2.00, as opposed to the $2.00 known value. That is, according to framing theory almost all of the subjects in our experiments have a "kink" in their preference for the card such that the value for keeping the card is greater than the value they would pay for the card. Similarly, framing theory holds that the preference for the ovals in Figure 1 is defined by the original choice and that any change of choice that results from the additional information provided by the thick lines involves a violation of an axiom of "invariance" and is thus a violation of rational choice. Framing theory is offered to fill the resulting void. Changes in the perception of the game form come to be interpreted as changes in preferences and thus as violations of some form of rationality.

The concepts of misconceptions and mistakes highlighted in this study break the crucial connection between preference and choice in framing theory. We know the stated choice is a mistake because we induced an objective preference, and this is confirmed by the systematic reduction in the mistake across rounds. Since the choice reflects a misconception rather than a preference there is there is no necessary reason for the axiom of invariance to be satisfied as the frame changes. Choices that do not satisfy the property of invariance can be mistakes and thus need not be based on framing theory. Interestingly, the theory of rational preference and choice, which framing theory seeks to reject, actually provides an explanation of our experimental results. The theory of bidding in first-price auctions explains part of the data and the dynamics of choice adjustment and learning through feedback and exposure to errors toward the optimal offer explain more.

Sensitivity to context is to be expected and is even part of the standard economic theory. The evidence from economics and the standard theory itself hold that changes in context can have substantial influence on choice. Indeed, many aspects of economics predict that context influences on choice. Changing information, prices, institutions, beliefs, etc. are all examples of context influence that are fully understood in terms of traditional theory. However, it does not follow that preferences, as opposed to choices or decisions, are influenced by context. Furthermore, it does not follow that the influences of context on choice should be of concern to those interested in theories of rationality.

Some important criticisms of standard economic theory suffer from limited robustness.[22] The variability of results is understandable if one accepts the evidence presented here that systematic misconceptions of the game form affect the widely-used BDM preference elicitation method. A root cause may be misconceptions related to game form together with a variety of instructions used by different researchers. However, we hasten to point out that we have produced no general theory of game form misconceptions. Since the nature of misconceptions is context dependent, in the absence of a specific theory, falsifiability of any proposed general theory is problematic.

Can the BDM be developed to accommodate both the need to avoid game form misconceptions while also avoiding contaminating procedures from the point of view of framing theory? We have not addressed that question, and how it might be addressed depends on one's understanding of framing and framing theory. Economics rests on the hypothesis that preferences exist, can be measured and that a clear distinction exists between a preference and a decision. The addition of random variables to model preferences from decision data such as the logit model used here are illustrations. By contrast, the theory of framing appears to rest on the assumption that preferences cannot be known independent of the frame and perhaps are even created/constructed by the frame. Thus, the constructed preference perspective of framing results in an unclear meaning of "preference measurement" and certainly leaves ambiguous the

[22] For example, some WTA/WTP gaps go away with greater subject experience (Plott and Zeiler, 2005; Isoni et al., 2011), anchoring and adjustment effects are much smaller in some studies (compare Fudenberg et al., 2012 to Ariely et al., 2003), and manipulations of expectations of a trade do not have predicted impacts on reference dependence (Goette et al., 2012).

meaning of “improved measurement.” More training or detailed descriptions, including a summary of the incentive-compatibility of the BDM mechanism sometimes used in instructions, changes the frame and thus the preference according to framing theory. Thus, it might be impossible to determine if measurement is improved under the maintained assumption of framing theory.

The discussion of BDM draws attention to a closely related controversy. Our experimental results, and in particular the changed choice for many individuals who were exposed to a mistake, suggest that experience works through a process of evolving game form recognition. Thus, according to that idea, the field experiments conducted by List (2003) differ from the data generated by untrained laboratory subjects because the subjects from the field are familiar with the game form and do not have the same game form misconceptions as untrained subjects or inexperienced participants in the field. Gigerenzer et al. (2008) gives us a hint suggesting that the concept of recognition heuristics might be useful in economics, which is consistent with a focus on the process of decision making as opposed the development of an underlying preference.

We were drawn to this research by a controversy that exists in the literature. We conclude that the controversy stems from a missing element of theory: A solid connection between the game form and individual's understanding of the game form. The needed theory might be related to perception, logic, learning or other phenomena. We do not know how to close the gap, and we suspect it will require input from a variety of disciplines outside economics. We hope that the experiment reported here calls attention to the fact that the task is not addressed by revealed preference theory and the gap is not closed by the theory of framing.

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