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FAILURE OF THE BECKER-DEGROOT- MARSCHAK MECHANISM IN INEXPERIENCED SUBJECTS: NEW TESTS OF THE GAME FORM MISCONCEPTION HYPOTHESIS

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JEL Classification: C8, C9

Keywords: Game form recognition, game form misconception, mistake, Becker-DeGroot-Marschak, preference elicitation.

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Failure of the Becker-Degroot-Marschak Mechanism in Inexperienced Subjects: New Tests of the Game Form Misconception Hypothesis*

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Substantial efforts have been devoted to understanding deviations from optimal behavior in games. Cason and Plot (2014, hereafter CP) propose that sub-optimal behavior may be explained by game form misconception (GFM), a failure of game form recognition, rather than by non-standard preferences or framing effects. Following CP's application of the GFM theory to the Becker-DeGroot-Marschak mechanism (Becker et al., 1964, hereafter BDM), this paper explores whether GFM can robustly explain bidding mistakes by inexperienced subjects. We derive two new tests of the GFM hypothesis based on comparing subject behavior in the misconceived task (BDM) and on the task it is misconceived for (a first price auction). While we do replicate Cason and Plot's original results, our additional tests are inconsistent with a first price misconception explaining observed deviations from optimal bidding in the BDM. At a minimum, additional forms of misconception are necessary to explain observed bidding behavior.

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1 Introduction

The Becker-DeGroot-Marschak mechanism (Becker et al., 1964, hereafter BDM) is a procedurally simple mechanism designed to elicit an individual's true valuation, willingness-to-pay (WTP) or willingness-to-accept (WTA), of a good. In the WTP case, the individual submits an offer price, a random asking price is then drawn and the individual buys the object at the random asking price if her offer weakly dominates the random asking price. Otherwise, no transaction takes place. In the WTA case, the situation we are primarily concerned with in this paper, the individual submits an asking offer, a random offer is generated and the individual sells the item at the random offer drawn if and only if the asking offer is weakly lower than the random offer. It is simple to show that the mechanism is incentive compatible for expected utility maximizers.¹

The incentive compatibility and the ease with which the BDM mechanism can be implemented have made it a popular research tool in the laboratory, and in the field as well. In marketing research, the BDM is used at points of sale and in focus groups to value consumer goods and product attributes (Wertenbroch and Skiera (2002), Lusk et al. (2001), Alevy et al. (2015)). The BDM has also been employed extensively for several decades to investigate various aspects of human preferences and behavioral anomalies (e.g. Boyce et al. (1992), Cubitt et al. (2017)). Most prominent among these are studies of the disparity between WTP and WTA. Standard economic theory predicts that the two should be close. Yet, starting with the seminal work of Kahneman et al. (1990), multiple experimental designs using the BDM have shown that WTA amounts often significantly exceed WTP. Many attribute this difference to behavioral bias and non-standard preferences such as the endowment effect, framing, reference point bias, and loss aversion (see Plott and Zeiler (2005) for an overview).

It has also been noted that behavior in other applications of the BDM can substantially differ from what should be expected from an incentive compatible mechanism. For instance, Bohm et al. (1997) find that bids in the BDM are sensitive to the upper bound of the random price distribution while theory predicts independence. Rutström (1998) finds different bid distributions for the BDM and the (also incentive compatible) Vickrey auction. Noussair et al. (2004) observe that the BDM is subject to severe biases and high bid dispersion. Vecchio and Annunziata (2015) show that the type of endowment (money or in-kind) given to subjects prior to a BDM experiment significant affects bids. Berry et al. (2015) find that BDM-inferred WTP for water filters were inconsistent with the decisions of individuals who were given a single opportunity to buy the same filter at a posted price. After comparing different experimental measurements of individual discount factors, Freeman et al. (2016) conclude that the BDM data appears to show systematic upward bias.

Attempts at explaining sub-optimal behavior in economics experiments using the BDM has lead researchers to postulate a number of theories. Most are based on some form of non-standard preferences, irrationality, or subjects being susceptible to framing effects. Plott and Zeiler (2005) hold a different view. They argue for the possibility that subjects have misconceptions of the game they play. They note that “experimenters are careful to control for subject misconceptions, [but] there is no consensus about the fundamental properties of misconceptions or how to avoid them. Instead, by implementing different types of experimental controls, experimenters have revealed notions of how misconceptions arise” (p.530).² They revisit the experiment of Kahneman et al. (1990), implementing all possible controls for subject misconception found in the literature and conclude that experimental procedures, rather than the endowment effect, are responsible for the

¹Karni and Safra (1987) showed that incentive compatibility is not ensured if the good is a lottery and Horowitz (2006) shows that this result need not be true for non-expected utility maximizers.

²Procedures used to control for subject misconception include using an incentive-compatible elicitation device, subject training, paid practice rounds, and the provision of anonymity for subjects.

WTA-WTP gap. Since then, a lively debate has emerged on the role of misconceptions in games and whether it provides a solid explanation for observed behavior. In a follow up to Plott and Zeiler (2005), Isoni et al. (2011) re-analyzed the data, replicated the study, and added new treatments to perform robustness checks. They confirm some of the findings of Plott and Zeiler (2005), but the additional analysis and robustness tests show that while misconception may explain the data when mugs are traded, it cannot explain a persistent WTA-WTP gap when lotteries are bought and sold.

Cason and Plott (2014, hereafter CP) propose a general theory to explain behavioral anomalies based on subject mistaken perception of the game they are playing. At the center of their theory of Game Form Recognition (GFR), or alternatively of Game Form Misconception (GFM), is the central hypothesis that some subjects make decision errors not because of non-standard preferences, but rather, because they confuse the game they are playing for another, perhaps more familiar game.

CP set out to demonstrate how the theory of GFM explains the data from an experiment with a procurement version of the BDM. Untrained and inexperienced subjects were given a card with an induced value of \$2 and an opportunity to sell it back (potentially for more). Participants stated an “offer price” to sell the card and if this offer price was smaller than or equal to a random, ex-ante unknown “posted price”, the subject sold the card at the random posted price. Otherwise, the card was redeemed for its face value of \$2. CP hypothesize that while some subjects correctly recognize the second price game form, others mistakenly approach the BDM as if it were a first price (FP) procurement auction. We refer to this conjecture as the First Price Game Form Misconception hypothesis (FP-GFM for short). This is a reasonable hypothesis given that first price auctions are commonly used, and that the only difference between the two mechanisms is the price received by a participant who’s bid is lower than the random price.

CP conclude from their analysis that “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.” (p. 1263). Bartling et al. (2015) have shown subsequently that bidding discrepancies can persist in subjects even after it has been positively ascertained that they correctly understand the BDM. This suggests that framing effects or non-standard preferences may still be at play. Similarly Quercia (2016) shows that BDM bids in a standard BDM differ from those when a strategy method is employed. Thus both papers raise general questions about the validity of theory of GFM when applied to the BDM, but neither addresses the FP-GFM hypothesis.

This is the goal of this paper. We revisit CP’s specific application of the theory of GFM to the BDM in order to shed additional light on the behavior of untrained and inexperienced subjects, and to further assess the role of GFM in explaining their behavior. We follow CP’s experimental protocol very closely in order to allow direct comparisons and replication of their results when subject behavior in the BDM is compared with theoretical predictions. We also add three new experimental treatments to further test the robustness of CP’s results. We conduct a first price auction, a within-subject comparison of the BDM and FP mechanisms, and add a new comparative static test. CP correctly argue that if a group of subjects does indeed exhibit FP-GFM (and bid substantially as game theory predicts for the equivalent FP auction), we should expect this group to be sensitive to parameter changes in a manner consistent with game theory. In their test, CP vary the upper bound of the distribution for the random posted price. We instead vary the number of random posted prices that the participant must “beat”. Together, the new treatments provide additional tests of the theory of GFM as applied to the BDM.

Although we broadly replicate CP’s single treatment results, our additional analysis produces new findings that are inconsistent with the hypothesis that FP-GFM explains observed sub-optimal

bidding behavior in the BDM:

(1) We reject the hypothesis that a higher proportion of subjects bid the BDM optimum in the BDM treatment than in the FP auction. This leaves us with no statistically identifiable subjects who understand the BDM and bid optimally. This demonstrates the importance of considering behavior in both the task of primary interest (the BDM) and the task it is hypothesized to be misconceived for (FP), rather than relying exclusively on theoretical predictions. This being said, we do find that the distribution of bids in FP and BDM treatments are different. Subjects bid less in FP than than the FP optimal bid but more than they do in the BDM. We argue in the Appendix, however, that these patterns are not inconsistent with a mix of risk aversion and FP-GFM.

(2) When we ask subjects to complete both the BDM and FP tasks simultaneously, we do not find a significant mass of bid vectors matching theoretical predictions. In fact, we do not find significant differences in the marginal distribution of bids for the BDM and FP. When considering the entire population of bid vectors, it appears that subjects treat the two games as the same task. Simultaneous presentation of the tasks with a warning that they are different did not result in better recognition of the games.

(3) The group of subjects who are identified as misconceiving the BDM does not submit optimal FP offers when they face two random prices. These last two results are inconsistent with the theoretical prediction that these subjects will bid optimally given their misconception. This conclusion holds not only for risk neutral individuals, but for any possible distribution of types of risk aversion in the subject population.

There is clearly a lot of similarities between the FP and BDM bids in our data. Yet, the evidence is not consistent with the existence of (only) two types of bidders, who could be risk neutral or risk averse and who could bid with noise. These results do not invalidate the general theory of GFM. Our rejection is limited to the specific FP-GFM hypothesis applied to the BDM. GFM might still explain the data, but additional forms of misconceptions beyond the FP type need to be hypothesized to explain observed bidder behavior.

This paper shows that testing the theory of GFM for a particular game is vastly enhanced by the ability to compare three distributions of data: the distribution of decisions on the misconceived task (e.g. BDM) done in isolation, the distribution of decisions in the game at the source of the misconception (e.g. FP) done alone, and the joint distribution of decisions for the two tasks performed simultaneously.

We briefly review the theory of GFM as it pertains to the BDM and our general approach in Section 2. Section 3 describes the experimental design and procedures. Section 4 presents the main results. It also compares our baseline treatment with CP's results. Section 5 summarizes our findings. An extension to risk averse bidders is presented in Appendix.

2 GFM of the BDM as a FP Auction

Column 1 of Table 1 summarizes the predictions of the FP-GFM hypothesis for the \$2 procurement game. Subjects who properly recognize the BDM would optimally bid \$2. The tests conducted by CP hypothesize that subjects who suffer from FP-GFM bid the optimal risk neutral bid of the equivalent FP procurement auction. This optimal bid is \$3.50 when the posted price is uniformly distributed over [0, 5]. It is worth noting that since CP analyze their data against these theoretically optimal bids only, it is implicitly maintained that subjects participating in an FP auction would bid optimally (with noise) if they were actually bidding in a FP auction (the second column of Table 1). Hence, CP's evaluation of the BDM focuses entirely on column 1 of Table 1.

Part of the difficulty with the theory of GFM is that testing it empirically requires formulating

a hypothesis that specifies how subjects misconceive the game they are playing. To further complicate matters, subject heterogeneity cannot be excluded. Some subjects may perfectly understand the game, and among those who do not, different subgroups might harbor different types of misconceptions. CP focus their empirical work on subjects who appear to be BDM optimizers and those who appear to misconceive the BDM for the more familiar FP auction. They also take the next logical step and argue that an experimenter who knows the game that is incorrectly conceived as the game being played can make predictions on how subjects should respond to changes in game parameters. GFM, they argue, results in systematic and fundamental bidding errors that can be described theoretically and tested for when properly specified.

Explicit in CP's modeling strategy is that even if subjects are of a given type (e.g. individuals who misconceive the BDM for a FP auction), individual idiosyncratic errors in computing the optimal strategy introduces noise in decision making around the intended strategy. Thus, their methodological approach is to consider groups of subjects who show signs of misconception in their BDM task and then feed this data into a model of optimal FP bidding with errors. They conclude that this group of subjects can reliably be characterized as behaving substantially according to the predictions of game theory if they were in a FP procurement auction. The subject's only systematic mistake in this case is to proceed as if they stood to receive their own offer price rather than the random posted price.

By comparing empirical bids to theoretical predictions for the FP auction under risk neutrality, CP maintain implicitly that while GFM errors are possible in the BDM, these subjects would make no GFM or other systematic errors if they were truly participating in a FP auction. This strikes us as a strong assumption since the evidence on the optimality of bidding in FP auctions is mixed, at least when one does not take into account subjects' risk attitude (Harrison (1990); Kagel and Levin (1993)). As such, it is worth investigating whether or not players exhibiting FP-GFM provide bids that are consistent not only to theoretical predictions (under risk neutrality or aversion), but also to bids in a directly comparable FP auction. Thus, we propose that testing for GFM requires a comparison of behavior in the misconceived game against strategies employed in the game that it is supposed to be misconceived for. The motivation for this test is clear. Suppose that subjects play Game A as per the theoretical predictions for an alternative Game B because of GFM. However, consider a scenario where subjects playing Game B do not play in a manner consistent with the theory for Game B. How valid, meaningful, or useful is it then to characterize observations from Game A as the result of subjects thinking that they are playing Game B and behaving as Game B optimizers? Why should we expect players in Game A to be playing according to the theoretical predictions for Game B if subjects in Game B do not do so themselves? By collecting parallel data on the task assumed to be causing misconception (here the FP auction), it is possible to compare subjects' bids in the FP auction and in the BDM and test whether the differences in bid distributions match the theoretical predictions of Table 1.

We also set up and analyze the results of two robustness tests. The first gives subjects an opportunity to correctly recognize the difference between the game they misconceive and the one they misconceive it for under the FP-GFM hypothesis. We do this with a within-subject treatment where subjects are asked to simultaneously complete the BDM task and parallel FP auction. Subjects in this treatment were given a general warning that the two tasks were different and were asked to carefully inspect the cards before making their offers. This treatment delivers additional information not available when each task is considered across subjects. The within-subject data provides a two-dimensional bid distribution (BDM and FP bids) which, according to GFM theory, should be generated by two types of bidders who bid with noise. Table 1 says that the mass of the joint distribution of bid vectors, denoted (BDM, FP) , should be found in the vicinity of only two points: $(2, 3.5)$ and $(3.5, 3.5)$ corresponding to the bid vectors for subjects with correct GFR and

with FP-GFM respectively. We show that this is not borne out by the data.

Finally, we investigate whether BDM bidders thought to be optimal FP bidders (through GFM) respond as expected to an increase in the number of random bids. If, as claimed by CP, misconceived subjects behave substantially as theory predicts (i.e. as FP optimizers), we should observe a decrease in their bid. Unfortunately we find no responsiveness to an increase in the auction's "competitiveness".

3 Experimental Design

3.1 Treatments

The principal strength of the BDM experiment performed by CP (and in this paper) is that the \$2 card given to subjects has an objective induced value that eliminates any other unobserved preferences. Indeed, it is difficult to argue that subjects could place any other value than \$2 on the card. This induced value framework provides a focused context to study why so many subjects bid differently than the optimum of \$2. With our focus on studying the robustness of the FP-GFM hypothesis from a variety of angles, the experiment performed in this study consists of four similar, though distinct treatments. In all treatments, subjects were given two cards worth \$2 each and were informed of a rule by which they could sell the cards back to the experimenter.

3.1.1 CP Replication: The Misconceived Task (BDM1)

The BDM1 treatment uses the same reverse BDM sale mechanism deployed by CP. The subject is instructed to read the card and write down an offer price. On the back side of the experiment card is a covered posted price randomly drawn from a uniform distribution on [0,5] (in one penny increments).³ Subjects are instructed to read the entire card but to uncover the posted price only after writing down their offer price. If the subject's offer price is less than or equal to the posted price, the subject sells their experiment card at the posted price. If the offer price is greater than the posted price, the subject sells their card for the nominal value of \$2. As previously discussed, the theoretically optimal offer for an expected utility maximizer only concerned with monetary payoffs is \$2.

BDM1 replicates the experiment performed in CP with the exception of two small modifications. First, the wording on the card was slightly edited for clarity. Second, and more importantly, our subjects were told that all possible posted prices between \$0 and \$5 had an equal chance of being drawn as the hidden posted price. Informing subjects of the distribution is a feature that CP acknowledge should have been included in their design.⁴ This treatment allows us first to verify that the CP results replicate, as well as to perform additional comparisons with the next three treatments.

3.1.2 The Task Hypothesized as the Source of Misconception: First Price Auction (FP)

The FP treatment uses a first price mechanism. The FP and BDM1 instructions are identical except for one critical detail. In the FP treatment, subjects are told that when their offer price

³We use a single upper bound (\$5) for all subjects while CP used others as well.

⁴Examples of the material used during the experiment (instructions, consent forms, experiment cards) can be found in the Appendix.

is equal to or below the hidden posted price, they sell the card for the offer price (instead of the posted price in BDM1). When their offer price is above, they receive \$2 as before.

With the random posted price distributed uniformly between \$0 and \$5, the optimal offer price for a risk neutral subject in this treatment is \$3.50. This treatment provides a behavioral benchmark for the FP auction obtained from the same subject pool and thus complements the analysis performed against theoretical predictions. Risk aversion can explain bids lower than \$3.50 in the FP. The appendix accounts for bidding under risk aversion and generalizes the analysis.

3.1.3 Simultaneous Completion of both Tasks (Within Subject — WS)

The WS (within-subject) treatment presents each subject with two experiment cards simultaneously. One of the cards is identical to the BDM1 card while the other is identical to the FP card. Importantly, subjects are notified by the instructions that the sale mechanisms on the two cards are different. They are not told specifically what the difference is but are asked to read both cards carefully before proceeding. The cards are coded as WS-BDM and WS-FP respectively.

We include this treatment in order to observe the behavior of subjects confronted with both a BDM and FP mechanism simultaneously. By explicitly telling subjects that the two cards implement different payment mechanisms, we expect that a greater proportion of them will correctly recognize each of the two games they are playing, and thus move the distributions of offers towards their respective optima.

3.1.4 Increased Competition (BDM2)

The BDM2 treatment differs from BDM1 in a single dimension. Rather than drawing a single posted price, two are drawn. Subjects are instructed that if their offer price is less than both posted prices or equal to the lowest posted price, they sell their card at the lowest of the two posted prices. If their offer price is greater than one or both of the posted prices, they sell their experiment card for \$2.

Our motivation for including this treatment in the experiment is to further test the behavior of subjects who exhibit possible FP-GFM. Introducing a second hidden price that the subject must “beat” in order to sell the card at the lowest of the random prices is akin to adding a third bidder to the auction and thus simulates an increase in competition. This change does not modify the optimal bidding strategy in the BDM. However, under the maintained assumption of risk-neutrality, the optimal bid in a parallel first price auction would decrease to \$3. The appendix generalizes the analysis to risk averse subjects.

If the FP-GFM hypothesis is correct for a group subjects (i.e., they act substantially according to game theory predictions in the equivalent FP auction), a comparison of the BDM1 and BDM2 offers should be consistent with the comparative statics of a FP auction. Most notably, the offer distribution for BDM2 should sit to the left (lower bids) of the distribution for BDM1 for subjects with GFM. In addition, the data for BDM2 should show a higher proportion of offers around \$3.00 (the optimal FP bid in a FP auction with two other bidders) and a lower proportion around \$3.50 (the optimal offer for BDM1). From our perspective, these comparisons provide potent tests of the FP-GFM hypothesis for the BDM.

3.2 Procedures

The instructions and decision cards are available in the Appendix. Subjects in all except the WS treatment performed two successive rounds of the same task, though the second was unannounced. The core of the analysis focuses primarily on the results from the first round (the evidence on the

second round is discussed mostly in the replication of CP analysis). We label first and second round data by adding “-1” and “-2” to treatment acronyms (e.g., BDM1-1 is the first round of BDM1; FP-2 is the second round of FP) where necessary.

In the BDM1, BDM2, and FP treatments each subject was handed a large envelope containing a research ethics consent form, detailed instructions on how to perform the experiment, an experiment card, and a smaller envelope. After subjects completed the experiment card, the instructions prompted them to open the smaller envelope containing a second experiment card and new instructions. The new instructions told subjects that they had an opportunity to sell a second card using the same procedures as before (but with a newly drawn hidden posted price). Subjects were instructed to complete this card and put all the material, except for a tag with an ID number on it, back in the large envelope. This tag was their ticket for payment. Payments to subjects were made in subsequent lab sections and lectures. The WS treatment followed a similar procedure except that both experiment cards were contained within the large envelope and subjects were asked to complete them simultaneously.

Experimental sessions lasted approximately twenty-five minutes and were run in first-year undergraduate classes at the University of Victoria (Canada). Subjects were not trained and were told that the purpose of the research project was to understand how participants take advantage of simple trading opportunities in different forms. All experimental material was prepackaged in envelopes and handed out in an alternating pattern, ensuring that each treatment’s envelopes were homogeneously distributed across the entire classroom. For every envelope of FP handed out, two envelopes of BDM1, BDM2, and WS were distributed. Subjects were informed that their neighbors were completing a different task and instructed not to talk to others until the experiment was completed.

A total of 579 subjects participated in three separate sessions that took place in arena-style classrooms over the period September 22-23, 2015. In total, 164 subjects participated in BDM1, 159 in BDM2, 171 in WS, and 85 in FP. In the first two sessions the subject to proctor ratio was roughly 30:1; in the third it was 18:1. Subjects were informed they could earn up to \$10. The average payout was \$4.91, the minimum was \$2, and the maximum was \$9.75. For convenience, payments payouts were rounded up to the nearest quarter dollar for payment. Subjects were not aware of the rounding up at the time of the experiment. All amounts quoted in the paper are in Canadian dollars.⁵

4 Results

Of the 164 subjects who participated in BDM1, 163 completed both experiment cards. The corresponding numbers are 158 of 159 subjects for the BDM2; 170 of the 171 subjects for the WS treatment; and 83 out of 85 subjects who participated in the FP auction. It is unknown why five subjects only completed one of the two cards presented to them; however, the data they provided is only used when appropriate.

⁵Subjects were admonished to strictly adhere to the instructions and procedures provided. Although we did not observe any deviations from the instructions, it is not possible to ensure with certainty that nobody peeled off the opaque sticker(s) covering the random price(s) before writing in their offer price. This protocol follows CP and was adopted in order to ensure comparability and replication

4.1 Overview of Data and Replication of Cason and Plott's Main Results

Figure 1 provides a comparative overview of our's and CP's data.⁶ It shows the cumulative density function of offer prices for our BDM1-1 treatment against i) all round one data from CP; and ii) CP's round 1 data for the subset of subjects who faced a maximum posted price draw of \$5. We will on occasion refer to this graph.

Table 2 presents summary descriptive statistics for all four treatments. We refer to this table throughout the remainder of the paper. Statistics are presented separately for the first and second cards in treatments with repetition, and for the two simultaneous tasks in the within subject (WS) treatment. The table first presents simple statistics on the distribution of bids and then computes the fraction of offers measured at key points in the distribution corresponding to optimal bids in the various treatments (\$2 for all BDM treatments, \$3.5 for FP with one random bid and \$3 for FP with two random bids). The table also reports the fraction of outlier bids (offers below \$.10 and above \$5) and data corresponding to CP's definitions of misconception.

We will also repeatedly refer to Tables 3, 4, and 5 which provide various tests of equality regarding different features of the distributions in the various treatments. Table 3 provides results of variance ratio tests for the equality of variances across the sub-treatments; Table 4 shows the results of Mann-Whitney U-tests, which test whether two independent samples come from populations with the same distribution; and Table 5 reports the results of Pearson's chi-squared tests of whether two samples came from distributions with the same median.⁷

Result 1. *Results 1-3 and 5 from CP are broadly replicated with comparable quantitative effects and statistical significance.*

Five main results on the BDM emanate from CP's paper. Recall that CP only conducted a BDM treatment and that our BDM1 used a comparable set of instructions. It follows that we can directly test and replicate four of CP's results (numbered 1, 2, 3, and 5).⁸ We compare our baseline findings in BDM1 with these four results. When relevant, we also add results from BDM2. However, it is worth keeping in mind that BDM2 differs from CP's treatment in that subjects compete against two random prices instead of one. We add relevant details from this treatment to the extent that they also corroborate CP's prior findings.

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

In BDM1-1, only 7.9% of subjects make an offer price within 5 cents of the optimal \$2 bid. In BDM2-1, a similar proportion of 8.8% of subjects offer within 5 cents of \$2. The corresponding number in CP is higher at 16.7%. As such, our results show an even lower proportion of subjects bidding optimally in the BDM. In addition, Wilcoxon sign-rank tests all strongly reject the null hypotheses that the medians of the BDM1-1 and BDM2-1 distributions are equal to \$2 ($p < 0.0001$). These statistical results confirms what one might suspect from inspecting Figure 1: untrained bidders do not generally behave as theory predicts for the BDM.

CP Result 2. A second round of decisions (after payoffs from the first round have been computed) increases the number of subjects making the optimal offer.

⁶CP's data is available at <http://www.journals.uchicago.edu/doi/suppl/10.1086/677254>. CP ran 5 treatments with different maximum posted price (4, 5, 6, 7, 8).

⁷Mann-Whitney U-tests and Pearson's chi-squared tests are used rather than t-tests, as treatment data are not normally distributed.

⁸Result 4 analyzes how bidders respond to a change in the upper bound of the random posted price. We cannot investigate it since we kept this parameter constant in our study.

The fraction of subjects offering amounts within 5 cents of \$2 increases to 13.5% in BDM1-2 and 13.3% in BDM2-2. Fisher's exact test gives p-values of 11.1% and 21.5%, respectively, indicating that this is not a statistically significant shift in either treatment. However, the difference in statistical significance, between our and CP results, may be explained by the fact that we test this hypothesis using BDM1 and BDM2 samples (about 160 subjects each) while CP use their entire sample, pooling different sub-treatments (244 subjects). If we pool the BDM1 and BDM2 data (which is similar to CP pooling data from sub-treatments with different supports for the random price), the increase in the fraction of offers within 5 cents of \$2 becomes statistically significant ($p = 0.0432$).

CP Result 3. *Subjects who 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.*

Table 6 provides detailed statistics for results 3 and 5. Of the 163 subjects who completed both BDM1 cards, 13 made offers within 5 cents of \$2 on the first card. Of these 13 subjects, ten (76.9%) offered the same amount in BDM1-2. Of the 150 subjects who did not offer within 5 cents of \$2 on the first card, 79.3% offered a different amount in BDM1-2. Similarly to CP, we strongly reject the hypothesis that those who choose optimally on the first card and those who do not choose optimally exhibit the same degree of choice stability (Fisher's exact test p-value < 0.001). We note that this result extends to the treatment with two random prices. The Fisher's exact test again strongly rejects equality of the stability of choices across optimal and non-optimal first card bidders ($p < 0.002$).

CP Result 5. *Subjects who were “exposed” to their mistake were more likely to choose a correct offer in round 2.*

A subject is said to be exposed to their mistake if, on the first BDM card they submitted a sub-optimal offer and could have increased their payoff by offering a different amount (i.e. closer to or equal to the optimal offer). Most exposed subjects redeem their card for its nominal value of \$2 but missed an opportunity to sell it for more through the BDM (i.e. they bid more than \$2 and the random price is between \$2 and their bid).⁹ Our data is not as sharp as CP's for result 5. The strong version of the result concerns moves to exactly the optimal offer. Table 6 shows that exposed subjects in round 1 were just as likely to move to a \$2 offer in round 2 as non-exposed subjects. However, and in line with CP's results, exposed subjects are more likely to move in the direction of the optimum than non-exposed ones. They are also less likely to move away from the optimum. Both results are statistically significant (Fisher's exact test p-value < 0.002) and replicate CP's data.

To sum up, our baseline results substantially agree with CP's main findings. This general validation of prior results establishes solid grounds for the interpretation of the new treatment data and their relevance to advancing our understanding of bidding by inexperienced subjects in the BDM. We do note a possibly lower proportion of optimal BDM bidders in our study and return to its implication below.

4.2 Revealed Misconception

Following CP, we asked subjects to report their payoff after they observe the posted price. A subject in a BDM treatment exhibits *first price misconception* (FPM) if she wins (i.e. makes an offer price

⁹Very few subjects end up selling the card for less than \$2 (they offer less than \$2 and the random price is between their offer price and \$2).

smaller than the posted price) but incorrectly requests to be paid her offer price instead of the posted price. By symmetry, we introduce the concept of *second price misconception* (SPM) if a subject in a FP treatment wins but incorrectly fills in the card to be paid the posted price instead of her offer price. These revealed misconceptions are explicit errors in the reported payment requested by subjects. They reveal something about a subjects' understanding of the game rules. Similarly, we also use the term “*possible misconception*” in reference to cases where a correct understanding of the rules cannot be asserted with certainty. These correspond to cases where a subject's offer prices were greater than the posted prices on both cards. As such, it is possible that the subject may have suffered from misconception, but this is not revealed because of the auction's outcomes.

Result 2. *FPM is found in all BDM treatments. SPM is almost nonexistent in the FP treatment but it is found in the WS treatment.*

The lower part of Table 2 presents evidence on FPM and SPM. As a benchmark, CP report that 11.8% of all subjects explicitly revealed a FPM on the experiment card. Our corresponding FPM rate in BDM1 is 13.4%. As these numbers accord quite well, it can be assumed that a group suffering from first price misconception, similar in relative size to that in CP, is present in our data. The proportion of subjects with possible FPM in BDM1 is 31.1%—this number is 33.5% in CP.

At the design stage, we hypothesized that presenting both cards simultaneously in the WS treatment would reduce the rate of FPM. It did not. At 9.9%, the rate of FPM in WS-BDM is not statistically different from the 6.1% observed in BDM1-1. The similar misconception rates in BDM1-1 and WS-BDM indicate that confronting subjects with both mechanisms simultaneously and prompting them to carefully consider the two cards does not affect the rate of FPM.

Interestingly, subjects make significantly fewer FPM mistakes in BDM2. For the data as a whole, we observe a 1.9% proportion of FPM. However, since BDM2 leads to fewer subjects winning at least one card, it is perhaps more appropriate to condition these statistics. In the BDM2, 53 subjects won at least one card (and thus could potentially reveal GFM). Of these, only 3 subjects (5.67%) made a single mistake each. In comparison, 22 subjects out of the total of 112 (19.6%) who won at least one card in BDM1 made at least one error. The proportions are significantly different ($p = 0.020$).

We finally take a look at SPM in the WS-FP treatment. For the data as a whole, SPM in WS-FP is observed in 7.6% of subjects, which is statistically larger than the corresponding figure, 1.2%, in FP-1. This increase, and the significant number of SPM in the WS-FP treatment is unexpected. If the rate of SPM in FP-1, is indeed the baseline rate, subjects who exhibit second price misconception in WS-FP display a treatment effect. Seeing both payment mechanisms together appears to have confused rather than helped these subjects properly recognize the two auction mechanisms.

4.3 Lessons from the First Price auction (FP1-1)

Result 3. *Subjects in the FP auction do not bid in a manner consistent with risk neutral expected profit maximization with noise.*

A risk neutral agent bidding in the FP treatment maximizes her expected payoff by offering \$3.50. Only 14% of subjects did so in FP-1 and only 10% did so in FP-2. The mean of the FP-1 distribution is \$3.30 and its median is \$3.25. All tests reject that the distribution is centered on the optimum offer with p-values < 0.03 (the same finding holds for FP-2).¹⁰ This finding contradicts CP's implicit premiss that there is no systematic deviation from risk neutral optimality in the first price auction. Contrary to CP's maintained assumption, that subjects with misconception in BDM

¹⁰While these moments are lower than the risk-neutral prediction, they are consistent with risk aversion.

would bid optimally in FP, we find that individuals in the FP treatment exhibit both systematic as well as idiosyncratic errors in bidding. Clearly, these bids in FP are consistent with risk averse bidding. The appendix generalizes the analysis to risk aversion.

Regardless of the source of the systematic bias, we must conclude that our subjects in the FP-1 task did not behave in a manner consistent with theoretical predictions for the first price auction. This raises an important methodological concerns regarding the validity of testing the theory of game form recognition only against the theoretical prediction of the game hypothesized to be the source of misconception.

Result 4. *Subjects bid more in FP-1 than in BDM1-1*

Figure 2 (panel 1) shows that the two cumulative distribution functions are ordered by first-order stochastic dominance. Inspection of Table 2 shows that the mean of FP-1 (\$3.30) is higher than that of BDM1-1 (\$2.93). The medians are similarly ordered (\$3.25 vs. \$3.00). The tests of Tables 3, 4, and 5 show that similarity of the two distributions is rejected at the 5% significance level in two of the three tests. Only the equality of the two variances cannot be rejected. Inspection of the two distributions reveals that subjects bid more in FP. Since the optimal FP bid is greater than the optimal BDM bid, the FPM hypothesis predicts that the distribution of FP-1 bids will stochastically dominate the BDM1-1 distribution, and it does in our data. This result, however, must be interpreted carefully in light of our next finding.

Result 5. *The proportion of subjects who bid near \$2 is the same in BDM 1-1 and FP-1: There is no evidence of BDM optimizers.*

The optimal bid in the BDM1-1 treatment is \$2. A total of 7.9% of our subjects offer $\$2 \pm \0.05 in this treatment. As they behave according the prediction of game theory, CP argue that such subjects correctly understand the BDM and bid optimally. However, the data does not support this interpretation. In a model of optimal bidding with idiosyncratic errors, we should expect that a number of subjects in the FP auction will offer \$2.00 if the variance representing idiosyncratic bidding errors is sufficiently large. Indeed, we find that 8.2% of FP-1 subjects bid within 5 cents of \$2 and this proportion is statistically indistinguishable from the corresponding figure (7.9%) in BDM1-1 ($p = 0.9323$). The same conclusion holds if we look at BDM2-1 instead. The proportion of offers within 5 cents of the optimum in BDM2-1 (8.8%) is not significantly different than the proportions of such offers in either BDM1-1 or FP-1. The equal proportions of \$2 bidders in the BDM and FP groups leads to the conclusion that we cannot statistically identify any BDM optimizers in our experiment.

We noted earlier that the proportion of \$2 bidders is higher in CP's data than ours. The absence of a FP treatment in CP's experiment, however, makes it impossible to firmly rule out the presence of BDM optimizers in their data. Looking back at Figure 1, however, we note that the density of \$2 bidders in all treatments shown is comparable to the density at other integer values (\$3 and \$4) or half-integer values (\$2.5 and \$3.5). There is arguably nothing noteworthy about the proportion of bidders at \$2, either when compared to the proportion of \$2 bids in the FP treatment, or to densities at other integer or half-integer points. Stated differently, a casual inspection of the distributions of bids in CP's experiment, even without comparable FP data, raises serious doubts about the wisdom of assuming that \$2 bidders are BDM optimizers.

4.4 Simultaneous Completion of both Tasks (WS)

In our within-subject treatment, subjects were presented with both the BDM1 and FP cards simultaneously. They were also warned that the two cards were different. We included this treatment

in order to give subjects an opportunity to differentiate the two game forms. Being shown the two cards simultaneously can have two effects on the choice of strategy. If comparing the cards helps subjects understand the two tasks, we would expect that fewer subjects will exhibit GFM. As a result, offer distributions should show less systematic bias and the two distributions will move away from each other, in the directions of the optimum offer vector presented in Table 1. Alternatively, doing both tasks together may increase confusion: subjects have to absorb and process more information, and the difference between the two cards is subtle. This raises the specter of increased complexity, which could lower task comprehension and increase both misconception and idiosyncratic errors.

Result 6. *When subjects are asked to complete both the BDM and FP tasks simultaneously, bidding strategies do not differ across tasks.*

Results of variance ratio and Wilcoxon matched-pairs signed-rank tests indicate that the distributions of offers in the WS-BDM and WS-FP cannot be distinguished statistically.¹¹ Figure 3 shows the CDFs of WS-BDM and WS-FP graphed one upon the other. The fact that the two curves are almost identical is surprising, but appears to indicate that subjects were not able to distinguish the two game forms from one another. Despite being explicitly told that the two cards have different payment mechanisms, subjects tend to behave more or less identically in both, and in a manner more consistent with a first price bidding behavior.

Interestingly, this treatment displays the highest fraction of errors in payoff computation (9.9% FPM in BDM and 7.6% SPM in FP). This is certainly consistent with the view that doing both tasks together increases confusion in payoff computation rather than helps subjects recognize the games correctly. Confusion about the difference between the two mechanisms, seen in the high rates of both first and second price misconception, may also be responsible for the statistically indistinguishable distributions between the two cards.

This finding should be contrasted with Bartling et al. (2015) who show that it is possible to reduce GFM (and induce subjects to reveal their true preference) using the strategy method. The strategy method decomposes the BDM task into simpler sub-tasks that appear to help comprehension. In our case, adding the FP task to the BDM task appears to decrease comprehension.

These findings also clash with CP's premiss that BDM bidders are composed of at least two groups: recognizing and misconceived subjects. If these two categories of bidders were present in large numbers, we should reject the hypothesis that the offer distributions are statistically the same. This is not the case. It could be that there are other groups of misconceived subjects but our treatments do not allow us to make progress in identifying them. As a side comment, note that the change in frame in WS appears to increase, rather than reduce GFM (if indeed the GFM theory remains the more likely explanation for the data), which suggests that GFM is context dependent.

We also compare the WS-BDM and WS-FP offers at the individual level in Figure 4. All data points are weighted by frequency: the larger the circle, the greater the number of subjects with offers at that point on the graph. It is evident that a majority of subjects offer similar amounts in both sub-treatments (i.e. along the 45° line), and that roughly the same number of subjects offer more in one sub-treatment than the other (as seen from the weights of the point above and below the 45% line).

Result 7. *Decision errors in the WS treatment point to poor optimizing behavior.*

Overall, 43.5% of subjects offered a higher amount in WS-FP, 35.9% offered a higher amount in WS-BDM, and 20.6% offered the same amount in both. This last figure increases to 24% if we

¹¹The two distributions are statistically indistinguishable from that of FP-1s, but statistically different from BDM1-1 at the 5% level.

consider bids within 5 cents of each other. A test of proportions fails to reject (at all usual levels of significance) that the proportion of subjects offering a higher amount in WS-BDM is equal to the proportion who offers a higher amount in WS-FP. Those who offered a higher amount in the WS-FP offer on average \$1.113 more (median is \$0.915). Those who offered more in the WS-BDM bid more by \$1.037 (median is \$0.950). Equality of these values cannot be rejected. Hence, decision errors where subjects offer more in the BDM sub-treatment are just as likely as instances in which subjects correctly (albeit, with considerable noise) offer more in the FP sub-treatment.

If the only systematic bias that exists in the data is a FPM by BDM subjects, both cards should be understood to be the same, and the game admitting a single optimum. Yet, the large majority of subjects make different offers. This is admissible in a model of idiosyncratic errors but it is worth noting that these errors appear independent, requiring a weak version of the bidding with errors model. To see this, consider a hypothetical situation where a subject is presented simultaneously with two FP cards. In a strong version of the model with errors, we could expect the subject to compute the optimal offer with an error and report the same offer on both cards. But what is observed under the maintained assumption of FPM is subjects who make computations with two distinct errors that are just as likely to produce FP offers that are smaller or greater than the BDM offer. This appears to point to a high degree of uncertainty or confusion, and little in the way of a strong optimizing component to subject's choice of strategy.

4.5 Response to Increased Competition: BDM1-1 versus BDM2-1

The purpose of the BDM2 treatment is to inspect the response of subjects who exhibit FPM in the BDM to a change in a game parameter. Adding a second random posted price to the BDM and stipulating that the participant must beat both in order to sell the card at the lowest of the two posted prices simulates the addition of a third bidder to the auction. This increase in the number of bidders in BDM2 leaves the optimal BDM offer unchanged at \$2. However, the optimal offer under FPM is now reduced to \$3.00 instead of the \$3.50 of BDM1. The addition of a second random price calls for a more aggressive (i.e., lower) bid in a FP procurement auction. Therefore, under the maintained hypothesis that non-optimal BDM bidders suffering from FPM bid in accordance with the theory of FP auctions, we hypothesize the distribution of BDM2-1 bids to shift to the left in response to an increase in the number of random bids.

Result 8. *An increase in competition in the BDM does not decrease bids.*

Note from Table 2 that the mean bid of \$3.27 in BDM2-1 is larger, not smaller (as expected under FPM) than the mean of \$2.93 in BDM1-1. Notice also that the medians and modes of the two distributions are all equal to \$3.00. Figure 2 shows the CDFs for BDM1-1 and BDM2-1 graphed one upon another. Note that the percentage of participants bidding within five cents of \$2 is no different than previously reported for the FP treatment. As such, there is once again little evidence of optimizing BDM bidders. Yet, the Mann-Whitney's two sample U-test gives a p-value of 0.059 while the Pearson's chi-squared test returns a p-value of 0.21. A variance ratio test shows that at the 1% level of significance, the two samples have different variances. There is therefore clear evidence that these samples come from different distributions. However, the evidence does not support the systematic shift in the direction predicted by FPM.

The proportions of offers within 5 cents of \$3.00 are 26.2% in BDM1-1 and 20.1% in BDM2-1. These figures are not statistically different from one another (p-value = 0.1947) and in the opposite direction expected under FPM. Similarly, the proportions of offers within 5 cents of \$3.50 in BDM1-1 and BDM2-1 are also statistically indistinguishable at all conventional levels of significance. These results cast further doubt on the claim that a group of subjects harboring a first price misconception

either behaves substantially as game theory predicts, or even that such a group actually exists at all. If a meaningful number of these subjects existed, there would be a greater proportion of offers within 5 cents of \$3.00 in BDM2-1 than BDM1-1. This is not the case.

Experimental evidence from FP auctions shows that bidders respond to the number of bidders by putting more aggressive bids (lower in our experiment) as predicted by theory (Kagel and Levin, 1993). However, we reject the prediction that GFM subjects respond to an increase in competition (decrease their offer with an additional bidder). FP-GFM clearly does not carry through in this dimension of the BDM. This result provides yet another piece of evidence that the hypothesis that misconceived BDM bidders behave like FP optimizers must be rejected.

Result 8 must be contrasted with Cason and Plot's Result 4. CP result 4 is derived from treatment variations on the upper bound, \bar{p} , of the random price distribution $U[0, \bar{p}]$. This upper bound took the values 4, 5, 6, 7, and 8. Optimal FP bid are then given by $1 + 0.5\bar{p}$. In doing this, CP also tested the sensitivity of the FPM hypothesis to a change in parameter. Note that from a theoretical standpoint, increasing the number of random offers from one to two as we did in our design is equivalent to decreasing \bar{p} from \$5 to \$4. CP show that the average bid increases almost monotonically with \bar{p} . In contrast, we find no response to an increase in competition when we increase the number of bidders.

5 Conclusions

CP's specific application of GFM theory to BDM were based on three key premisses: (a) bidders are composed of two groups, BDM optimizers and misconceived subjects, (b) some misconceived subjects confuse the BDM for a FP auction, and (c) all bidders make decisions with noise. This paper develops three new treatments to explore the robustness of the hypothesis that a specific type of GFM (misconception of the BDM as a FP auction) can explain observed bidding patterns in the BDM. Two of the treatments explore predictions of the FP-GFM hypothesis regarding subject behavior in the misconceived task (BDM) and the task it is misconceived for (FP). We also extend the analysis to allow for risk averse subjects and provide a framework for testing the theory in the face of subject heterogeneity (here the degree of risk aversion in the FP auction). While our replication of CP's single BDM treatment produces results that are broadly consistent with their premises and empirical findings, the new treatments do not deliver support for the FP-GFM hypothesis. Instead, we observe that:

1. Under any model of bidding with noise, we would expect to see bids around the induced value. In our data, the proportion of \$2 bids was equal in the FP-1 and BDM1-1 sub-treatments, indicating no statistically identifiable BDM optimizers. This result demonstrates that data from the game causing the misconception can be very instructive in testing the theory of FP-GFM.
2. Showing subjects both the BDM and FP tasks simultaneously did not help subjects correctly recognize the games they were playing. The behavior observed in this treatment cannot be rationalized as FP-GFM.
3. An increase in competition (through the presence of two random offers in BDM2) does not increase the aggressiveness of offers as the FP-GFM hypothesis predicts.

These findings imply that a the application of GFM where it is only postulated that misconception of the BDM are of the FP variety cannot explain all features of observed bids. The appendix generalizes this conclusion for any distribution of risk aversion in the subject population.

Economists have long been puzzled by bidding behavior in the BDM and in second price auctions more generally. Many explanations have been offered but no consensus has emerged on a viable theory that can robustly explain the data. While the theory of GFM offers a promising framework to interpret systematic deviations from optimal behavior in games, our analysis does not support the conclusions that participants in the BDM are composed of only two group of optimizers: those who recognize the BDM and those who misconceive it for a FP auction. The fact that changing the upper bound of the posted price affects bids (CP Result 4) but that increasing the number of competing bids does not (our result 3), could open a new avenue to explore behavior and extend the scope of subject's misconception in the BDM. Overall, our results appear to reinforce prior conclusions by Bartling et al. (2015) and Quercia (2016) that misconceptions do not entirely explain observed behavior in the BDM.

The data collected for this experiment does not lend itself very well to the evaluation of alternative theories. A pessimistic, but speculative view, is that subjects understand little of the BDM (and perhaps even of the FP auction) and predicate their bid on a combination of the induced value and the upper bound of the offer price. Our data and CP's (in particular Figure 1), is consistent with naive bids roughly half way between the two values. Such a strategy with random errors and heaping at increments of \$0.25 would spuriously produce results that are consistent with FP-GFM when the BDM data is analyzed without the hindsight of the FP treatment. Such heuristics could also explain why subjects respond to a change in the upper bound (as shown by CP), but not to a change in the number of random offer prices (as shown in BDM2).

Yet, the many similarities between BDM and FP bids also suggests that many subjects may indeed be suffering from FP misconception. That the specific FP-GFM hypothesis is insufficient to explain the data does not invalidate the general theory. It is likely that subjects are distributed across more than one type of GFM and that new formulations of the misconception hypothesis would allow a better understanding of bids. More generally, the theory is relevant to those who design mechanisms to achieve particular ends, such as truthful revelation, because it provides an approach to identify systematic and predictable mistakes by untrained subjects. Until CP's contribution, such a theory of perception was a missing element in our understanding of behavioral errors. As with any new significant progress, the theory provides new tools but also challenges us to learn where and how to apply it. In the case of bidding errors by untrained subjects in the BDM, progress has been made but many questions remain.

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Table 1: GFR and GFM: Optimal Bids

	BDM	FP
Subjects with correct GFR	\$ 2	\$ 3.5
Subjects with FP-GFM	\$ 3.5	\$ 3.5

Table 2: Descriptive Statistics

	BDM1-1	BDM1-2	BDM2-1	BDM2-2	WS-BDM	WS-FP	FP-1	FP-2
mean (\$)	2.93	2.82	3.27	2.93	3.19	3.24	3.30	3.20
median (\$)	3.00	2.94	3.00	3.00	3.14	3.32	3.25	3.23
mode (\$)	3.00	3.00	3.00	3.00	3.00	4.00	4.00	3.00
sd (\$)	0.98	1.17	1.21	1.21	1.07	1.11	0.92	0.91
variance ($\2)	0.97	1.36	1.47	1.47	1.14	1.24	0.85	0.83
max (\$)	5.00	8.70	10.00	7.00	7.00	9.00	5.10	5.00
min (\$)	0.00	0.00	1.00	0.00	0.01	0.49	1.00	1.00
offer ≤ 0.10 (count)	6	6	0	4	3	0	0	0
1.95 \leq offer ≤ 2.05 (count)	13	22	14	21	10	12	7	3
3.45 \leq offer ≤ 3.55 (count)	16	9	16	14	26	18	13	8
2.95 \leq offer ≤ 3.05 (count)	43	25	32	21	35	24	11	16
offer ≥ 5.00 (count)	0	1	4	3	1	1	2	0
offer ≤ 0.10 (%)	3.7%	3.7%	0.0%	2.5%	1.8%	0.0%	0.0%	0.0%
1.95 \leq offer ≤ 2.05 (%)	7.9%	13.5%	8.8%	13.3%	5.8%	7.1%	8.2%	3.6%
3.45 \leq offer ≤ 3.55 (%)	9.8%	5.5%	10.1%	8.9%	15.2%	10.6%	15.3%	9.6%
2.95 \leq offer ≤ 3.05 (%)	26.2%	15.3%	20.1%	13.3%	20.5%	14.1%	12.9%	19.3%
offer ≥ 5.00 (%)	0.0%	0.6%	2.5%	1.9%	0.6%	0.6%	2.4%	0.0%
First Price Misconception (per round, count)	10	15	2	1	17	-	-	-
First Price Misconception (in either round, count)		22		3	17	-	-	-
Second Price Misconception (per round, count)	-	-	-	-	-	13	1	2
Second Price Misconception (in either round, count)		-		-	-	13		3
Possible Misconception, but not shown (count)		51		105		67		42
First Price Misconception (per round, %)	6.1%	9.2%	1.3%	0.6%	9.9%	-	-	-
First Price Misconception (in either round, %)		13.4%		1.9%	9.9%	-	-	-
Second Price Misconception (per round, %)	-	-	-	-	-	7.6%	1.2%	2.4%
Second Price Misconception (in either round, %)		-		-	-	7.6%		3.5%
Possible Misconception, but not shown (%)		31.1%		66.0%		39.2%		49.4%
N	164	163	159	158	171	170	85	83

Theoretical optima with GFR: BDM1, BDM2, & WS-BDM: \$2.00; FP & WS-FP: \$3.50

Theoretical optima under first price misconception: BDM1 & WS-BDM: \$3.50; BDM2: \$3.00

Table 3: Results of Variance Ratio Tests for the equality of variances

	BDM1-1	BDM1-2	BDM2-1	BDM2-2	WS-BDM	WS-FP	FP-1	FP-2
BDM1-1		0.7114** (0.0306)	0.6602*** (0.0088)	0.6586*** (0.0085)	0.8482 (0.2899)	0.7807 (0.1123)	1.138 (0.5140)	1.1645 (0.4439)
BDM1-2			0.9281 (0.6372)	0.9258 (0.6265)	1.1923 (0.2574)	1.0975 (0.5493)	1.5995** (0.0175)	1.637** (0.0136)
BDM2-1				0.9975 (0.9874)	1.2847 (0.1090)	1.1825 (0.2839)	1.7234*** (0.0063)	1.7638*** (0.0048)
BDM2-2					1.2879 (0.1060)	1.1855 (0.2774)	1.7277*** (0.0061)	1.7682*** (0.0047)
WS-BDM						1.0864 (0.5901)	1.3415 (0.1322)	1.373 (0.1077)
WS-FP							0.6862* (0.0544)	1.4916** (0.0432)
FP-1								1.0235 (0.9169)

Table shows F-statistics with p-values in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 4: Results of Mann-Whitney Two-Sample U-tests (are both samples drawn from populations with the same distribution?)

	BDM1-1	BDM1-2	BDM2-1	BDM2-2	WS-BDM	WS-FP	FP-1	FP-2
BDM1-1		1.095 (0.2737)	1.890* (0.0588)	0.456 (0.6487)	2.163** (0.0306)	-2.758*** (0.0058)	-2.498** (0.0125)	-2.044** (0.0410)
BDM1-2			-3.106*** (0.0019)	-0.762 (0.4459)	-3.347**** (0.0008)	-3.601**** (0.0003)	-3.359**** (0.0008)	-2.948*** (0.0032)
BDM2-1				2.846*** (0.0044)	-0.104 (0.9173)	-0.568 (0.5703)	-0.763 (0.4455)	-0.274 (0.7840)
BDM2-2					-2.276** (0.0228)	-2.594*** (0.0095)	-2.498** (0.0125)	-2.060** (0.0394)
WS-BDM						-1.020 (0.3079)	-0.710 (0.4780)	-0.138 (0.8901)
WS-FP							-0.172 (0.8635)	0.410 (0.6820)
FP-1								0.809 (0.4183)

Table shows U-statistics with p-values in parentheses.
Wilcoxon matched-pairs signed-rank test used when data is matched.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 5: Results of Pearson's Chi-Squared Tests (Equality of sample medians)

	BDM1-1	BDM1-2	BDM2-1	BDM2-2	WS-BDM	WS-FP	FP-1	FP-2
BDM1-1		-	1.5744 (0.210)	0.0267 (0.870)	3.8147* (0.051)	7.5763*** (0.006)	5.939** (0.015)	4.3484** (0.037)
BDM1-2			5.4765** (0.019)	1.5719 (0.210)	9.3036*** (0.002)	14.7374**** (0.000)	11.2209*** (0.001)	8.9643** (0.003)
BDM2-1				- (0.501)	0.4531 (0.292)	1.1102 (0.139)	2.1845 (0.2980)	1.0833
BDM2-2					3.1331* (0.077)	6.5691** (0.010)	5.2218** (0.022)	3.751* (0.053)
WS-BDM						- (0.353)	0.863 (0.688)	0.1611
WS-FP							0.1255 (0.723)	2.0719 (0.150)
FP-1								- -

Table shows χ^2 statistics with p-values in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 6: Adjustment of Round 1 to Round 2 Offers for Subjects Choosing Incorrectly in BDM1

	Exposed to Round 1 Error	Not Exposed to Round 1 Error
Total Subjects	41 (100%)	109 (100%)
Move onto optimum (\$2)	3 (7.3%)	8 (7.3%)
Move Toward Optimum	25 (61.0%)	35 (32.1%)
Choose same offer ratio	7 (17.1%)	25 (22.9%)
Move away from optimum	6 (14.6%)	41 (37.6%)

Figure 1: Cumulative Distribution Functions for BDM1-1 and CP's Round 1

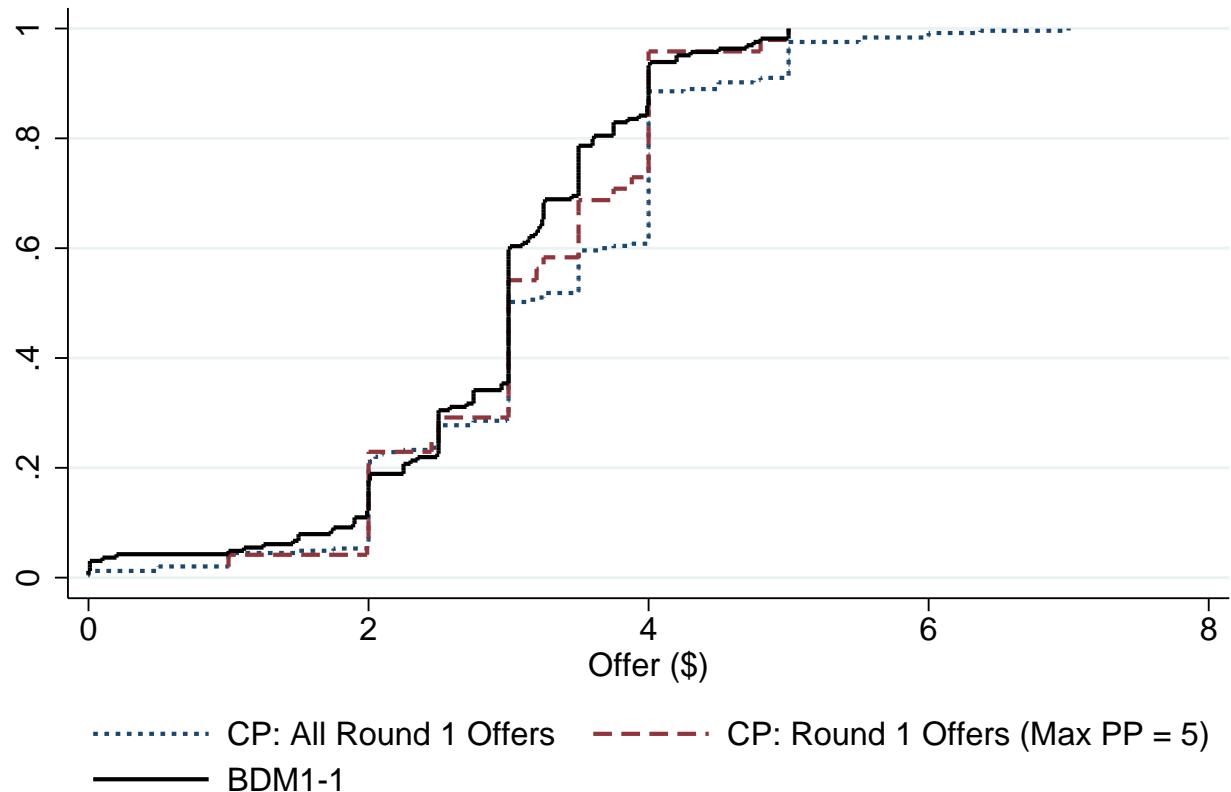


Figure 2: Cumulative Distribution Function of BDM1-1 against FP-1 and BDM2-1

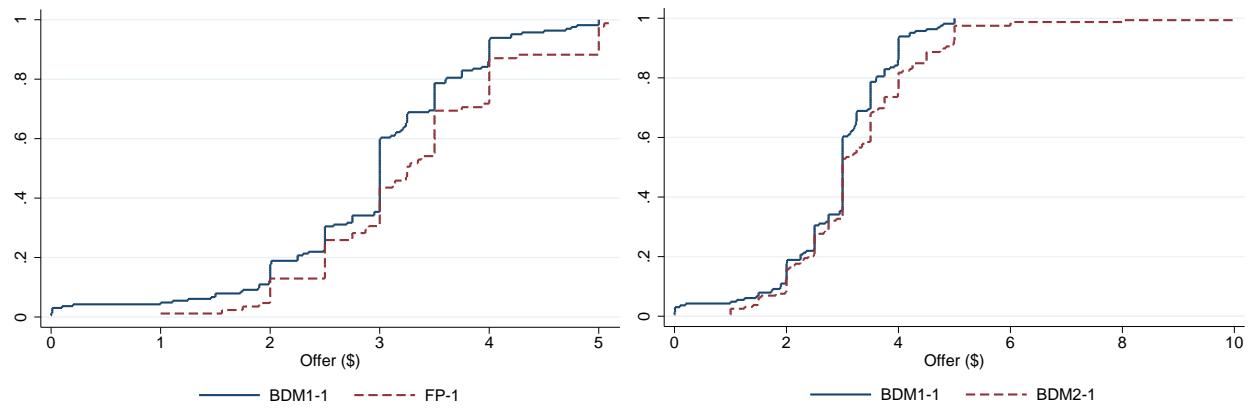


Figure 3: CDF Comparison of WS Sub-treatments

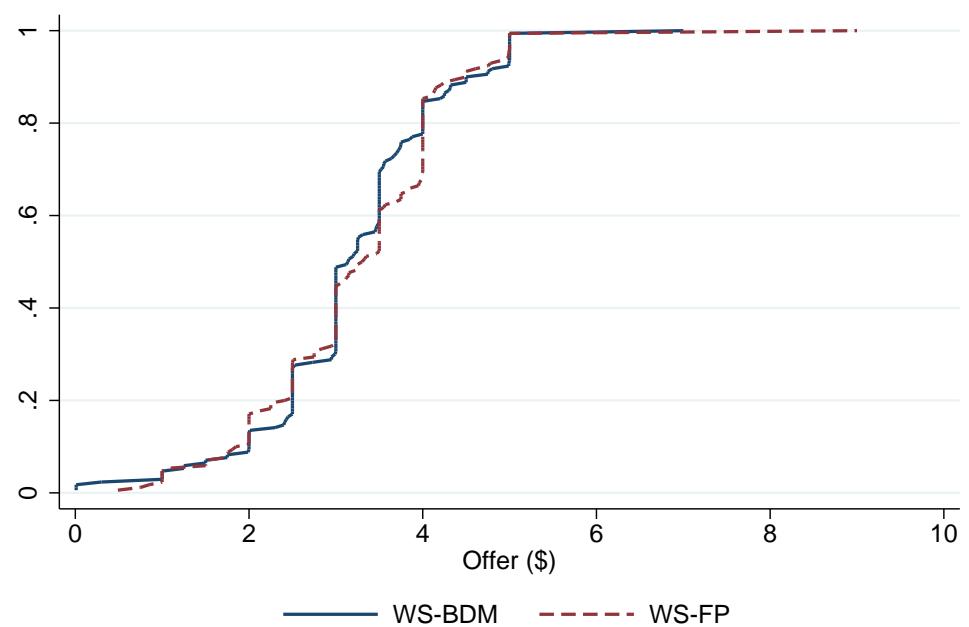
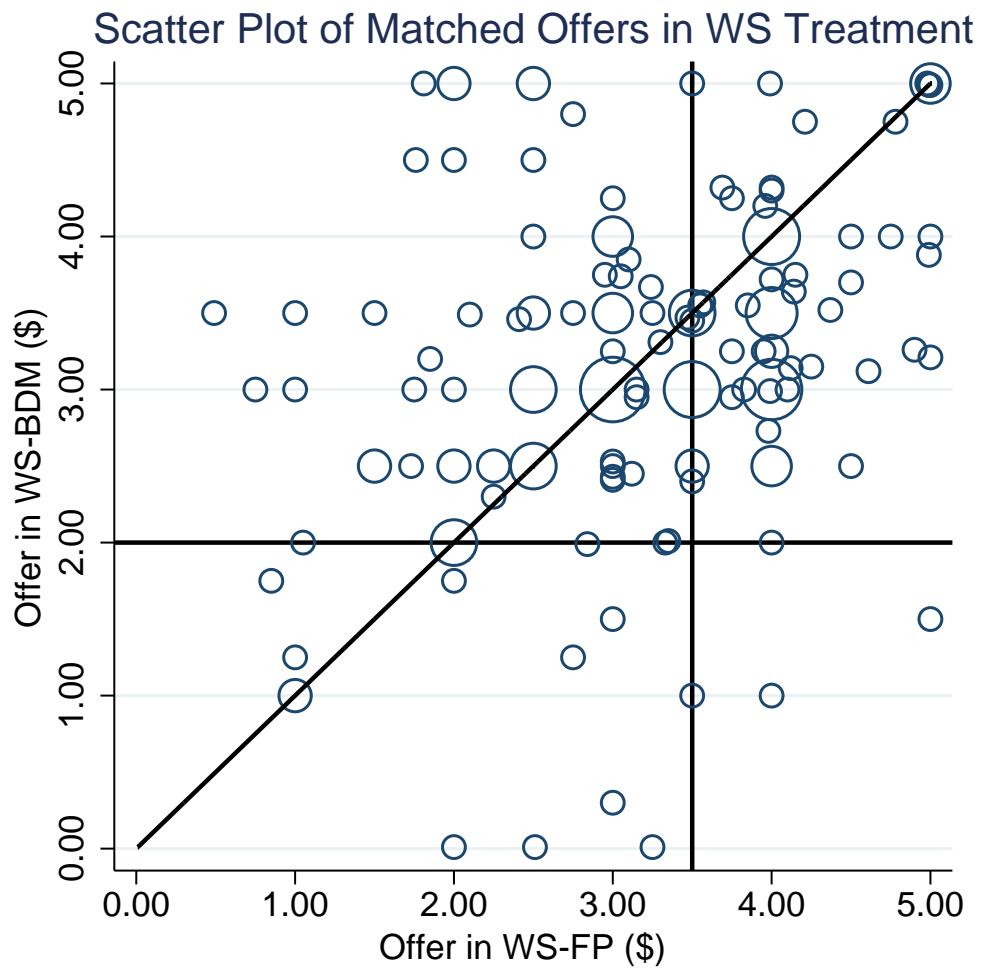


Figure 4: Scatter plot of Matched Offers in WS Treatment



Appendix A: Analysis with GFM and Risk Averse Subjects

General Analysis with GFM and Risk Averse Subjects

This Appendix extends the analysis to risk averse subjects and shows that the main conclusions presented in the text carry over. The analysis presented here is more complicated because there are now two dimensions of consumer heterogeneity: risk aversion and GFM. A formal theoretical framework demonstrates that GFM cannot explain some key features of the bid distributions even when one allows for risk averse subjects. Proposition 1 and 2 derive implications of GFM theory regarding the distribution of subjects' strategies. Table 7 generalizes Table 1 to risk averse bidders and illustrates how we apply the theoretical framework to draw inference in our treatments. Section 5 shows that the results presented in Section 4 violate the implication of Proposition 1 and some implications of Proposition 2.

A1. Theoretical Framework

A subject of type $x \in X$ selects strategy $s \in S$ for game g_a where $g \in G$ denote the game type and $a \in A$ is a parameter that can be changed. In Table 7, the subject type captures risk preference (risk neutral or risk averse), the games played are BDM and FP, the strategies are bids, and the game parameter is the number of bids the players is competing against (BDM2 has two random bids). In general, x could be distributed with unknown CDF that we denote by $H()$ and pdf $h()$. We also denote by $s(g_a|x, \tilde{g}_a)$ the optimal (under standard theory) strategy in game g_a for a player of type x who plays games g_a and \tilde{g}_a simultaneously. The optimal strategy with a single game is $s(g_a|x)$. With risk averse subjects and random payoffs we typically have $s(g_a|x, \tilde{g}_a) \neq s(g_a|x)$. For the sake of simplicity, we assume that there is a unique optimal strategy. Applying the theoretical prediction to each type, and aggregating across types using $H()$, we obtain a population distribution of optimal strategy. If subjects play games g_a and \tilde{g}_a , we denote that distribution for game g_a by $F^*(s|g_a, \tilde{g}_a, H)$. We could add a random error to the individual strategies, as CP do in their empirical model, and this would not change the main results.

The experimenter observes a distribution of strategy for each game played. With two games, we denote by $F(s|g_a, \tilde{g}_a)$ the observed distribution of strategy for game g_a . Under GFR the inference problem is stated as follows: Does there exist a type distribution $H()$ such that the predicted strategy distribution matches the observed strategy distribution?

$$F(s|g_a, \tilde{g}_a) = F^*(s|g_a, \tilde{g}_a, H).$$

With a single game, this identity becomes $F(s|g_a) = F^*(s|g_a, H)$. Take, for example, the case of the BDM in Table 7. The answer is negative because the predicted bid distribution should have a mass at the subject's induced value (\$2 in first line and first column) under RN or RA. But the experimental distribution shows that subjects typically bid more than their induced value. Adding a random bidding error would not change this conclusion. Something else is needed to rationalize the bid distribution.

CP adds an additional source of player heterogeneity that they call game form misconception. A subject may misconstrue the game she is playing for a different game. The researcher does not know whether a subject properly recognizes the game she is playing. Instead, the researcher must infer this from the observed strategy distribution. Formally, denote by $\alpha(m|g, x)$ the probability that a subject of type x misconstrue game g as game m , where $g, m \in G$. Note that GFM says that a subject's misconception holds for any value of the parameter a . When faced with game g_a , player x does not always play $s(g_a|x)$. Instead, she plays the optimal strategy corresponding to game m , $s(m_a|x)$, with probability $\alpha(m|g, x)$. We model $\alpha(m|g, x)$ as a probability because not all subjects of type x may have GFM.

Table 7: Game Form Recognition and Misconception: Optimal Bids

		BDM	FP	BDM 2
Risk Neutral Subject	Subject with GFR	\$ 2	\$ 3.5	\$2
	Subject with FP-GFM	\$ 3.5	\$ 3.5	\$3
Risk Averse Subject ^a (single task) ^b	Subject with GFR	\$ 2	$b_1 \in (2, 3.5]$	\$2
	Subject with FP-GFM	$b_1 \in (2, 3.5]$	$b_1 \in (2, 3.5]$	$b_2 \in (2, b_1]$
Risk Averse Subject (two tasks — WS) ^c	Subject with GFR	\$ 2	$b_3 \in (b_1, 3.5]$	
	Subject with FP-GFM	$b_4 \in (b_1, 3.5]$	$b_4 \in (b_1, 3.5]$	

^a The values (b_1, b_2, b_3, b_4) depend on the risk preferences of the agent. The optimal bid in the BDM is \$2 if the agent has weak preferences over distributions ordered by first order stochastic dominance.

^b The bid b_1 is the optimal bid for a risk averse agent who performs a FP auction once. A risk averse agent bids less in the BDM2 than in the BDM.

^c Risk decreases in the two-task case (WS treatment) because the agent receives two independently distributed payoffs. A risk averse agent bids a higher amount (equal for both tasks under GFM) relative to what she would bid in the FP auction alone ($b_3 > b_1$ and $b_4 > b_1$).

With two games we obtain that misconception may influence strategies through an indirect channel. Say type x has no misconception about game g_a , $\alpha(g_a|g_a, x) = 1$. Misconception for the second game can influence her strategy on the first game. She plays strategy $s(g_a|x, \tilde{m}_{\tilde{a}}) \neq s(g_a|x, \tilde{g}_{\tilde{a}})$ in the first game with probability $\alpha(\tilde{m}_{\tilde{a}}|\tilde{g}_{\tilde{a}}, x)$. In Table 7 line WS, a subject bids a different amount in FP depending on whether she has GFM in BDM. As before, denote by $F^*(s|g_a, H, \alpha)$ and $F^*(s|g_a, \tilde{g}_{\tilde{a}}, H, \alpha)$, the optimal distribution of strategy in a population with type distribution $H()$ and GFM distribution $\alpha()$.

The main difference of GFM over GFR is that the researcher has two degree of freedom, $H()$ and $\alpha()$, to rationalize the observed bid distribution. Under GFM, the inference problem is stated as follows: Does there exist a pair of functions $(H(), \alpha())$ such that the predicted strategy distribution matches the observed strategy distribution?

$$F(s|g_a, \tilde{g}_{\tilde{a}}) = F^*(s|g_a, \tilde{g}_{\tilde{a}}, H, \alpha) \quad (1)$$

The optimal strategy, $s(g_a|x, \tilde{g}_{\tilde{a}})$, is unchanged under GFM. Subjects still behave optimally for the game they believe they are playing. GFM, however, introduces a new source of player heterogeneity, $\alpha()$, which captures the fact that players may not recognize correctly the game they are playing. GFM puts much structure on the data. The only free parameters that can rationalize the observed strategies are the function $H()$ and $\alpha()$. Multiple treatments, that vary both a and g , must be consistent with a single pair of functions $(H(), \alpha())$, and the function $\alpha()$ must be independent of a , while the function H must be independent of both a and g .

To illustrate, take the case of BDM1 and BDM2 and assume that GFM can happen only from BDM toward FP, that is, $\alpha(FP|BDM, x) \geq 0$ and $\alpha(BDM|FP, x) = 0$. In the case of BDM2, the game played is the same but the parameter a is changed. We say that misconception is present if there is a x such that $\alpha(FP|BDM, x)h(x) > 0$.

Proposition 1. Assume misconception is present. $F(s|BDM2) > F(s|BDM1)$ for some $s \in S_0 \neq \emptyset$.

The proof follows from Table 7. Any type x who is misconceived bids less in BDM2 than in BDM1 since $b_2 < b_1$. If misconception is present, we obtain that S_0 must contain $[s(BDM1, x), s(BDM2, x)]$. Proposition 1 implies that the mean bid should be higher under BDM2 than BDM1. GFM says

even more in a within-subject treatment (subjects play both BDM and FP). We can compare the distribution of strategies in the within-subject treatment and in the single task treatments (subjects play BDM and FP separately).

Proposition 2. *Assume misconception and risk aversion are present. For some s , we have.¹²*

$$F(s|FP, BDM) < \text{Min}(F(s|FP), F(s|BDM, FP)) < \text{Max}(F(s|FP), F(s|BDM, FP)) < F(s|BDM).$$

PROOF: Take a given type x . This type is misconceived with probability $\alpha(FP|BDM, x)$. The observed bids on FP alone, BDM alone, FP played together with BDM, and BDM played together with FP are respectively:

$$\begin{aligned} b_{FP} &= b_1 \\ b_{BDM} &= (1 - \alpha(FP|BDM, x))2 + \alpha(FP|BDM, x)b_1 \\ b_{FP|BDM} &= (1 - \alpha(FP|BDM, x))b_3 + \alpha(FP|BDM, x)b_4 \\ b_{BDM|FP} &= (1 - \alpha(FP|BDM, x))2 + \alpha(FP|BDM, x)b_4 \end{aligned}$$

Inequalities $b_1 < b_4$ implies $b_{BDM} < b_{BDM|FP}$. Inequality $b_1 > 2$ implies $b_{FP} > b_{BDM}$. Inequality $b_3 > 2$ implies $b_{FP|BDM} > b_{BDM|FP}$. Inequalities $b_3, b_4 > b_1$ imply $b_{FP|BDM} > b_{FP}$. Putting these results together, we obtain,

$$b_{BDM} < \text{Min}(b_{FP}, b_{BDM|FP}) < \text{Max}(b_{FP}, b_{BDM|FP}) < b_{FP|BDM}.$$

This inequality holds for any x . The next step is to aggregate strategy distributions. We have, for example,

$$\begin{aligned} F(s|FP) &= \int_X I(b_{FP}(x) \leq s)h(x)dx = \int_X I(b_1(x) \leq s)h(x)dx. \\ F(s|BDM) &= \int_X I(b_{BDM}(x) \leq s)h(x)dx \\ &= \int_X (1 - \alpha(FP|BDM, x))I(2 \leq s)h(x)dx + \int_X \alpha(FP|BDM, x)I(b_1(x) \leq s)h(x)dx. \end{aligned}$$

Since $b_1(x) > 2$ for any x , we obtain $F(s|FP) < F(s|BDM)$. Aggregating similarly across types x delivers the remaining inequalities. *QED*

Proposition 2 implies that in the most general case with risk aversion and GFM:

$$3.5 > E(FP|BDM) > \text{Max}(E(FP), E(BDM|FP)) > \text{Min}(E(FP), E(BDM|FP)) > E(BDM) > 2.$$

Three benchmark cases are insightful. With no risk aversion and no misconception, we obtain the most restrictive prediction

$$E(FP|BDM) = E(FP) = 3.5 > 2 = E(BDM|FP) = E(BDM).$$

With risk aversion and without misconception, we obtain

$$3.5 > E(FP|BDM) > E(FP) > E(BDM|FP) = E(BDM) = 2.$$

¹²Under GFM and RN, we obtain, $F(s|FP, BDM) = F(s|FP) < F(s|BDM, FP) = F(s|BDM)$ since $b_{FP} = b_{FP|BDM} = 3.5 > b_{BDM|FP} = b_{BDM} = 2$. This case is not interesting because it cannot explain FP bids.

With risk neutrality and misconception, we obtain

$$E(FP|BDM) = E(FP) = 3.5 > E(BDM|FP)) = E(BDM) > 2.$$

With risk neutrality, distribution of strategy in a given game is independent of the other games the subject is playing.

A2. Application: BDM and FP We apply this framework to our treatments. The two games are FP and BDM. We leverage the implications of Proposition 1 and 2. Our main findings are as follows:

1. Take FP1 and assume all subjects are RN ($H()$ is degenerate). This corresponds to the basic CP benchmark. Result 3 rejects prediction $E(FP) = 3.5$. We conclude that there does not exist a function $\alpha()$ such that condition (1) holds for FP1. This rejects CP explanation under a RN assumption. The bid distribution in FP, however, is consistent with risk averse subjects who bid with noise.
2. Take BDM1 and FP1. There exists a pair of functions $H()$ and $\alpha()$ such that condition (1) holds. In particular, prediction $3.5 > E(FP) > E(BDM) > 2$ is consistent with Table 2 and Figure 2 (left panel). The basic CP benchmark holds with RA subjects.
3. Take BDM1, FP1, WS-BDM, WS-FP, BDM2 separately. For each treatment, there exist a pair of functions $H()$ and $\alpha()$ such that equation (1) holds. See Table 2 and Figures 2 and 3. Thus, GFM passes our test when each game is considered separately as done in CP's main treatment.
4. Take BDM1 and BDM2 jointly. There do not exist a pair of functions $H()$ and $\alpha()$ such that condition (1) holds. Proposition 1 implies that $E(BDM2) > E(BDM1)$ which is rejected (see Tables 2 and 5).
5. Take WS-BDM, WS-FP, FP and BDM jointly. There do not exist a pair of functions $H()$ and $\alpha()$ such that equation (1) holds. Proposition 2 says that this equation implies that $E(FP|BDM) > E(BDM|FP)$ and $E(FP|BDM) > E(FP)$ which are both rejected (see Tables 2 and 5). Note, however, that the other inequalities from Proposition 2, $3.5 > E(FP|BDM)$ and $\text{Min}(E(FP), E(BDM|FP)) > E(BDM) > 2$, are not rejected in Tables 2 and 5.

To sum up, a simple version of GFM with two games, BDM and FP, and any distribution of RA cannot explain bidding strategies in all treatments taken jointly. GFM and RA can explain bid strategies in each treatment in isolation. But this is not sufficient. According to GFM, a single distribution of heterogeneity should explain all treatments.

Clearly, the bidding strategies reveal much misconception amongst subjects. But a simple application of GFM where players can be risk averse and can confuse only BDM for FP is not sufficient to explain bidding strategies in all treatments. To rationalize subject's strategies, one may have to assume that some subjects do not misconceive the BDM only for FP. It is not clear, however, what other game the BDM could be misconstrued for. Alternatively, misconception may happen on other elements than just game form alone, which would be a more radical departure from the CP framework.

(Online) Appendix: Decision Cards and Instructions

(To be published as online supplementary material.)

DECISION CARD USED FOR BDM1 TREATMENT AND WS-BDM SUB-TREATMENT:

DECISION CARD

This card is worth \$2.00 to you.

You can sell it by giving us an offer price.

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

You can uncover and view the posted price **only after you have written down your offer price below.**

The posted price was drawn randomly between \$0 and \$5 (in increments of \$0.01). Every possible value had an equal chance of being selected.

If your offer price is **below or equal to the posted price** on the back of the card, then you sell your card at the posted price.

If your offer price is **above the posted price** on the back of this card, then you do not sell your card, but you do collect the \$2.00 value of the card.

Write down your offer price: _____

The posted price is under the tape. It is to be viewed only after you have written down your offer price on the other side.

COVERED POSTED PRICE HERE

Check the appropriate box to calculate your earnings:

My offer price is **below or equal to the posted price.**
Pay me the posted price of \$_____

My offer price is **above the posted price.**
Pay me \$2.00.

Your ID number:

DECISION CARD USED FOR BDM2 TREATMENT:

DECISION CARD

This card is worth \$2.00 to you.

You can sell it by giving us an offer price.

Located under the tape on the other side of this card are two posted prices.

You can uncover and view the posted prices **only after you have written down your offer price below.**

The posted prices were drawn randomly between \$0 and \$5 (in increments of \$0.01). Every possible value had an equal chance of being selected.

If your offer price is either **below both posted prices, or equal to the lowest of the two posted prices** on the back of the card, then you sell your card at the lowest of the two posted prices.

If your offer price is **above one or both of the posted prices** on the back of this card, then you do not sell your card, but you do collect the \$2.00 value of the card.

Write down your offer price: _____

The posted prices are under the tape. They are to be viewed only after you have written down your offer price on the other side.

Check the appropriate box to calculate your earnings:

My offer price is **below both posted prices or equal to the lowest one.**
Pay me the lowest of the two posted prices:
\$_____

My offer price is **above one or both of the posted prices.**
Pay me \$2.00.

Your ID number:

DECISION CARD USED FOR FP TREATMENT AND WS-FP SUB-TREATMENT:

DECISION CARD

This card is worth \$2.00 to you.

You can sell it by giving us an offer price.

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

You can uncover and view the posted price only after you have written down your offer price below.

The posted price was drawn randomly between \$0 and \$5 (in increments of \$0.01). Every possible value had an equal chance of being selected.

If your offer price is **below or equal to the posted price** on the back of the card, then you sell your card at your offer price.

If your offer price is **above the posted price** on the back of this card, then you do not sell your card, but you do collect the \$2.00 value of the card.

Write down your offer price: _____

The posted price is under the tape. It is to be viewed only after you have written down your offer price on the other side.

Check the appropriate box to calculate your earnings:

My offer price is **below or equal to the posted price.**
Pay me my offer price of \$ _____

My offer price is **above the posted price.**
Pay me \$2.00.

Your ID number:

FIRST SET OF INSTRUCTIONS USED FOR BDM1, BDM2, AND FP TREATMENTS:

INSTRUCTIONS (1)

All material is packaged in a specific order. Please move through it in that order.

- 1) Read and sign the consent form (if you would like to take a copy of the form with you, please raise your hand and we will give you an additional copy).
- 2) Carefully read the instructions on the decision card.
- 3) Make and write down your decision as instructed on the card.
- 4) Peel the tape off the back of the card only after you have written down your offer price on the front of the card.
- 5) Compute your earnings by following the instructions on the back of the card.
- 6) Open the second envelope and follow the instructions within.

INSTRUCTIONS USED FOR WS TREATMENT:

INSTRUCTIONS

All material is packaged in a specific order. Please move through it in that order.

- 1) Read and sign the consent form (if you would like to take a copy of the form with you, please raise your hand and we will give you an additional copy).
- 2) Your envelope contains two decision cards. Carefully read the instructions on **both** decision cards before making any decision. **NOTE** that the way in which you can sell each card is **different**.
- 3) Make and write down your decisions as instructed on each card. **NOTE** that you may choose a different offer price on each card.
- 4) Peel the tape off the backs of each card only after you have written down your offer prices on the front of both cards.
- 5) Compute your earnings by following the instructions on the back of each card. **Remember** that these computations are **different**.
- 6) Locate and keep the square ticket with your ID number. You will need to present it for payment next week.
- 7) Place all material (except the square ticket with your ID number) back in the large envelope. We will collect it at the end of the experiment.

SECOND SET OF INSTRUCTIONS USED FOR BDM1 AND FP TREATMENTS:

SECOND SET OF INSTRUCTIONS USED FOR BDM2 TREATMENTS:

INSTRUCTIONS (2)

Enclosed is a second card, also worth \$2, that you can sell using the same procedure as the first one, but the card has a new random posted price.

- 1) Carefully read the instructions on the decision card.
- 2) Make and write down your decision as instructed on the card.
- 3) Peel the tape off the back of the card only after you have written down your offer price on the front of the card.
- 4) Compute your earnings by following the instructions on the back of the card.
- 5) Locate and keep the square ticket with your ID number. You will need to present it for payment next week.
- 6) Place all material (except the square ticket with your ID number) back in the large envelope. We will collect it at the end of the experiment.

INSTRUCTIONS (2)

Enclosed is a second card, also worth \$2, that you can sell using the same procedure as the first one, but the card has new random posted prices.

- 1) Carefully read the instructions on the decision card.
- 2) Make and write down your decision as instructed on the card.
- 3) Peel the tape off the back of the card only after you have written down your offer price on the front of the card.
- 4) Compute your earnings by following the instructions on the back of the card.
- 5) Locate and keep the square ticket with your ID number. You will need to present it for payment next week.
- 6) Place all material (except the square ticket with your ID number) back in the large envelope. We will collect it at the end of the experiment.

CONSENT FORM:



Participant Consent Form

AN EXPERIMENTAL STUDY of GAME FORM EFFECT

You are invited to participate in a study of auctions being conducted by Dr. Daniel Rondeau. Dr. Rondeau is Professor in the department of Economics at the University of Victoria. You may contact him, if you have further questions, at 342 Business and Economics Building, 250-472-4423 or by email at rondeau@uvic.ca. You may also contact Dr. Pascal Courty, Professor of Economics, BEC 368, 250-721-8544 or by email at pcourty@uvic.ca.

Purpose and Objectives

The purpose of this research project is to understand how participants take advantages of simple trading opportunity of different forms.

Importance of this Research

Research of this type is important because it will allow governments in Canada to refine the sale of public assets (such as timber) and allocate them to their best possible use. It will also help us understand how individuals perceive and react to different individual decision problems.

Participants Selection

You are being asked to participate in this study because you are a student at the University of Victoria.

What is involved

If you agree to voluntarily participate in this research, your participation will require you to make either one or two decisions on paper. The experiment lasts between 10 and 15 minutes and is conducted here, today, in class.

Risks

There are no known or anticipated risks to you by participating in this research.

This experiment is completely independent from this course. Absolutely nothing related to this experiment will affect your grade in the course or your class standing.

Benefits/Compensation

If you agree to participate in this study, you will have an opportunity to earn between \$0 and \$10. On average, participants will earn between \$2 and \$5. The exact amount will vary based on your choices and chance. The exact amount of compensation can therefore vary between participants.

Voluntary Participation

Your participation in this research must be completely and voluntary. If you do decide to participate, you may withdraw at any time without any consequences or any explanation. If you do withdraw after you started writing on your answer sheet, the answer sheet will be destroyed and none of your data will be used.

On-going Consent

You may be invited to participate in additional sessions of a similar experiment in the future. Should this be the case, you will be asked to sign a new consent form.

Anonymity

At no time will we divulge any personal information compromising your anonymity. However, you will be sitting in a room with other participants. At no time will you be asked to reveal personal information other than when you sign a receipt in exchange for your payment. Receipts are collected for the sole purpose being reimbursed for research expenses. They will be sent to accounting by an administrative assistant. Your instructor will not have access to them and the researchers will not use information provided on the receipt.

Your signed consent form also include your name and signature. Once completed, your consent form will be put in a sealed enveloped kept in locked cabinet until its destruction by confidential shredding in 12 months from now.

Your instructor will not consult the consent forms at any time.

The data kept by researchers does not include your name or any other information that would allow your identification.

Confidentiality

Your confidentiality and the confidentiality of the data will be protected. All of the data you provide during the experiment will be associated only with a subject ID number that could never be traced back to you or personal information about you.

Dissemination of Results

It is anticipated that the results of this study will be shared with others through academic publications and scholarly presentations at conferences and seminars.

Disposal of Data

Your signed consent form will be kept for one year in a locked office. The signed form will be shredded securely in 12 months. Your receipt will be kept as financial records (for accounting purposes – not by the researchers) as per the rules of accounting and financial audits.

The data from this study will be kept indefinitely on computers secured by passwords. Remember that no personal identifier will be associated with your data.

Contacts

Individuals that may be contacted regarding this study include Dr. Daniel Rondeau (contact information above).

In addition, you may verify the ethical approval of this study, or raise any concerns you might have, by contacting the Human Research Ethics Office at the University of Victoria (250-472-4545 or ethics@uvic.ca).

Your signature below indicates that you understand the above conditions of participation in this study, that you have had the opportunity to have your questions answered by the researchers, and that you agree to participate in this research project.

<i>Name of Participant</i>	<i>Signature</i>	<i>Date</i>
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A copy of this consent will be left with you, and a copy will be taken by the researcher.