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

Author(s): Timothy N. Cason and Charles R. Plott
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Misconceptions and Game Form Recognition: Challenges to Theories of Revealed Preference and Framing

Timothy N. Cason

Purdue University

Charles R. Plott

California Institute of Technology

This study explores the tension between the standard economic theory of preference and nonstandard theories of preference that are motivated by an underlying theory of framing. A simple experiment fails to measure a known preference. The divergence of the measured preference from the known preference reflects a mistake, arising from some subjects' misconception of the game form. We conclude that choice data should not be granted an unqualified interpretation of preference revelation. Mistakes in choices obscured by a possible error at the foundation of the theory of framing can masquerade as having been produced by nonstandard preferences.

I. Introduction

This paper addresses a tension that exists among competing theories regarding fundamental properties of preferences. On one hand, the stan-

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dard theory of preference postulates that individuals have preferences over outcomes and those preferences are independent of the feasible set of outcomes. On the other hand, nonstandard preference theories, such as those based on the theory of framing or endowments, hold that preferences are dependent on and perhaps even constructed from the context faced by the choosing individual and might have no particular existence outside that context.[1] We suggest that the tension is exacerbated by a specific form of mistake made by individuals in standard choice elicitation procedures, especially when combined with the usual convention of equating choice with preference and is further exacerbated by the absence of an integrated theory of perception.

We perform an experiment similar to testing a scale by measuring a known weight. This allows a choice based on a preference to be distinguished from a choice based on a mistake. The experiment employs the Becker, DeGroot, and Marschak (1964) method to measure the preference for an object for which the subject's preferences are known—a card that can be redeemed from the experimenter for $2. All theories agree that the preference value the subject places on the card is $2. However, subjects' choices systematically involve a mistake that we identify as a failure of game form recognition. As a consequence, instead of revealing the known $2 preference, the choices masquerade as reflecting properties often cited as evidence of nonstandard preferences.

From the simple experiment we identify four ingredients that contribute to the tension between standard and nonstandard preference theory. The first ingredient involves a practice common to both revealed preference theory and framing theory. Both tend to interpret choice as revealing, if not defining, a preference. The possibility of systematic mistakes implies, however, that researchers in general should not simply define choice, without qualification, as measuring preference with an error term added and should be careful in interpreting systematic deviations from the standard model as evidence of alternative preferences. Second, close examination reveals an error in the theory of framing as it is applied to the structure and measurement of preference theory in economics. The issue is addressed in Section II. A third ingredient stems from the fact that the Becker-DeGroot-Marschak (BDM) method of eliciting preferences is not reliable. Sections III and IV develop a method for measuring its inaccuracy. We emphasize that our interest is not in

[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?" (i). Some may consider framing as an unstructured catchall for context dependence, but without structure and supporting theory, it is difficult to envision how it could be rejectable and to take seriously proposals to modify policy and law to reflect properties of preferences derived from framing theory. For broad insights into the evolving controversy, see Levine (2012).

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, it is an aside to the issue we pose; in any case, researchers using the BDM in choice experiments employ a wide variety of instructions and examples. The fourth ingredient is the fact that subject mistakes can be interpreted as evidence of a particular form of preference. Sections V and VI show that our data appear to demonstrate a sensitivity to context that is often described as evidence that preferences are constructed from framing. Our analysis reveals, however, that this apparent frame-based pattern in the data can be a consequence of a specific type of mistake by the decision makers. Many decision makers appear to confuse the second-price auction incentives of the BDM with a first-price auction, which is a failure of game form recognition. The paper concludes with observations from the literature and highlights difficulties rejecting preference theories based on framing and also suggests possible constructive interpretations of nonstandard preferences that can be useful for policy.

II. Mistakes, Revealed Preference, and Framing

While many forms of misconceptions are possible, the misconception studied here is a "failure of game form recognition." It is a failure of the decision maker to recognize the proper connections between the acts available for choice and the consequences of choice, which, by necessity, are associated with the method of measuring preferences. If the individual fails to understand the connection between acts and outcomes, the choice of acts can be misleading about the preferences over outcomes. In such cases, choice cannot be equated with preference over consequences.

The connection between the consequences of acts and the acts themselves is sufficiently obvious as part of the theory of choice in economics that it would seem to require no discussion. Together they form a "feasible set" of consequences from which the choice is selected. Clearly, choices and decisions do not reveal preference 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*. That type of misconception will be called a failure of game form recognition.[2] The mistaken choice

[2] The concept of a game form reflects the traditional tools of game theory in which distinctions are made among game structures that connect acts to outcomes, preferences over outcomes, and decisions that are the choices from among acts. Much of economic theory proceeds on the assumption that these elements are known and are treated as "common knowledge." When the elements are not known, information and information sets are key concepts that might be extended to deal with the misunderstanding of the game form, but this issue is not part of the analysis here.

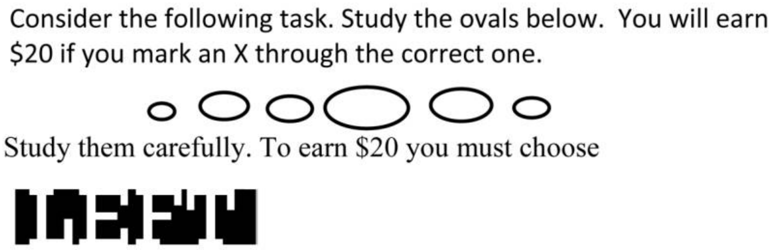


FIG. 1

should not be interpreted as a preference for *Y*. 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 fine print too small to read. Mistakes, decision error, and noise can complicate inferences about fundamental economic primitives, and these complications call for stochastic and heterogeneous models. (For an important application to decision making when agents face risk or uncertainty, see Wilcox [2008, 2011].) This motivates the empirical approach presented below in Section VI. As noted by Kőszegi and Rabin (2008), one must control for the confounds of mistakes and (false) subjective beliefs before claiming that choices are consistent with nonstandard preferences.

A simple example of an optical illusion illustrates the subtleties. The example highlights the importance of perception for research on preference. It also demonstrates the influence on game form recognition and the difficulty in rejecting any theory when game form recognition is an issue.[3] Consider the task represented in figure 1 in which the subject is given a monetary incentive to choose a specific oval. The subject is asked to follow the instructions and choose one of the ovals as directed.

If you are similar to many people, a well-known optical illusion will prevent you from seeing that your maximum payoff occurs if and only if you choose the small oval on the left. Because of this misperception, 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." For those who still have problems seeing the word, the symbol, bracketed by black lines, becomes LEFT.)

The example illustrates how incorrect inferences about preferences can emerge from the convention of equating preference with choice in the presence of misconceptions of the game form.[4] Naturally the sub-

[3] Tversky and Kahneman (1986) use an optical illusion to suggest that, by analogy to principles governing vision, preferences are subject to context.

[4] Failures of game form recognition have been documented elsewhere in the literature and are known to be a source of anomalies in experimental work (Chou et al. 2009; Rydval,

ject's preference is to choose the oval that produces the most money, but the subject may not understand the relationship between the acts (the choice of oval) and the consequences of the acts (the money received). In the absence of a precise specification, classical revealed preference theory would just treat the preferences as random. Unconstrained imagination can produce many plausible theories. 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. This cannot be resolved without additional theory or observation.

The theory of framing developed by Kahneman and Tversky is an important step toward filling the need for a theory of perception and the process through which the game form becomes understood. They offer their theory as an alternative to a broad theory of rational choice, but their approach is indirect. Preferences are equated with choices, as is typical with revealed preference methodology, but the concept of rational choice is not explicitly defined. The specific theory they seek to replace is not stated. Instead of specifying and defining a theory of rational choice, Kahneman and Tversky assume that rational choice must exhibit consistency and coherence as defined by a concept of "procedural invariance." They assume that it is a necessary condition. Thus, if procedural invariance is rejected in the data, so is the unstated theory of rational choice.

The concept of procedural invariance draws heavily on the theory of revealed preference. In particular, if the decision makers' understanding and perception of a feasible set of consequences are not changed, then a choice reflecting preference, the revealed preference, would not change (except as randomly perturbed). The "feasible set of consequences" is naturally defined by the game form, the connections between acts, and the consequences of acts. If the perception of the feasible set is changed even when the real feasible set has not changed, as could be the case if the acts and consequences are described differently, then the standard theory does not predict that the choice should remain the same. Indeed, revealed preference theory suggests that choices are expected to change if the perception of the feasible set changes. The role of perception in making that connection between choice and the feasible set of consequences is a crucial part of the theory. When the perceived feasible set changes, the concept of procedural invariance does not apply and a sys-

Ortmann, and Ostatnicky 2009; Cox and James 2012). Harrison (1990) introduces the idea of "games of (potentially) inconsistent information" to describe circumstances in which the subjects' beliefs may not correspond to the objective probability distributions assumed or known in the underlying theoretical model. Game form recognition is nicely illustrated by the Tower of Hanoi example in Harrison and List (2004) and McDaniel and Rutström (2001).

tematic change in choice cannot be interpreted as a change in preferences and is not a violation of rationality in the sense of economic theory. Perception of the feasible set occupies a key role in the theory when analyzing preferences and the context effects associated with theories of framing.

Game form misconceptions reveal difficulties with the theory of framing. Tversky and Kahneman's concept of a "frame" is firmly tied to the perception of the game form, the connection between acts and outcomes. Tversky and Kahneman (1981) make that 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" (453). Thus, the Tversky and Kahneman concept of a frame includes the whole of the game form. Changes in the frame involve changes in the game form and changes in the perception of the feasible set as defined by the game form. The frame thus merges variables that the game form separates. Traditionally, economics separates the theory of preferences over outcomes from the feasible set of outcomes as defined by the relationship between the instruments of choice (the acts) and the consequences of acts—the outcomes. If the perception of the relationship between acts and consequences changes and the perception of the feasible set has changed, then choice changes due to perceived changes in the feasible set can be mistakenly interpreted as changes in preferences. Different frames in the Kahneman and Tversky sense that result in different choices are not violations of procedural invariance if the subject's perception of the set of options is different. If different frames lead to different understandings of the game form, different choices cannot be interpreted as reflecting different preferences. Thus, choices that change in response to frame changes are not direct evidence of changing (or labile) preferences. Violations of procedural invariance in the Tversky and Kahneman sense are not necessarily violations of rational choice in the revealed preference sense. Tests must include a control and tests for game form misconceptions.

Many experiments show the influence of a frame, which leads Tversky and Kahneman (1986) to draw the inference that rational choice has no behavioral foundation and conclude that the standard theory of preference must be changed. However, as they note, if the frame is transparent, then the choices satisfy key conditions such as dominance and so invariance tends not to be violated (S272). They highlight this interpretation in the abstract of this important paper: "Alternative descriptions of a decision problem often give rise to different *preferences*, contrary to the principle of invariance that underlies the rational theory of choice. . . . Invariance and dominance are obeyed when their application is *transparent* and often violated in other situations" (S251; emphasis added). If the pattern of results for nontransparent frames were viewed as mistakes derived from game form misconceptions, Tversky and Kahneman could have concluded that confused subjects make choices that do not seem rational and turned the analysis to the application of standard theory for nonconfused subjects.[5] Of course, a focus on the nature of subject confusion and how misperception of the game form can lead to properties of system and market behavior, some undesirable and some desirable, would join an analysis with a long history of economics research with that focus.[6]

Picking up the analysis of preference where Tversky and Kahneman leave the theory is easier said than done. Testing a theory of preference based on framing presents a challenge. The preference, which the theory seeks to explain, is determined by the context of the measurement including the methods used to measure it. According to the theory, 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. This reflects a deep problem of testability, to which we will return in the final section of the paper in the light of the experimental results.

III. Untangling the Concepts: Preference Measurement and the Becker-DeGroot-Marschak Method

Our approach to untangling the concepts while respecting the need to maintain as much observability as possible is to focus on the preference measurement method. We study commodities, acts, and consequences that are observable and for which subjects have clearly identifiable preferences.[7] The exercise is based on an uncontroversial preference, with no objective risk or uncertainty to bring expected- or nonexpected-utility theories into play. We can therefore use that preference to assess the

[5] In addition to a theory of preference, Kahneman and Tversky introduce a special theory of subjective probability that is closely related to game form recognition. A "question-induced beliefs" conjecture has been associated with the BDM procedure that can influence choice similar to those predicted by nonstandard preference theories. Similarly, the omission of the "fact" that Linda is single can reduce challenging paradoxes related to probability assessments in a classical anomaly (see Charness, Karni, and Levin 2008, table 2; 2010). The issue of subjective probabilities is not addressed in this paper (see Plott and Zeiler 2011).

[6] A wide range of economic models are based on the failure of game form recognition. Examples include the competitive model in which individuals make an obvious mistake when considering prices as constants. The Cournot model of price adjustment has competitors constantly making the mistake that their rivals' prices will not change. Monopoly in a general equilibrium model acts with extreme myopia when failing to recognize how its decisions can ripple back through the economy to influence its decision-making environment (see the discussion in Plott [1996]).

[7] We focus on commodities because they are a fundamental building block in economics, as opposed to the more abstract concept of "prospects." The "prospects" of prospect theory are defined in terms of subjectively determined reference points. Thus, prospects differ from person to person, reflect no common unit of measurement, and need not be observable. The focus on commodity spaces in economics stems from their central role in defining an observable feasible set and in connecting preferences to scarce resources and the laws of supply and demand. The common unit of measurement addresses the need for a concept of "units" that can be summed across agents, captures the concept of market price per unit, and defines the basic concepts of equilibrium and efficient allocations in precise terms.

accuracy produced by the BDM measurement method. An accurate theory and method of measurement should accurately return the measurements of things for which measurements are known. The method is like using a known weight to test the accuracy of a scale. Since the preference is known, this provides an opportunity to trace any observed departure from the known preference to the measurement methods and an assessment of what form the unobserved and uncontrolled perception of the game form takes.

The preference is for dollars and for a card that is directly translated into $2 with certainty. As emphasized by Kahneman, Knetsch, and Thaler (1990, 1328), preference inducement of this form implies that the subjects should value the card at its induced value. Nonstandard theories of preference do not differ from the standard theory. All theories agree. The rate of substitution for the card and money is "two" just like the rate of substitution of $5 bills for $10 bills is "two," as it is demonstrated in market transactions every day. Indeed, the experiment itself has an internal consistency check on the rate of substitution.[8] We pose an experiment that is widely used in studies of framing theory, the willingness to accept as measured by the BDM. We also perform the experiment in an environment that minimizes the influence of the experimenter and training, which have both been implicated in affecting measurements in earlier scientific analysis.

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 nonincentivized 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 auc-

[8] 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 a scrap 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, in all 264 cases they took the $2, including 217 cases in which subjects stated a BDM willingness-to-accept value greater than $2. Logic, theory, and data reveal that the subjective value of the card was the objectively known and uncontroversial $2.

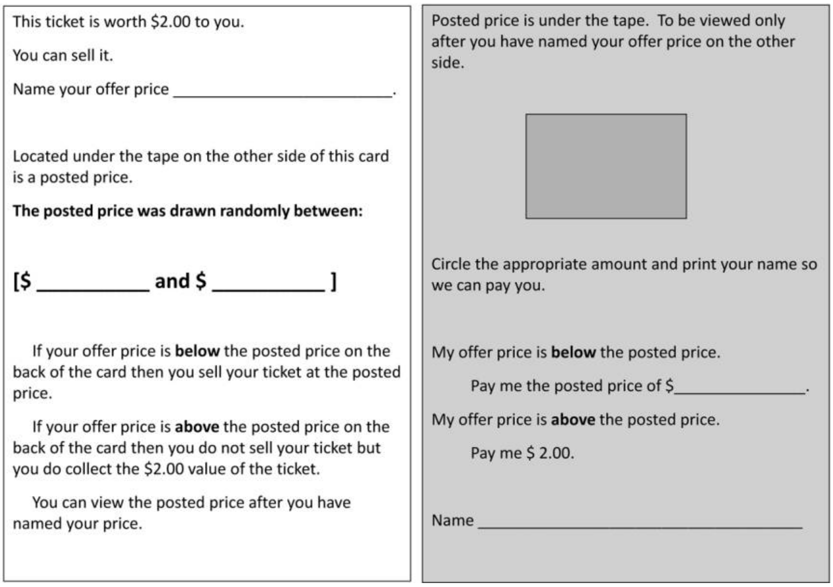
tions and public goods. For example, it shares the same (dominant strategy) incentive properties as the second-price Vickrey auction. It is also widely used as a tool for preference measurement in growing and important new subfields of economics such as behavioral economics and neuroeconomics.

The reliability of the BDM has been the subject of considerable research, and our experimental design is extremely simple relative to other applications in the literature.[9] In 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 the BDM in which the preference for the object is not known and is sought through the application of the BDM mechanism. 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 the BDM to measure the preference, as if we did not know what the 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 the card is worth \$2. 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 are clearly printed on the card and the upper limit differs randomly across subjects. If the posted price is above the subject's offer price, the subject is paid the posted price; if not, the subject is paid

[9] See, e.g., Kagel and Levin (1993; indirectly through the study of second-price auctions), Bohm, Lindén, and Sonnegård (1997), Irwin et al. (1998), Grether et al. (2007), James (2007), and Urbancic (2011). 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 are chosen from a price list (Vossler and McKee 2006; Murphy, Stevens, and Yadav 2010), although the use of a coarse grid of possible valuations does not provide narrowly defined valuation estimates and thus is a relatively weak test. Harstad (2000) compares ascending-bid English auctions and second-price auctions and identifies the key role of feedback for promoting learning. Rutström (1998) documents less overbidding in the BDM compared to second-price auctions. 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, Robin, and Ruffieux (2004a, 2004b). Others have trained subjects using different lotteries before eliciting values of objects (Plott and Zeiler 2005). Later comments by Isoni, Loomes, and Sugden (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.

Front Side of Card | Back 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.

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 ____________________________________

FIG. 2.—Decision form used in both rounds

the $2 for the card. After the subject states an offer price, the opaque tag on the back can be removed, revealing the predrawn random posted price. 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. 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 as an offer price. Failure to state $2 reflects a mistake. A subject offering a price higher than $2 will never receive more and can receive less for the card than a subject offering $2. If the subject offers $2 for the card, he receives $2 if the random posted price is less than or equal to $2, but he receives the posted price whenever the posted price is above $2. Thus, subjects who offer the card at values strictly greater than $2 redeem the card at $2 when the posted price is above $2 but below the subject's offer price. Regardless of the probabilities of various draws, a failure to offer $2 means that the subject simply failed to take the opportunity to receive extra 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 when faced with a nearly identical choice. After the subject completes the question on the back of the card, which reinforces attention to 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 that the $\$\bar{p}$ on the second card is usually different from the $\$\bar{p}$ on the first card, but because of 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.

The application of BDM in this environment differs from typical applications along four dimensions. First, in contrast to 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 that 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 from the difference between two $5 bills and one $10 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, 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 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. Thus, the experimental design can produce evidence of failure of game form recognition. With the data in hand, we then ask if the choices that superficially support a theory of constructed preference based on a process of framing are explained as mistakes due to a failure of game form recognition. That examination is contained in Section VI.

IV. Experimental Procedures

Because the experiment was so brief, we conducted it during class time rather than recruiting volunteers to attend a lab session. In particular, 245 subjects participated 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 two or three 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, 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 themselves 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 (30–40 students) in arena-style seating; 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.[10] The card was identical to the first, except that it was a different color and the maximum posted price was likely to be different because it varied randomly across subjects for both cards. 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 VI, it does influence the expected payoff consequences of suboptimal offer prices.

V. Results: Data Patterns

The prominent patterns of the data are stated here as a series of results relevant for the implications to be addressed in the subsequent sections. While the limited reliability of the BDM is of general interest, it has al-

[10] The data were collected on three different dates over 15 weeks. None of the main data patterns, such as the frequency of optimal offer prices in either round or the increase in optimal offers from round 1 to round 2, are different across dates. This suggests that little information about the experiment "leaked" out to affect choices made by later subjects, which is not surprising for this large campus of nearly 40,000 students.

ready been well documented, including in many of the studies noted above in footnote 9. The first two results indicate that the proportion of optimal choices ($2) 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 3*A* 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¢ of the $2 true value. A greater fraction of subjects chose offers near $3 and near $4 than near the optimal offer. These

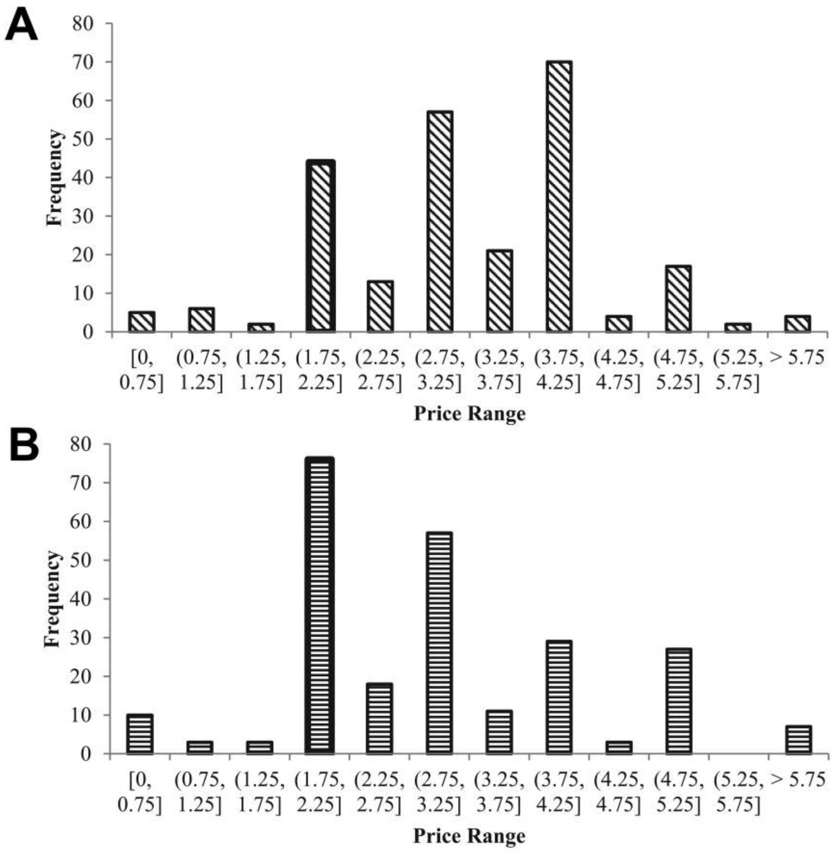


FIG. 3.—Offer price distribution on first choice (*A*) and second choice (*B*)

large deviations from the induced value of \$2 are similar to the minimal information treatment in Irwin et al. (1998), in which subjects were not given information about how the BDM mechanism operates.

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

Support: Figure 3*B* shows that the number of subjects indicating an offer price within 5¢ of the \$2 true value increases to 76 out of 244 (31.1 percent) on the second, repeat decision.[11] The data strongly reject the null hypothesis that the rate at which subjects state an offer price within 5¢ of \$2 is equal on the first and second decisions (Fisher's exact test p-value < .01).[12] Previous experiments using the BDM with induced values have also documented improved performance following repetition (e.g., Noussair et al. 2004a).

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¢ of \$2) on the first card. Of these 203, 159 (78 percent) chose a different offer price on the second card and 44 (22 percent) indicated the same offer price. Of the 244 subjects, 41 chose near \$2 on the first card. Of these 41, 35 (85 percent) chose the same offer price and 6 (15 percent) 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 < .01).

These results demonstrate that the misconceptions subjects apparently have about the BDM procedure are distinct from potential framing effects, which we elaborate in the next section. One possible interpretation is that the frame changes when subjects observe different upper limits of the posted price and the frame is the same if the upper limit of the posted price remains the same. 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 percent) who observed the same upper bound (and thus the exact same frame) in rounds 1 and 2

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

[12] This result is robust to using alternative thresholds, such as offer prices exactly equal to \$2, or 10¢ or 25¢ within \$2. The number of offers "close" to \$2 on the second decision is 76 regardless of whether the threshold to define "close" is 5¢ or 25¢ because the 14 offers near but not equal to \$2 were all within 2¢ of \$2 (others were at least 50¢ away from \$2). The data suggest no evidence that could be attributed to a "status quo" bias or "endowment effect" that cannot be explained by the well-known effects of transaction costs.

but who did not offer within 5¢ of $2 in the first round changed their offer in the second round. While nonoptimal subjects who received a different upper limit in the two rounds changed their offer price more frequently (133 out of 157, 85 percent), framing theory does not explain the frequent change in behavior even when the frame stayed the same across rounds. Moreover, those subjects who chose optimally (presumably those with no misconceptions) tend to have stable choices, even when the frame (interpreted as the random price upper bound) changes.

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 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 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 nonoptimal price offers is related to the maximum of the posted price range.

Support: Table 1 summarizes the mean price offers for each of the five upper bounds in the two rounds for offers not within 5¢ of $2. The trend is for offers and standard errors to increase as the upper bound increases, 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 are 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¢ of $2

	Range				
	[$0, $4]	[$0, $5]	[$0, $6]	[$0, $7]	[$0, $8]
			A. Round 1		
Mean offer	2.98 (.11)	3.35 (.13)	3.50 (.18)	3.93 (.14)	3.80 (.21)
Observations	45	39	39	40	41
Percent offer $2 ± 5¢	10%	19%	22%	17%	16%
			B. Round 2		
Mean offer	2.73 (.13)	3.08 (.20)	3.37 (.25)	3.85 (.19)	4.16 (.36)
Observations	32	35	28	41	32
Percent offer $2 ± 5¢	32%	27%	44%	18%	35%

Note.—Standard errors are in parentheses.

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

Range	Range [$0, $4]	[$0, $5]	[$0, $6]	[$0, $7]
	A. Round 1			
[$0, $5]	.013**			
[$0, $6]	.001***	.176		
[$0, $7]	.000***	.007***	.135	
[$0, $8]	.000***	.003***	.076*	.784
	B. Round 2			
[$0, $5]	.007***			
[$0, $6]	.001***	.474		
[$0, $7]	.000***	.005***	.056*	
[$0, $8]	.000***	.007***	.040**	.423

Note.—Tests exclude offers within 5¢ of $2. Table entries denote p-values for two-tailed Wilcoxon tests.
* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

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¢ 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 = .049) and significantly less likely to move even further away from $2 ($p$-value = .024) on round 2.[13]

[13] These statistical tests 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 .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 toward 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 an important 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 toward or onto the optimal ratio of 0.

VI. 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 task understanding but with noise, and (*C*) theories based on specific game form misconceptions. Theories within a class tend to rest on the same or similar basic principles, but the basic principles differ across classes. 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 induced value card is objective, constant, and known. If the preference was not known, one could conclude that the preference for the commodities resulted from framing. However, a close examination of the

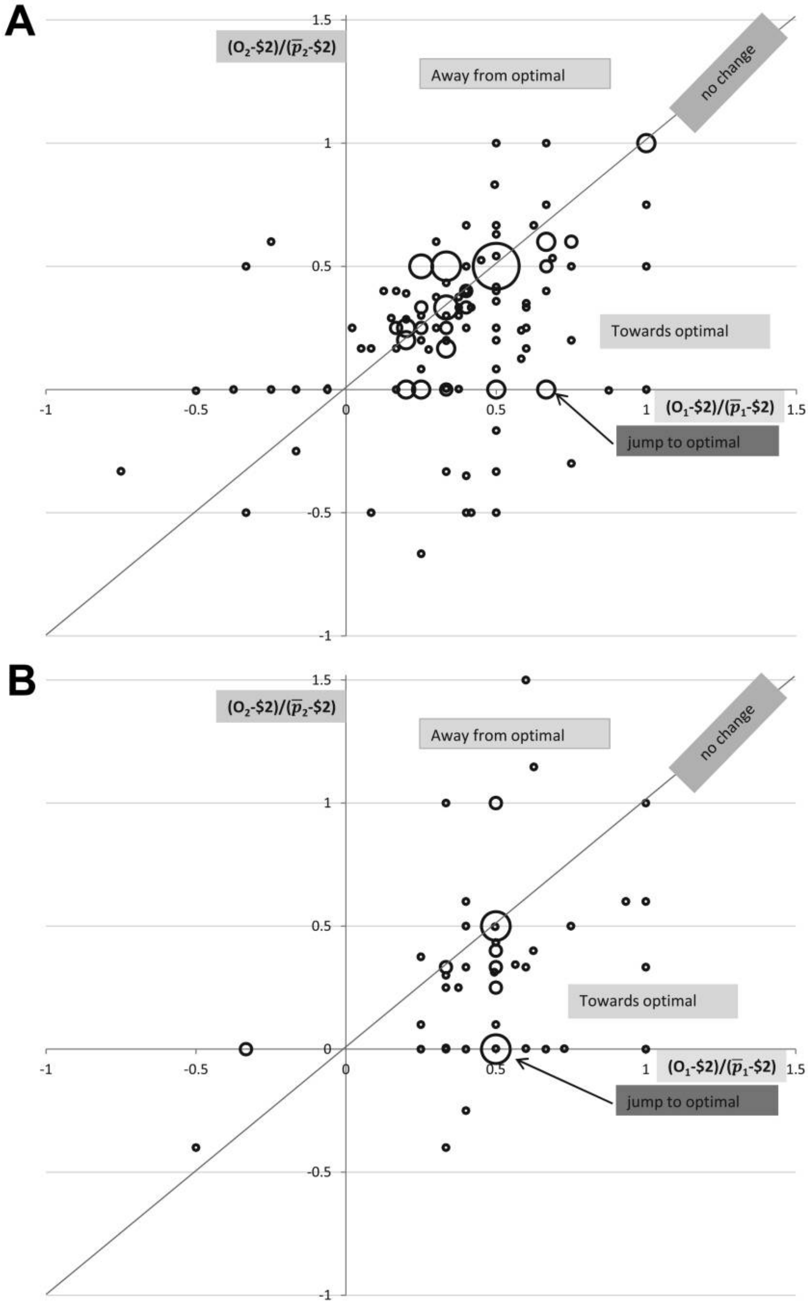


FIG. 4.—*A*, Offer ratios and changes for subjects not exposed to round 1 error. *B*, Offer ratios and changes for subjects exposed to round 1 error.

choices demonstrates that a case for framing is not convincing. The data are better and more completely explained by a mixture of some subjects who understand the BDM mechanism and submit optimal offers and others who have a specific type of game form misconception. A discussion of the general theory of framing is reserved for Section VII.

A. *Theories of Framing*

Our data exhibit patterns that could be interpreted as confirming evidence for framing. We are not asserting that the choices exhibited in the experiment represent preferences constructed through a framing process, as we hold no disagreement with the insights from Kahneman et al. cited above that this should not be the case for induced value items. The point is that while the data are consistent with choice patterns associated with theories of framing, a completely different assessment emerges when comparing these patterns to theories of mistakes stemming from game form misconceptions. The interpretations of preferences are different when the role of perceptions and mistakes is considered as an alternative theory. Before turning to that assessment, consider first the four theories suggested by framing listed below. Although they have differing origins, their empirical implications are similar so they are not distinguishable for this simple experiment.

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 [WTA]) is greater than the buying price (willingness to pay [WTP]). According to the intuition of 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 an induced value card worth \$2, some might question whether the necessary "sense of ownership" will develop, so an "endowment effect" due to loss aversion may not be observed.[14] However, the data clearly show BDM measurements of WTA that are substantially more than \$2. These patterns are reported in results 1, 2, and 4. If subjects' WTP for a \$2 card is near this induced value (as in Irwin et al. [1998]) or less than \$2 (as observed for noninduced value objects), it seems reasonable to conjecture that the WTA we have documented is greater than the WTP. In

[14] Lange and Ratan (2010) and Banerji and Gupta (2014) formalize the idea that second-price auctions and the BDM mechanism remain value-revealing institutions for induced value items even under reference-dependent and loss-averse preferences. We make no claim that our experiment has other implications based on an unobserved "sense of ownership" of the card. We refer the reader to discussions of "assignments" in Heffetz and List (2014) and discussions of "enhancements" in Plott and Zeiler (2011).

this case a WTA-WTP gap consistent with an "endowment effect" would be observed, even though it is not expected for an induced value item. Thus, one might conclude that sellers require compensation for the consumption value of the ticket plus additional value for the lost "ownership" of the ticket, due to loss aversion. Indeed, these data are consistent with what some would describe as a "widely observed" pattern in the literature.[15]

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. Losses loom greater than gains, and this motivates a high offer price, especially when the anticipated selling price of the item is high. While the expectations of trading are not manipulated or directly observed in our experiment, 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's expectations and how those expectations may depend on the distribution of the random posted price (Banerji

[15] For example, Knetsch, Tang, and Thaler (2001, 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."

and Gupta 2014). An initial interpretation of our data is that the subjects expect not to trade and that the predictions of the Kőszegi and Rabin model are supported given the high offer prices stated by subjects.[16] 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 could be interpreted). More importantly, on the basis of the convention of defining choices as preferences, the theories are reporting to have identified and measured a preference contrary to what was induced. As was established in Section III, we know that the true preference for the card is $2, but framing theories suggest that the measured preferences differ from $2. Result 4 demonstrates that subjects who exhibit the features exhibited by theories of framing tend to be those who 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 toward the optimal choice. The patterns of choices across rounds (results 3 and 5) are more consistent with learning than with framing.

B. *An Optimal Model with Noise*

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. 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 data set, only 28 percent of subjects who offer more than 5¢ away from the correct offer of $2 suffered any monetary cost from their suboptimal offer. Moreover, the likelihood of being exposed to a mistake is

[16] While the data from the experiment can be interpreted as support for Kőszegi and Rabin (2006), our experiment is clearly not the way to test their model. Indeed, like other framing-based theories, their theory does not predict an endowment effect in our setting for the reasons given by Kahneman et al. (1990) that endowment effects should not occur for induced value objects. Nevertheless, the high average WTA observed in our data could be interpreted as evidence for an endowment effect in the absence of the further analysis we apply below in Sec. VI.C.

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 offer 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

$$E[\pi] = 2\text{Prob}(b > p) + E(p|p > b)\text{Prob}(p > b).$$

For the uniform distribution, this simplifies to[17]

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

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

For example, consider a subject indicating a suboptimal offer price of \$3. The likelihood that this subject will see a random draw between \$2 and \$3 resulting in a loss relative to the correct offer price of \$2 is one-eighth when the range is [\$0, \$8] but is one-fourth when the range is [\$0, \$4]. The expected loss from this suboptimal offer price is very small for both ranges, but it is twice as great when the random posted price ranges between [\$0, \$4], 12.5¢, rather than [\$0, \$8], 6.25¢. 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 a systematic misconception of the BDM mechanism. In what follows we will refer to this as the "optimal" or "correct" model with noise.[18]

[17] Note that the brief instructions on the decision card did not state that the randomly posted price was drawn from the uniform distribution, since the exact distribution is not relevant for the incentive-compatible properties of the BDM. Calculation of the expected payoff from each offer does require an assumption for this distribution, and it seems plausible for many subjects to assume the uniform distribution that was actually used, just as Bayesian analysis often assumes a uniform (noninformative) prior based on the principle of indifference.

[18] Given the importance of risk preferences in the "flat payoff" literature, it seems sensible to generalize the objective function beyond risk neutrality. We considered including constant relative risk aversion in our model estimates reported below but found that the best-fitting parameters featured implausible levels of risk aversion for the optimal model with noise and did not reject risk neutrality for the first-price auction misconception model described in the next subsection. As an alternative it would be valuable to determine how risk aversion varies across subjects and is related to observables (e.g., as in Harrison [1990] and Harrison and Rutström [2008]), but we have too few choices per subject for such analysis and did not collect sociodemographic data.

C. *Failure of Game Form Recognition*

The theory of game form misconception in this context holds that the patterns of data are not due to 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 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. Of course, in the absence of specific, testable predictions, the concept of a mistake can be applied to explain any pattern of choices.

Although the results indicate that some subjects chose price offers of \$2 and apparently understood the BDM mechanism, other subjects filled out their cards incorrectly, and this suggested a specific type of misconception. Recall that subjects were asked to write on 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. This does not appear to be a deliberate "mistake" because they would earn more by correctly indicating that they should be paid the drawn random price. (We noticed these mistakes when viewing their cards to prepare the money payment envelopes and paid subjects the correct, higher amount.) These subjects appear to believe that the payment mechanism is similar to a first-price procurement auction in which the lowest offer wins and is paid the offer 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 offer was above the drawn random price.[19]

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

[19] These 82 subjects include two who offer the optimal \$2, but since their drawn random offer price was less than \$2, we do not know whether they had a misconception. These offers are possible in the misconception model with noise developed in this section. 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 offer 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 received a payment only if their asking price was below the posted price and thus stated an asking price below \$2. The prominence of \$4 among the price offer distributions, especially when inexperienced (fig. 3*A*), suggests that other misconceptions with an optimal offer of \$4 are possible; the data suggest, however, that misconceptions that imply a positive relationship between the offer and the maximum of the random price distribution (table 2) are more common. One can also imagine misconceptions emerging from the task itself. A subject faced with such a simple task as selling \$2 for \$2 might speculate on what the experimenters had in mind. We are unable to associate that possibility with any specific form of behavior that might affect our analysis or conclusions.

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

$$\tilde{E}[\pi] = 2\text{Prob}(b > p) + b\text{Prob}(p > b), \tag{2}$$

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 $E(p|p > b)$ in the second term of the expression.) We developed this alternative misconception model following the data collection when we observed directly the errors subjects made when filling out their payment cards. If we had anticipated this first-price auction misconception, we could have explained to subjects the distribution of the random offer price since it affects the expected payoffs for different price offers, even though it does not affect the incentive properties of the BDM.[20] For the uniform distribution, which is a reasonable assumption without additional prior information, the expected payoff simplifies to

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

If the subject maximizes this incorrect expected payoff expression with respect to the offer b, then he will set $\tilde{b} = 1 + 0.5\bar{p}$. Importantly, this incorrect offer depends positively on the maximum price drawn in the random offer distribution, similarly to the random mistake in the optimal model with noise. Also, note that this offer function results in a constant ratio for $(\tilde{b} - \$2)/(\bar{p} - \$2) = 0.5$, which appears prominently in figure 4 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:

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

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

[20] Such an intervention is accompanied by a risk that misconceptions are compounded through the subjective probabilities. See, e.g., the "question-influenced beliefs" conjecture of Plott and Zeiler (2011).

differences in their expected payoffs. For $\lambda = 0$, subjects are completely insensitive and choose all feasible offers with equal probability. As $\lambda \to \infty$, 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; indeed, the subjects who (correctly) state an offer price of \$2 clearly reject this particular model of mistakes. 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 is 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 $\lambda^{1\text{st}}$ and the observed choices y_i:

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

where y_i is an indicator for offer i being in a bin within 5¢ of b_j.[21] Similarly, the conditional log likelihood based on the assumption that the optimal and correct model is true (denoted with an OPT superscript) is

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

Note that other than the different payoff sensitivity parameters, these log likelihoods differ only in whether the correct expected payoff expression $E[\pi]$ from equation (1) or the misconceived expected payoff expression $\tilde{E}[\pi]$ from equation (3) is used.

RESULT 6: Among the subjects who do not choose offers within 5¢ 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. Column 1 is based on all the data and indicates some small differences in fit between the two models, but for the round 1 offers, the log likelihood is considerably higher for the first-price misconception model. The confidence intervals for λ overlap in that column, however, and subjects who offer the correct \$2 are unlikely to have the first-price misconception or make errors. Column 2

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

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

Model	All Data (1)	Excluding Offers within 5¢ of $2 (2)	Subjects Revealing Misconception, or Possibly Holding It (3)
	A. Round 1		
Optimal model λ^{OPT}	.99	.56	.48
	(.149)	(.130)	(.141)
90% confidence interval	[.81, 1.26]	[.34, .73]	[.25, .74]
Observations	245	204	111
Log likelihood	−985.4	−826.8	−449.4
First-price auction misconception model λ^{1st}	1.18	1.83	3.05
	(.184)	(.408)	(.624)
90% confidence interval	[.88, 1.49]	[1.30, 2.56]	[2.13, 4.20]
Observations	245	204	111
Log likelihood	−954.2	−769.3	−398.2
	B. Round 2		
Optimal model λ^{OPT}	1.12	.30	.01
	(.244)	(.164)	(.166)
90% confidence interval	[.82, 1.51]	[.09, .49]	[0, .41]
Observations	244	168	111
Log likelihood	−979.7	−685.7	−451.6
First-price auction misconception model λ^{1st}	.59	1.03	1.71
	(.115)	(.239)	(.237)
90% confidence interval	[.39, .82]	[.72, 1.53]	[1.34, 2.23]
Observations	244	168	111
Log likelihood	−980.5	−660.9	−420.0

Note.—Standard errors are in parentheses.

therefore excludes subjects who submitted offers within 5¢ of $2, and here the estimated payoff sensitivity λ terms diverge significantly. For both rounds, the λ 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 $2 do not have the correct idea about the mechanism, they are not merely making random errors that are related to the economic cost of the errors. Their offers are better characterized by the first-price misconception model augmented with a modest level of decision error. Finally, column 3 displays estimates for the 111 subjects who are most likely to have the misconception, either because they reveal it directly on their decision cards ($n = 29$) or because on both of their cards their offer was above the drawn random price, so we cannot rule out this type of misconception ($n = 82$). Obviously the misconception model fits much better for this subset of subjects.

Table 5 reports estimates for a 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 best describes the data (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:[22]

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

The results in column 1 show that nearly two-thirds of all the offers are more consistent with the misconception in round 1. The probability that an offer is more consistent with the misconception model is estimated reasonably accurately, and for round 1, the 90 percent confidence interval never includes an equal likelihood of the two models (i.e., $\theta^M = 0.5$). Offers are better approximated by the first-price misconception model, although this model predicts offers that exceed observed mean offers when the maximum random price takes on its highest values.

Columns 2 and 3 allow the mixture probability θ^M to be a linear function of dummy variables corresponding to the different subsets of subjects considered in the different columns of table 4. A dummy variable D picks up the increase in the probability of the misconception for subjects who either offer a price that differs by more than 5¢ from \$2 (col. 2) or reveal or may have the first-price misconception (col. 3) as $\theta^M = \theta_0 + \theta_1 D$. The omitted case (captured by the intercept θ_0) represents the misconception probability for subjects who submit offers at or near \$2 or who reveal that they do not have a misconception. These subjects are best classified by the optimal model; for the others the θ_1 estimates indicate that the likelihood of a misconception is highly significant.[23]

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 known preference. A direct application of revealed preference theory does not suggest a reason why. Application of framing theories leads to a substantial

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

[23] While in principle it is possible to combine the two categories with two dummy variables into one regression, there is considerable overlap between the subjects who do not offer near \$2 and who may have the first-price misconception. This complicates the interpretation of the dummy variables. A specification with a full set of interactions also leaves some categories with a small number of cases, making their estimates unreliable.

TABLE 5
MAXIMUM LIKELIHOOD ESTIMATES OF FINITE MIXTURE MODEL LOGIT CHOICE ERROR PARAMETER λ AND LIKELIHOOD OF FIRST-PRICE AUCTION MISCONCEPTION MODEL θ^M

		Misconception Likelihood $\theta^M = \theta_0 + \theta_1 D$	
Model	(1)	(2)	(3)
		A. Round 1	
Payoff sensitivity λ	4.49	5.59	5.06
	(.839)	(.735)	(.787)
90% confidence interval	[3.41, 6.08]	[4.51, 6.99]	[3.77, 6.44]
Misconception Prob θ^M	.65		
	(.046)		
90% confidence interval	[.59, .74]		
Intercept Prob θ_0		.00	.41
		(.00)	(.070)
90% confidence interval		[.00, .00]	[.31, .53]
Dummy on offers not on $2 θ_1		.85	
		(.033)	
90% confidence interval		[.79, .89]	
Dummy on possible misconception θ_1			.50
			(.078)
90% confidence interval			[.37, .62]
Observations	245	245	245
Log likelihood	−932.4	−884.9	−913.1
		B. Round 2	
Payoff sensitivity λ	2.65	4.39	2.40
	(.824)	(.948)	(.699)
90% confidence interval	[1.68, 4.67]	[3.26, 6.25]	[1.94, 4.45]
Misconception Prob θ^M	.42		
	(.059)		
90% confidence interval	[.34, .54]		
Intercept Prob θ_0		.00	.00
		(.00)	(.028)
90% confidence interval		[.00, .00]	[.00, .11]
Dummy on offers not on $2 θ_1		.76	
		(.052)	
90% confidence interval		[.67, .85]	
Dummy on possible misconception θ_1			.99
			(.096)
90% confidence interval			[.71, 1.00]
Observations	244	244	244
Log likelihood	−962.5	−913.9	−927.8

NOTE.—Standard errors are in parentheses.

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 at least two groups. One group understands the game form as a second-price auction and behaves substantially as game theory predicts. Another group has a misconception of the game form as a first-price auction and under that model behaves substantially as game theory predicts. The mixture of these groups leads to a pattern of mean offers that might be expected from framing or endowment effects, even though classical "rational choice" models from auction theory give a reasonably accurate 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.

VII. Concluding Observations and Summary

The experiment we report demonstrates the failure of game form recognition 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 simple measurement methods. Choices cannot be interpreted reliably as revealing preferences. Second, the influence of context can be misinterpreted as evidence supporting a class of nonstandard preferences because the data generated by the BDM can be mistakenly interpreted as a preference constructed through framing effects. In particular, the failure of game form recognition can masquerade as support for the theory of framing, such as preferences constructed from reference points. In part, the problem can be traced to the foundations of the theory of framing, where the failure of game form recognition is incorrectly defined as a violation of procedural invariance and thus as a failure of rationality and as evidence of nontraditional forms of preferences.

Our research strategy is to study commodities with an induced preference that is so obvious 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 inadvertently 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 existence of mistakes causes no particularly new problems for the theory of revealed preference. Many instances of mistakes and poor measurement of one form or another are addressed in the literature, and the addition of randomness can produce extremely powerful models (e.g., Echenique, Lee, and Shum 2011). However, our experiment demonstrates that systematic mistakes can be incorrectly interpreted as special forms of preferences. Logic calls either for a specification of the mistake and a test for the mistake or for an improved method of measurement. We were able to identify the mistake with some precision in our experiment, and in other experiments the mistake might also be easy to specify. The example with the word "LEFT" in figure 1 suggests that the concept of information might be useful in dealing with mistakes when attempting to reconcile competing theories. The choice from among the ovals does not reveal a fully informed preference until additional information is provided.[24]

The simplicity of our experiment provides insights concerning the nature of preferences and the tension between standard preference theory and nonstandard preference theory. It also addresses the problem of rejectability of framing theory mentioned in Section II, that according to the theory, the process of observing can affect the observed. Framing theory holds that the preference is influenced by the methods used to observe and measure it. Consequently, experiments leading to a rejection of nonstandard preferences can be dismissed as having inadvertently influenced the preference. For example, 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 well trained, the WTA/WTP gap for mugs is observed (Plott and Zeiler 2005; Isoni et al. 2011). Kőszegi and Rabin (2006) dismiss those experiments and presumably the replications, based on a concern that the training prevents the formation of appropriate reference points.[25] Kahneman asserts that by training subjects with the BDM, Plott and Zeiler were leading subjects to choose according to the theory preferred by the experimenter.[26] Yet, the experiments reported here appear to suggest a WTA/

[24] 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, adding horizontal black lines to fig. 1 above and below the puzzle-shaped figures can be interpreted as information, as can the helpful hint to look at the white parts and not the black puzzle-shaped figures.

[25] For instance, Kőszegi and Rabin (2006, 1142) argue that "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."

[26] Kahneman (2011, 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. Plott and Zeiler also

WTP gap since the asking price for the card is above the known value. The "gap" in our experiment reflects a mistake as opposed to a preference constructed from framing, and the conditions under which it goes away cannot be attributed to experimental conditions that influence the frame and thus change a preference.

The concepts of misconceptions and mistakes highlighted in this study break the crucial connection between preference and choice in framing theory. We know that the stated choice is a mistake because we induced an objective preference, and the fact of a mistake is confirmed by the systematic reduction of the mistake across rounds. Since the choice reflects a misconception rather than a preference, there is no support for a claim that the axiom of invariance is violated as the frame changes, and there is no inconsistency with rational choice. Choices that do not satisfy the Kahneman and Tversky property of invariance can be mistakes and thus need not reflect a nonstandard preference based on framing theory. In fact, 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 toward the optimal offer, through feedback and exposure to errors, explain more.

Framing effects are well documented. By highlighting subject mistakes, we are not suggesting that framing effects do not exist, but rather how they should be interpreted. Anomalous results such as those reported here may not occur only because of this particular measurement method, since other methods have also returned evidence consistent with frame-influenced choices, including the possibility of frame-induced mistakes. Framing influences could also affect important choices in the field, especially those considered infrequently and by individuals with limited abilities to evaluate alternatives such as retirement portfolio and insurance choices (Thaler and Sunstein 2008). Our results suggest that when choices appear inconsistent with standard theory, a failure of game form recognition could be part of the explanation. Consequently, researchers and policy makers should consider choices made in unfamiliar environments as possibly reflecting mistakes, and not as evidence for nonstandard preferences that might be influenced by reference points or other factors associated with framing effects. Under this interpretation, policy interventions to reduce mistakes and misconceptions can be part of the process of aligning individuals' choices with their own preferences. While frame-induced mistakes are possible, so also are frame-induced mistake corrections.

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included experiments in which the subject experience part of training was absent but these experiments were overlooked by Kahneman as were data in which subjects were presented with degenerate lotteries after training. See Plott and Zeiler (2011).

The issue of mistakes has important implications beyond the very simple experiment reported here. In particular, some widely cited criticisms of standard economic theory suffer from limited robustness that could be due to mistakes.[27] The variability of results reported in the literature is understandable if one accepts the evidence presented here that systematic misconceptions of the game form accompany the widely used BDM preference elicitation method. A root cause may be misconceptions related to game form together with a variety of BDM instructions used by different researchers. However, we hasten to point out that we have produced no general theory of game form misconceptions. Indeed, since the nature of misconceptions is context dependent, falsifiability of any proposed general theory of the failure of game form recognition is problematic. There is a need to state a specific theory of the misconception in each case.

Can the BDM be developed to accommodate the need both to avoid game form misconceptions and also to avoid 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.[28] Economics rests on the hypothesis that preferences exist and can be measured and that a clear distinction exists between a preference and a decision. Decisions are often modeled as complex processes that can reflect rules of thumb, simplifying as-

[27] 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, Levine, and Maniadis [2012] to Ariely, Loewenstein, and Prelec [2003]), and manipulations of expectations of a trade do not have predicted impacts on reference dependence (Goette, Harms, and Springer 2012). More recently, Heffetz and List (2014) demonstrate that the assignment of commodities does not influence the preferences of the individual to whom they are assigned and is thus not associated with nonstandard preferences.

[28] The related literature does hold suggestions. 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. The key role of mistake exposure in second-price auctions is clearly documented by Kagel and Levin (1993), who report that as a result of exposure to bid rejections, bidders have a deeper understanding of the rules and adjust their bidding behavior accordingly. Similarly, the data produced in field experiments conducted by List (2003) and Harrison and List (2008) 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. Similarly, Engelmann and Hollard (2010) demonstrate that practice and experience eliminate the trade asymmetry typically associated with WTP and WTA differences. Gigerenzer et al. (2008) give 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 to the development of an underlying preference. A similar suggestion related to a process of recognition can be found in Myerson (1997), which he refers to as "salient perturbations." General axiomatic concepts of rationality and the importance of context are developed in Aizerman and Aleskerov (1995).

sumptions, reference points, incomplete logic, and other phenomena that can be associated with solving problems or assessing information while the theory of preference occupies a different status. The additions 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 meaning of "improved measurement" since, according to the theory, the preference itself is influenced by the measurement process. More training or detailed descriptions, including a summary of the incentive compatibility of the BDM mechanism sometimes used in instructions, change the frame and thus influence the preference according to framing theory. Thus, it might be impossible to determine if measurement is improved under the maintained assumption of framing theory.

We were drawn to this research by a tension that exists in the literature. We conclude that the tension stems from a missing element of theory: a solid connection between the game form and an individual's understanding of the game form. The needed theory might be related to perception, a concept that receives great emphasis by Tversky and Kahneman, who helpfully initiate specific axioms to capture departures of perceptions from reality. Logic, learning, or other phenomena could be important keys as well. Such tools are welcome additions to an effort to identify failures of game form recognition in economic processes. We do not know how to close the gaps among the various sciences involved in the controversy about the theoretical foundations of preferences, and we suspect that it will require input from a variety of disciplines outside economics. Our experiment and analysis suggest that the key to understanding framing effects may be changing perceptions and not labile preferences.

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