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Abstract

Bidder's choice (or "right-to-choose") auctions are of particular interest to parties who wish to sell multiple similar goods. Economic theory has shown that this type of auction, where the high bidder wins the right to choose one good from among the available goods, results in higher revenue than traditional good-by-good auctions, if bidders are risk-averse. Most theoretical and experimental work focuses on bidder's choice auctions where bidders value only one of the available goods. We report results from lab and field experiments that examine price revelation and multi-good demand, both of which are common in bidder's choice auctions used in field settings. We find that while price revelation does not have a significant effect on revenue, multi-good demand mutes the theoretical revenue superiority the bidder's choice mechanism. This is consistent with the notion that the perceived risk of losing one's most preferred good is softened when there is a chance to win other goods. This result implies that bidder's choice auctions should be used in settings where each bidder is likely to strongly prefer one good over the others, though this need not be the same good for every bidder. Further, this work demonstrates the complementarities of the field and laboratory settings to answer questions which are not clearly resolved using only one setting.

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I. Introduction

Ashenfelter and Genesove (1992) reported results that they argued "should surprise most economists." In a study of condominium sales in New Jersey they found that unit prices varied significantly with the method of sale. Units sold at auction were valued more highly than those sold through bilateral negotiation. The auction institution that yielded higher revenues was a "bidder's choice" auction (also known as a "right-to-choose" auction) in which the winner, rather than receiving a specific condominium, received the right to choose their preferred unit from among those remaining.[1] Bidder's choice auctions are also commonly used in the sale of customized telephone numbers, antiques, bank branches following mergers, and other sequential sales of multiple similar goods. Theorists and experimentalists have explored the issue raised by Ashenfelter and Genesove (1992) considering more generally the allocation of multiple heterogeneous goods to a pool of bidders. To create a clean counterfactual recent research has studied sequential (or good-by-good) auctions alongside the right-to-choose institution, rather than the bilateral bargaining observed in the field (Goeree, Plott and Wooders 2004; Burguet 2007; Eliaz, Offerman and Schotter 2008; Alevy, Cristi, and Melo 2010).

Burguet's (2007) theoretical development demonstrates that the bidder's choice auction raises higher revenue than a simple sequential auction when bidders are risk averse. The mechanism can "thicken markets" by creating competition across goods that are evaluated independently of each other in the sequential setting.[2] Existing experimental studies provide some support for Burguet's theory, though there are puzzles in the data on the role of risk aversion (Goeree, Plott and Wooders 2004; Eliaz, Offerman and Schotter 2008). Further, these studies examine the relatively simple case in which each bidder has positive value for only one good (single-good demand).[3] Our study makes novel contributions by studying the bidder's choice auction in complementary lab and field settings, exploring the

[1] According to the National Association of Realtors, a "bidder's choice" auction is: "a method of sale whereby the successful high bidder wins the right to choose a property from a grouping of similar or like-kind properties. After the high bidder's selection, the property is deleted from the group, and the second round of bidding commences, with the high bidder in round two choosing a property, which is then deleted from the group…" This process continues until all goods have been sold.

[2] Intuitively, the possibility that one's preferred good will be chosen early makes the value of the later auctions less certain. Risk-averse buyers therefore are willing to pay a premium to secure their favored good in an early round.

[3] For example, Eliaz et al. (2008) perform an experimental test of the theory where the high bidder drops out after he has won in the first phase of the auction, and the remaining bidders place bids for the right to choose from among the remaining goods. However, there are many instances in the field where it is the norm for winning bidders to remain in the auction.

implications of bidder demand for multiple goods. Our approach uses the induced value setting in the laboratory to help resolve open questions from the field experiments.

In the field setting, we conduct a "framed field experiment" that combines elements of traditional field studies such as homegrown values for real goods and a diverse population of consumers, with experimental controls that provide insight on the performance of the bidder's choice auction (Harrison and List 2004). To examine demand for multiple goods we compare bidder's choice and sequential auctions of a variety of consumer goods using a diverse pool of subjects in Reno, Nevada. In contrast to the theoretical results and to previous experimental work, we find that the bidder's choice mechanism fails to increase revenues in this environment. Consequently, the second part of our study uses a lab experiment that focuses on two elements of bidder's choice auctions (multi-good demand and price revelation) that have not been fully explored and may be influencing results in the field. We find that price revelation does not have a significant effect, multi-good demand significantly mutes the revenue superiority of the bidder's choice mechanism.

Multi-good demand in the bidder's choice setting has many applications. For instance, winning condominium bidders frequently choose a condo that they plan to rent out and continue bidding for the remaining condos, demonstrating that they have values for multiple units. Harstad (2009) presents anecdotal evidence of winning bidders in art auctions choosing an artwork and remaining to bid for further rights to choose. He also discovered that mergers or acquisitions in the banking industry, where branches are sold via bidder's choice auctions, result in more branches sold than the number of purchasers. This indicates that some purchasers must attempt to purchase several branches in different locations, implying multi-good demand.[4]

The U.S. Bureau of Land Management has considered using bidder's choice auctions to sell wild horses, a policy initiative which inspired our original field experiment. In this experiment, bidders presumably had positive values for all three of the goods (an iPod package, a hiking equipment package, and a wine package) and bidders continued to bid in all phases of the auction. In addition, the winning price in each phase was revealed, similar to sales in real estate or antiques via bidder's choice auction. The results indicate that the theoretical revenue superiority of the bidder's choice mechanism under risk aversion may be overstated. However, since personal values for the objects were private, it is impossible

[4] Additionally, it is easy to imagine that a firm may have positive value for more than one phone number or web address. For instance, Comcast owns both 1-800-COMCAST and 1-800-XFINITY. Google owns various misspellings of "google.com" to ensure users can reach their search engine, even if they are typing too quickly.

to know for sure how the bidders updated their beliefs regarding values in each round. Further, as we show in our extension to the theory, the effects of risk aversion are muted when bidders have a chance of obtaining surplus from multiple goods.

The extension to the theory and the lab experiment, aim to bridge the gap between extant theory and the field. Our treatments allow us to isolate the effects of multi-good demand and price revelation. The design is a 2x2x2 factorial that varies informational conditions, demand characteristics and auction format. Information conditions differ in whether bidders are informed of the winning price (the second-highest bid) in each auction phase. The price is revealed (concealed) in the "I" ("NI") treatment. Bidders draw random values for all three goods (only one good) in the "MG" ("SG") treatment. Following the extant experimental literature, this 2x2 factorial is embedded in both the bidder's choice, or right-to-choose, auction institution ("RTC") and a sequential, or good-by-good auction ("GBG").

We find that price revelation does not have an effect on revenues, but the revenue premium is significantly higher under single-good demand than multi-good demand.[5] This is consistent with the notion that the perceived risk of losing one's most preferred good is muted when there is a chance to win multiple goods. Further, this result implies that bidder's choice auctions should be used in settings where each bidder is likely to strongly prefer one of the goods over the others, though this need not be the same good for every bidder.

The paper proceeds as follows: Section II reviews the literature and identifies the contribution of this research. Section III extends the extant theoretical work to the cases considered in our experiments. Sections IV and V detail the field experiment and the laboratory experiment, respectively, including design choices and results. Finally, a discussion is provided in Section VI.

II. Literature Review

2.1 Theoretical Research

Ashenfelter and Genesove (1992) inspired much of the subsequent work on pooled auctions and bidder's choice auctions when they observed declining prices in successive rounds of condominium sales.[6] The authors hypothesized that bidders who were aware that waiting may lead to a lower price

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[5] The revenue premium is calculated as the revenue from a bidder's choice auction minus the revenue from a corresponding standard good-by-good auction.

[6] While this paper focuses on bidder's choice auctions, research on similar pooled auctions are worthy of mentioning. Menezes and Monteiro (1998) show that a simultaneous pooled auction also yields the same revenue as a standard

were risk averse; the bidders did not want to shade their bids as theory would predict because they were afraid of losing the condo. Gale and Hausch (1994) compared the theoretical revenue of a right-to-choose auction to that of a standard sequential auction and found that the former is larger. However, their model is limited to a two-bidder, two-good case.

Burguet (2005 and 2007) formalized the theoretical right-to-choose auction model that guides much recent lab and field experimentation, and serves as a benchmark for the new developments in this study, detailed in Section III. His results demonstrate that the right-to-choose auction should raise more revenue than the sequential good-by-good auction when bidders are risk averse, extending results to the case of many bidders. Burguet also shows that right-to-choose auctions are efficient and concealing information as to which goods have been selected allows the seller to achieve higher revenue.

Burguet touches briefly on the topic of taste diversity (less than perfect substitutability among the goods). Taste diversity gives rise to what is later referred to as non-persistent competition in the literature; the extreme case is each bidder having positive value for only one good. He shows that greater taste diversity may increase seller revenues even if it reduces buyers' willingness to pay for some objects. To our knowledge, this dimension of taste diversity has not previously been tested in the lab or field and this is one of the main contributions of our paper. The variance of values over goods for each bidder has been overlooked in much of the literature, yet this dimension is an important gap between the theory and the field, as described in the introduction.

Harstad (2010) points out that persistent competition (multi-good demand) is the norm in many instances of bidder's choice auctions. He builds a theoretical model where bidders have positive values for multiple goods and demonstrates that, under risk neutrality, the distribution of equilibrium revenue from a standard good-by-good auction is a mean-preserving spread of the distribution of revenue from a right-to-choose auction. His discussion comments on the risk averse seller's preference for a right-to-choose auction, but does not comment on the risk preferences of the bidders in the base model. Harstad extends the model to include cases where bidders may believe that one good is valued over the other goods by the majority; he refers to this good as "the usual favorite". This modification may lead a

sequential auction, though their model uses a first-price rather than a second-price standard auction (in contrast to the related literature). Salmon and Iachini (2007) provide an experimental analysis of pooled auctions and find that pooled auctions yield substantially higher revenues than ascending auctions. They find that this increase in revenue is not due risk or loss aversion, and they instead provide an attentional bias hypothesis where bidders overweight the surplus from winning their most preferred good as opposed to a lesser preferred good. These pooled auctions, while similar to bidder's choice auctions, are different in that bidders are not aware of the "remaining" goods when they place their bids; the second-highest bidder wins the second right-to-choose, but he is not aware of this outcome when he places his bid.

winning bidder to choose a good other than his most preferred in order to reduce competition in future rounds. While we do not model this specifically (values in our design are drawn randomly), a few of our bidders do choose goods that are not their most preferred. This may indicate some gravitation toward a "usual favorite" belief, or may simply be a mistake by these bidders.

2.2 Experimental Research in the Laboratory

Experimental work on bidder's choice auctions is somewhat sparse. Goeree et al. (2004) find that bidder's choice auctions raise more revenue than standard sequential ascending auctions under risk aversion. The authors are able to compare observed bids with theoretically predicted bids to estimate a common risk aversion parameter: on average, their bidders have the utility function: $u(x) = x^{0.39}$. Goeree et al. recognize the value of testing multi-good demand. In their concluding remarks they note that, "One extension is to consider bidders who value more than one item. It is an open question whether the revenue superiority of the ascending right-to-choose auction extends to richer valuation structures where the simultaneous ascending auction has proven to perform well." This paper aims to fill this gap in the existing literature.

Our experimental design closely follows that of Eliaz et al. (2008), who demonstrate that right-to-choose auctions raise more revenue than the theoretically optimal auction and show how withholding information or restricting quantity can benefit sellers. However, they argue that risk aversion may not be the only factor contributing to aggressive bidding in right-to-choose auctions. They incorporate a "no information" treatment where bidders do not know which good has been selected as they bid in each phase (similar to a pooled auction).[7] In this treatment, risk averse bidders are expected to bid below the risk-neutral bid (instead of above the risk-neutral bid as predicted in a regular right-to-choose treatment) since they face a lottery over which good they will win. The authors find that bidders in the "no information" treatment nonetheless raise their bids, implying that a different behavioral phenomenon may be at work. By calculating the equilibrium bids for many different numbers of participants, the authors are able to show that bidders behave as if they are competing with more than the eight subjects in the experiment. The intuition is that bidders perceive the competition to be bigger than it actually is; they distort the probability their good will be taken in each phase and do not realize that they only need to compete with the one other person who values their same good.

[7] This "no information" treatment is not to be confused with the "no information" treatment in our experiment; Eliaz et al. refer to no information on goods selected, whereas we refer to no information on prices.

We would expect this behavior to be muted or absent in our design. In our multi-good demand treatments, bidders are, in fact, in competition with every other bidder in their group (all bidders have values for every good). Therefore, for this bias to hold, bidders would have to believe that they are in competition with people who do not exist, which seems unlikely. Further, if this bias was solely responsible for the revenue superiority of the bidder's choice mechanism, we would not expect a significant difference between the bidder's choice auctions and the benchmark auctions for multi-good demand in full information treatments. However, we do find that the revenue premium is significant, even though it is diminished greatly from the single-good demand case. This paper, however, abstracts from analyzing this in detail and rather focuses on establishing the differences in revenue between single and multi-good demand.[8] The other main finding of Eliaz et al. – that quantity restriction may increase seller surplus by allowing the seller to keep one good without losing revenue – presumably would hold for our multi-good treatments as well, though we do not test this explicitly.

2.3 Experimental Research in the Field

To our knowledge, there exists only one prior field study on bidder's choice auctions.[9] Alevy et al. (2010) find support for Burguet's theory by selling water volumes that differed by reservoir source and time of availability to farmers in Chile's Limari Valley. Farmers had the opportunity to bid for irrigation water in two treatments: a standard sequential auction and a bidder's choice auction. Individual risk attitudes were also elicited. Arguably, the farmers had strong preferences for specific goods (volumes of water at a specific time and place) – the authors state, "bids decline substantially for the less preferred goods in both auction institutions, reinforcing the finding of heterogeneity in preferences" – suggesting that the model more closely resembles a single-good demand situation than multi-good demand.

In the present paper, on the other hand, the three goods auctioned in the field experiment (an iPod, hiking equipment, and fine wine) presumably have some substantial value to every bidder. In fact, the three goods had almost exactly the same retail value so it is not unreasonable to assume that the bidders had similar values for the three goods (or that at least that the variance of values was less than the variance of values in the Alevy et al. (2010) field work). Our field experiment thus resembles a situation

[8] All of the treatments conducted by Eliaz et al. assume bidders only have positive value for one good. Bidders drop out of the auction if they have already won or if their good has already been selected.

[9] By field study, we are referring to experiments that did not occur in an experimental laboratory. In the field study discussed here, participants' values for the goods were private and homegrown (i.e. the values were not induced) and participants bid and paid with their own money.

with more persistent competition than in previous work. This, coupled by the fact that we do not find support for the original theory in the field (despite clearly risk averse participants), suggests that the revenue superiority of bidder's choice auctions does not hold (or is muted) by multi-good demand.[10] Our subsequent theoretical development and lab experiment, therefore, seeks to test the robustness of the field result.

III. Theoretical Background

3.1 Single-good Demand

Burguet (2007) illustrates the revenue superiority of the bidder's choice auction with a simple example. Two bidders each have unit demand for one of two goods. Each bidder is equally likely to prefer either good – thus bidders prefer the same good with probability one half and different goods with probability one half. Payoffs are normalized so that the winner receives one (1) minus the price for winning the preferred good, and zero (0) minus the price for winning the non-preferred good. The price paid is equal to the second-highest bid. The goods are auctioned off in two phases where both bidders place bids for the right to choose their preferred good in phase one. The winner in the first phase does not participate in phase two. In the second phase, the remaining bidder has an equal chance of receiving either the preferred or non-preferred good. Expected utility in the second phase is given by the right-hand side of the following equation.

$$u(1-R) = \frac{1}{2}u(1) + \frac{1}{2}u(0) \tag{1}$$

In the first phase, bidders will not be willing to pay more than R, which will make them indifferent between the two phases. Normalizing $u(1) = 1$ and $u(0) = 0$ allows one to easily see that $R = 1/2$ for a risk neutral bidder and $R > 1/2$ for a risk averse bidder. The bid of $R > 1/2$ represents the seller's revenue for a bidder's choice auction with risk averse bidders. A standard second-price good-by-good sequential auction, on the other hand, would yield revenue equal to one half regardless of the bidders' risk preferences; if both bidders prefer the same good, the seller receives one (1), and if the bidders prefer different goods, the seller receives zero (0). Therefore, under risk aversion, the bidder's choice auction raises more revenue than the standard good-by-good auction. Intuitively, a bidder in a bidder's choice auction faces a tradeoff between paying more and the risk that her preferred good is not

[10] In our field experiment, bidder's choice auctions and good-by-good auctions yield approximately the same revenue.

available in the second phase. A risk averse bidder is willing to bid higher in the first phase to avoid the risk of losing her preferred good.

Eliaz et al. (2008) extend this theory to account for infinite bidders and infinite goods. As noted, they also add a dimension of quantity restriction. However, the bid function that these authors derive applies to single-good demand.[11] Since our experiments involve both single-good and multiple-good demand, we continue with Burguet's example by modifying it to account for bidders with values for multiple goods.

3.2 Multi-good Demand

When bidders have positive values for multiple goods they need not drop out after winning. Extending Burguet's (2007) example, we now assume both bidders have positive value for both goods: one (1) for the preferred good and α for the less-preferred good where $0 < \alpha < 1$. Again, there is a fifty percent chance that the two bidders prefer the same good and a fifty percent chance that they prefer different goods. Expected utility in the second phase is now represented by the right-hand side of equation 2:

$$u(1 - X) = \frac{1}{2}u(1 - \alpha) + \frac{1}{2}u(0) \qquad (2)$$

To elucidate, let us refer to the winning bidder in the first phase as "Bidder A" and the other bidder as "Bidder B." If the bidders prefer *different* goods, Bidder A chooses her preferred good in the first phase and bids up to α in the second phase. Bidder B bids up to 1 in the second phase since her preferred good is still available, but pays a price of α (the second-highest bid). If the bidders prefer *the same* good, both bidders have values of α for the remaining good in the second phase. Since the second phase is essentially a second-price good-by-good auction for the remaining good, both bidders will bid up to their value. Consequently, Bidder B receives a payoff of zero: either she doesn't win or she wins and pays the second-highest bid (α).[12]

In the first phase, a bid X which makes her indifferent between winning in the first phase and facing the lottery in the second phase. This is represented in the left-hand side of equation 2. As in

[11] The theoretical bid function derived by Eliaz et al. (2008) assumes risk-neutrality of the bidders. Therefore, the bids that we observe are higher than what would be predicted by their theory. In their experiment, the authors use a benchmark treatment (a second-price sealed-bid good-by-good auction), where risk preferences have no effect, as a comparison for the bidder's choice mechanism. We use this same benchmark in our experiments.

[12] Assume, here, that there exists a tie-breaking rule given that the bidders are completely identical.

Burguet's example, X will be larger under risk aversion than risk neutrality; the bidder will be willing to give up some surplus in order to secure her preferred good in the first phase and avoid the lottery. In comparing X in this example to R from Burguet's original model of single-good demand, it is clear that $X > R$; a bidder will bid higher in the first phase under multi-good demand in this model. However, this is simply the result of increasing demand for the goods (the good that had zero value to each bidder in the single-good demand case has positive value in the multi-good demand case).[13]

The more interesting result answers the question, "which case (single versus multi-good demand) raises more revenue *above the benchmark*?"[14] First, we will show that the bidder's choice mechanism raises the same revenue (in expectation) as the benchmark good-by-good auction under risk neutrality for multi-good demand.[15] (Recall that under non-persistent competition, Burguet showed that risk neutrality yields expected revenue equal to $1/2$ in both the bidder's choice auction and the benchmark.) Under multi-good demand, risk neutrality leads to an expected revenue equal to $X + \alpha$ in both auction formats.

In the benchmark, the seller's revenue is equal to $1 + \alpha$ if the two bidders prefer the same good and $\alpha + \alpha$ if the two bidders prefer different goods. Therefore, expected revenue is:

$$GBG\ Revenue\ (MG) = \frac{1}{2}(1 + \alpha) + \frac{1}{2}(\alpha + \alpha) = \frac{1}{2} + \frac{3}{2}\alpha.$$

In the bidder's choice format, the seller's revenue is equal to the price paid in the first phase plus the price paid in the second phase: $X + \alpha$. Since we are considering a risk-neutral bidder, we can normalize $u(x) = x$ so that the bidder's first phase bid function becomes the following equation.

$$1 - X = \frac{1}{2}(1 - \alpha) + \frac{1}{2}(0)$$

[13] Note that both of these simple models use one (1) as the value of the preferred good. Since this value is constant and the value for the non-preferred good has increased, demand has increased. We choose to model the values in this way for simplicity of comparison. Similarly, the values for both single and multi-good demand treatments are drawn from the same support in our experiment. This reflects the choice that a seller may face when choosing an auction mechanism: given fixed bidder values, is it better to use the bidder's choice auction when competition persists or does not persist? Or, similarly, should I use a bidder's choice auction or a standard good-by-good auction when I believe that bidders have low variance in their values? What about when they have high variance?

[14] This is what we refer to as the revenue premium of the right-to-choose mechanism: the right-to-choose revenue minus the good-by-good revenue. We are essentially asking which of the following is greater: (the risk averse R – the risk neutral R), or (the risk averse X – the risk neutral X)?

[15] Recall that this result was shown more formally by Harstad (2010).

Solving for X yields $X = (1/2) + (1/2)\alpha$. Adding α for the price paid in the second phase provides the expected seller's revenue for the bidder's choice format.

$$RTC\ Revenue\ (MG) = \frac{1}{2} + \frac{1}{2}\alpha + \alpha = \frac{1}{2} + \frac{3}{2}\alpha.$$

Now we show that the revenue premium of the bidder's choice format is higher under multi-good demand than single-good demand simply by comparing the variance of the second-phase lotteries. Risk aversion should cause a bidder to be willing to give up some surplus in the first phase to avoid facing a lottery in the second phase. Given a particular level of risk aversion, should a bidder raise her first-phase bid (over the risk neutral bid) more under single or multi-good demand? It is simple to show that the variance of the second-phase lottery (the right-hand side of the bid function) under single-good demand is $1/4$ and the variance of the second-phase lottery under multi-good demand is $(1/4) + (1/8)\alpha^2 - (1/4)\alpha$. Since $0 < \alpha < 1$, the former variance must be larger than the latter[16]. Intuitively, a bidder is more afraid of losing her most preferred good in the first phase when she does not have a chance at positive surplus in later rounds.

PROPOSITION 1: The risk averse bidder should raise her first-phase bid higher (over the corresponding risk-neutral bid) under single-good demand than multi-good demand because the variance of the alternative lottery in the second phase is greater.

We predict, therefore, that the revenue premium will be higher in single-good demand treatments than multi-good demand treatments. This result would be consistent with Burguet's discussion of increased seller revenue with increased taste diversity. Further, we predict that bidding behavior will reflect risk preferences; a more risk averse bidder will bid higher, given their value. Finally, we predict that a greater variance in values for a bidder in a multi-good demand treatment will lead to that bidder submitting a higher bid, given that the bidder is risk averse.

We realize, however, that risk aversion may not be the only force driving possible results. Recall one of the secondary results of Eliaz et al. (2008) mentioned earlier. The authors calculate equilibrium bids for different numbers of hypothetical competitors given the random value draws in their experiment. They find that bidders behave as if they are competing with five other bidders, when in reality, they are only competing with the one other bidder who values the same good. This bias could conceivably affect behavior in multi-good demand auctions as well. However, bidders would have to perceive that the

[16] A proof is in Appendix A.

competition encompasses more participants than were actually participating (for the bias to work in the same direction). Under multi-good demand, bidders do compete with all five other participants in their group; in order for this bias to cause raised bids, bidders would have to believe they were competing with more than five other people, even though there are only six people in each group.

It could be the case that the bias exists under single-good demand, but does not exist under multi-good demand – i.e. the bias is the reason for the revenue superiority of the bidder's choice format when bidders only value one good, but multi-good demand eliminates this bias because bidders do compete with everyone in their group. If this is the case, we would expect that revenue under multi-good demand would be the same for both the bidder's choice auction and the benchmark. Our aim is to provide explanations for varying field results and this behavioral bias could very well be at work in the field.

Another seemingly feasible behavioral bias could result from bidders only using their highest value (value for their most preferred good) to determine their bid in multi-good demand treatments as long as their most preferred good is still available. Previous literature has shown that experimental subjects in pooled auctions may weight their most preferred outcome more heavily than less-preferred outcomes due to an attentional bias (Salmon and Iachini 2007).[17] If this is the case, we would predict that single and multi-good demand treatments would yield the same or very similar revenue premiums.[18]

3.3 Information

Our field experiment result differs from Alevy et al. (2010) with respect to support for theory: our field experiment does not support the revenue superiority of the bidder's choice mechanism while the 2010 field work does. We can identify two major differences between these field experiments and previous laboratory experiments: information revelation and single versus multi-good demand.[19] In order to attempt to explain the contradictory results, we must vary each of these attributes individually and

[17] See literature review.

[18] If the attentional bias was complete (i.e. the bidders only used their most preferred good in determining their bid), then we would expect the revenue premium to be exactly the same for single and multi-good demand (given identical values for the most preferred good). If the attentional bias only caused bidders to underweight outcomes associated with their less preferred goods by some proportion, we would expect the revenue premium to be larger than in the absence of the bias. This is due to the fact that the existence of less-preferred outcomes in our design actually decreases the revenue premium (bids are not raised as high above the risk-neutral bid).

[19] Recall that the variance in bidders' values (which can also be thought of as the persistence of competition, the level of taste diversity, or the level of heterogeneity in preferences) presumably differed between the two field experiments.

simultaneously, which results in a 2x2x2 design. Our lab experimental design is explained further in the following section.

Price information may allow bidders to update their beliefs regarding the bounds of the value distribution. The distribution is always uniform over the support [1, 100], but public prices will allow some expectation of the realization of these values. This, in turn, may alter a bidder's expectation of the probability of winning in subsequent phases based on the updated order statistic. We predict that treatments where prices are revealed after each phase may exhibit different results in the second and third phases than treatments where information is withheld (the first phase should be unaffected since prices are not revealed until after the first phase is complete).

As a preview, our field results indicate that in some cases, bidders who placed the second-highest bid in the first phase actually decreased their bid in the second phase. These bidders probably thought that they would win in the second phase after finding out that their bid set the price in the first phase. They decreased their bid in attempt to gain extra surplus, but did not take into account that it is theoretically optimal for every bidder to raise their bid in each subsequent phase (given that their most preferred good is still available) until submitting a bid equal to their value in the final phase.[20] We predict that this behavior of decreased bids in the second phase may occur in our lab experiment as well. To test this, we execute additional experimental sessions so that each of our other four treatments (bidder's choice and standard good-by-good, for each single and multi-good demand) are executed both with and without information revelation.

IV. Field Experiment

4.1 Experimental Design

To study the bidder's choice institution in the field, we conducted 30 auction markets in the spring and fall of 2008. Subjects were randomly assigned to 16 markets in which the bidder's choice (hereafter "BC") institution was implemented and 14 markets in which the sequential good-by-good auction (hereafter "GBG") institution was implemented, using a between-subjects design. A total of 155 subjects participated in the study. With the exception of three BC and two GBG markets which had six bidders, the markets contained five bidders each.

[20] This optimal path of shading bids less and less in each phase is supported by the bid function derived by Eliaz et al. (2008).

Subjects were recruited from the Reno population with outreach to the community taking place through flyers in local stores and publicity in community organizations. Subjects were also recruited from existing databases of non-students who had participated in previous field experiments, and from University of Nevada Reno staff. Sessions were held on both the north and south side of Reno in accessible locations as well as on the University of Nevada Reno campus. Statistical tests indicate that participants do not significantly differ across the BC and GBG treatments in demographic characteristics that include gender, age, education, and income, or in personality traits.

To cleanly observe the impact of the auction institution, the goods for sale in the BC and GBG auction settings were identical. The goods, or more appropriately bundles, consisted of (i) hiking equipment that included a backpack, water filtration device, and first aid kit, (ii) an Apple iPod and speaker system, and (iii) three bottles of high quality wines. Each bundle had a retail value of approximately $250. Within each market the goods were sold in three auction phases. In each phase, a single good was allocated to the highest bidder using a second-price rule. In the BC institution, the good sold was the right to choose from the remaining bundles, which varied with the auction phase and market history. In the GBG institution, the good for sale was announced prior to the auction. The order in which goods were sold in the GBG auctions was determined randomly prior to the first auction phase.

The auctions were hand-run, with bidding cards for three phases distributed to participants at the start of the session. In all sessions, treatment specific instructions on the bidding process were distributed to participants and read aloud by the experimenters. An example of allocation through the second-price rule was discussed in detail. After reading the instructions, but before submitting bids, subjects had the opportunity to visually inspect the goods.[21]

In addition to the auction, each session included a risk elicitation protocol, and a short survey. The risk elicitation closely followed the multiple price list protocol popularized by Holt and Laury (2002) and consisted of a series of 10 binary choices between a safe and risky lottery. The payoffs were $200 and $160 for the safe lottery, and $385 and $10 for the risky lottery. The probability of gaining the higher payout increased from 10% to 100% across the ten choices. In this implementation subjects were paid with a one-third probability, with the outcome determined independently across subjects after the questionnaire was completed. To determine payoffs, experimental monitors would (i) roll a 10-sided die to pick one of the questions for potential payment and (ii) roll a 6-sided die to determine if subjects were

[21] The full instructions are available upon request.

paid based on their response to the selected question. Subjects were paid the outcome of their choice if a 1 or 2 resulted from the die roll and received nothing otherwise.

The final element of each session was a survey which included (i) the collection of demographic data, (ii) the elicitation of personality traits, and (iii) the cognitive reflection test (CRT), which contains three questions intended to measure impulsivity and intelligence (Frederick 2005). Subjects received $2 for each of the CRT questions answered correctly. A series of 40 questions contained in the International Personality Item Pool (IPIP) were used to measure the traits of assertiveness, sociability, performance motivation, risk-taking, confidence, beliefs about intelligence, and efficacy. The personality items were measured using a five-point Likert scale.

4.2 Field Results

Figure 1.1[22] illustrates that most of our participants are risk averse; it shows the proportion of participants in each risk preference group. T-tests show that the proportions are statistically different between auction types for the risk-loving group (p-value = 0.04), but not for the risk-neutral or risk averse groups (p-values = 0.87 and 0.15 respectively). Since risk posture is irrelevant for GBG auctions and BC participants are highly risk averse, we expect BC theory to hold.

Each participant was asked to rank the 3 goods from "Most Preferred" (a ranking of 1) to "Least Preferred" (a ranking of 3). Figure 1.2 demonstrates that while the IPod package was preferred over the wine and hiking packages, the preferences are very similar between BC and GBG auctions. However, we do find a significant difference in preferences between treatments for the hiking and IPod packages (p-values = 0.02 and 0.01 respectively). The wine package preferences are not statistically different between treatments (p-value = 0.81). Since revenues are driven by those who have the highest values for each good, we also examine the proportions of participants who ranked each good as their most preferred (illustrated in Figure 1.3). The proportions are not statistically different between treatments for the hiking or wine packages (p-values = 0.09 and 0.11 respectively), but are statistically different for the IPod package (p-value = 0.00). Again, however, we do find that the ordering of the goods is the same across treatments. We acknowledge that a difference in preferences could affect our results in part; however, we show later in the section that it is not the primary cause for our main findings.

[22] All figures are in Appendix C.

Since the majority of our auction participants are risk averse, BC theory tells us to expect higher revenues from the BC auctions than the GBG auctions. However, we do not find a significant difference in revenues between the two types of auctions (t-test p-value= 0.61). Table 1.1[23] includes average revenues for each phase and average market revenues. The average revenues in the GBG markets are not statistically different between phases, ruling out any order or wealth effects.

In case a lack of variation in preferences is driving the result, we temporarily eliminate any markets where all participants' most preferred good was the same. One GBG auction and four BC auctions meet this condition. The remaining markets' revenues are reflected in Table 1.2. BC auctions yield higher revenue than GBG auctions, but the difference is not significant (p-value = 0.78). Although this result is more in line with theory, we expected BC revenues to be significantly higher than GBG revenues.

RESULT 1: In contrast to theoretical prediction, the bidder's choice auction does not raise higher revenue than the good-by-good auction in the field experiment.

To further explore why our results are not in line with theory, we examine bidding behavior. We would expect that the third phase of BC auctions would have the same result as GBG auctions since both are second-price auctions for one good. The average bids for GBG auctions and Phase 3 of BC auctions are compared in Table 1.3. The IPod package never made it to the third phase in the BC auctions. We cannot reject that the average bid in GBG auctions is different from the average bid in the 3rd phase of BC auctions for wine (t-test p-value= 0.17, Mann-Whitney p-value= 0.30). However, we do reject the null for hiking at the 5% level: the average bid in GBG auctions is significantly higher than the average bid in the 3rd phase of BC auctions (t-test p-value= 0.01, Mann-Whitney p-value= 0.06). What might have happened during the course of the BC auctions to cause bidders to bid less in the 3rd phase than in GBG auctions for the same good? One major difference in the format of BC auctions relative to GBG auctions is that 1st and 2nd placed bidders in BC auctions get feedback.

We hypothesize that bidders in BC auctions may have changed their values for the goods over time. Past lab experiments have shown that BC auctions result in higher revenues, but the authors assume that the value a participant has for a good at the start of the auction remains the same throughout; participants are assigned a value and this cannot change during the experiment. It is easily possible, however, that participants in our field experiment update their values based on others' bids. A participant

[23] All tables are in Appendix B.

may see the winner in the first or second phase choose a good other than the one they believed was most valuable. Since all participants are aware of the second-highest bid (the amount the winner pays), the participant may believe he made a mistake judging the value of the good.

In addition to the monetary values of the goods, the participant may update his belief on the *relative* values of the goods. For instance, if a participant sees the IPod and the wine packages get chosen in the first and second phases, he may update his belief on the popularity of hiking relative to listening to music and drinking wine. If he finds that hiking is not as popular an activity as he originally believed, he may not bid as high for the good. Finally, a participant may get discouraged in a BC auction by watching others winning over him and choosing their favorite goods. In a GBG market, on the other hand, a participant may not be discouraged by losing in an auction for his least favorite good; he knows he was not really trying to compete with the other participants for that good.

We also analyze the revenues in GBG auctions versus the last phase of BC auctions and the findings are in line with the comparison of the bids (see Table 1.4). We cannot reject the null hypothesis that there is a difference in revenues for wine (t-test p-value= 0.88, Mann-Whitney p-value= 0.93). We can reject the null for hiking, but only at the 10% significance level when using a t-test (t-test p-value= 0.08, Mann-Whitney p-value= 0.04). We further investigate behavior by analyzing bids in more detail.

Next, we examine the first phase of BC auctions in comparison with GBG auctions. We would expect that bidders would shade their bids in the first phase of BC auctions and, in fact, they do (see Table 1.5). Bids are compared between GBG and Phase 1 of BC by declared most preferred good. In other words, the first column includes the average bid in Phase 1 of BC for participants who preferred the hiking package and the average bid in GBG "Hiking" auctions for participants who preferred the hiking package. The average bid for the most preferred good in GBG auctions is not significantly higher than in the first phase of BC auctions for the wine and hiking packages. We cannot reject the null in t-tests or Mann-Whitney tests at the 5% or 10% levels. However, the difference is significant for the IPod at the 10% level (t-test p-value= 0.08, Mann-Whitney p-value= 0.08). Note that current theory does not specify *how much* bidders will shade during the first phase of a BC auction, but just that they will decrease their bid from their true value. This is what we observe.

RESULT 2: Although some anomalies exist, bidding behavior is generally in line with theory when comparing 1^{st} and 3^{rd} phase bids between BC and GBG in the field experiment.

We further analyze bidding behavior by calculating the change in bids for each participant over time in BC auctions. Table 1.6 displays the change in bids for individuals whose most preferred good is still available in the next phase. For instance, the first cell displays the average change in bids between Phase 1 and Phase 2 for participants whose most preferred good is the hiking package if the hiking package is still available (the hiking package was not chosen by the first winner). We find mixed support for the theory here; some bidders decreased their bids and some increased. We would have expected all bidders to increase their bids if their preferred good was still available.

To delve deeper, we examine how bidders change their bids by initial rank. Table 1.7 summarizes the results. Each bidder was ranked from highest bid (rank=1) to lowest bid (rank=5 or 6 depending on number of participants in the market) in each phase. We find that bidders who were ranked 2nd lower their bids on average for the next phase. Bidders who were ranked 2nd knew their rank because the price paid by the winner was announced. Bidders who were ranked greater than 2nd did not know their rank, but did know that they were not ranked first or second. It turns out that bidders who were ranked 2nd were responsible for drops in bids; bidders ranked 3, 4 or 5 increased their bids on average.

This contradicts the traditional theory; bids should continue to increase in each phase when the bidder's most preferred good is still available. In phases prior to the last phase, bidders should shade their bids just enough so that they are indifferent between winning and facing the lottery that occurs in the last phase. As phases progress, this shading should become less and less, assuming the most preferred good is still available. (In the last phase, which is essentially a good-by-good auction for the remaining good, bidders should bid their value.) This result leads to speculation over whether bidders may have updated their expectations of the goods' values as new information, such as the first good selected, was revealed. For instance, one subject may believe that the Wine package would be the most popular (and therefore possibly easier to resell), but is surprised when the winner in the first phase chooses the iPod. The subject now lowers his private value for the Wine, even though his bid should theoretically increase in the second phase. This updating cannot be controlled in the field setting since we do not observe private values. Consequently, it is difficult to conclude why exactly the BC institution did not raise higher revenues than GBG auctions. This difficulty motivates the second portion of this research, the laboratory experiment, which will be discussed in later sections.

RESULT 3: Bidders who are ranked 2nd in the BC auction in Phase 1 decrease their bids in Phase 2 which contradicts theory.

Next, we explore how demographics and personality measures affect bidding behavior using regression analysis. We find that when a bidder's most preferred good *or* second most preferred good is still available in an BC auction, he increases his bid, as expected. Bidders also increase their bids significantly in GBG auctions for their most preferred goods. Table 1.8 provides these regression results. In addition, we find that sociability is a significant negative predictor of BC bids whereas confidence has a significantly positive impact on GBG bids.[24]

As expected, an indicator for a risk-averse individual is significant in predicting BC bids but not GBG bids. However, the direction of impact is not in line with theory; risk-averse individuals should bid more than risk neutral or risk seeking individuals because they do not want to risk losing their preferred good. Instead, we find that risk-averse individuals bid less. Rather than having aversion to losing their preferred good, our bidders are averse to paying too much for a good. According to theory, BC auctions produce higher revenues only if bidders are risk averse. The negative coefficient on our risk aversion indicator could partially explain why we see equivalent revenues between the two auction types.

We also examine how bidders behave in comparison with theory by constructing an indicator for circumstances where bids should have increased in BC auctions. If a participant's most preferred good is still available, they should always increase their bid in the next phase. They should also increase their bid if their least favorite of the remaining goods gets chosen. For instance, if the order (by preference) of goods taken for a participant is "1, 3, 2" (most preferred good taken in 1st phase, least preferred good taken in 2nd phase, 2nd most preferred good taken in 3rd phase), the participant should increase his bid from the 2nd phase to the 3rd phase. If the preference order of goods taken is "2 1 3", the participant should increase his bid from the 1st phase to the 2nd phase, but theory is silent on what he should do from the 2nd phase to the 3rd phase (it depends on how much he has been shading and the difference in value to him of the goods).

We find that in more than half of cases (54%) where theory predicts a bid increase in BC auctions, participants actually decrease their bids or leave their bids unchanged. This result alone demonstrates that the theoretical BC bidding strategy is not followed in the field, regardless of where BC versus GBG preferences or revenues stand. One could argue that participants do not understand the optimal BC bidding strategy. However, we already saw that BC bidders are, in fact, shading their bids across the board (for all goods) during the first phase. It seems quite unlikely that this could be a coincidence;

[24] Sociability and confidence are personality measures derived from the International Personality Item Pool (IPIP) questions mentioned previously.

instead, participants probably underestimated how much other bidders would shade or made emotional decisions based on the outcomes of each phase. This caused theory to break down during the second and third phases.

Table 1.8 reports the effects of demographics and personality measures on an indicator of whether a participant increased their bid. A Probit model is used and the sample is restricted to instances where theory says the participants' bids should have increased. An indicator for above-average education is significant but in the opposite direction from what one might expect; participants are less likely to increase their bid when they should if they are educated. This may be due to over-analyzing the bidding strategy. The results of an IQ quiz are more intuitive; smarter participants are more likely to increase their bids when they should. Confidence, efficacy and sociability are also significant predictors of how likely a participant is to follow theory. Notice that our indicator for risk aversion still has a negative coefficient, though not significant here.

As previously discussed, it is difficult to determine exactly why theory broke down in this field study. As is the nature of field studies, private values are unknown; further, any updating of private values are also unknown. Contrary to theory, risk aversion does not appear to play a role, as it is insignificant in our econometric analysis regardless of how the parameter is defined.[25] Further, we observe bidding paths that are illogical, unless participants' private values changed throughout the auction. These inconsistencies motivate the second stage of our research: the laboratory experiment. In the lab, we are able to control values by inducing them. Further, we can isolate possible confounding points which have not yet been explicitly tested in the literature. Specifically, we isolate price revelation (providing information on the prices of winning goods, which may have led to some of the aforementioned behavioral biases), and persistent competition (subjects having value for multiple goods) which, as discussed, should mitigate the revenue advantages of bidder's choice auctions.

V. Lab Experiment

5.1 Experimental Design

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[25] Using the results of our Holt and Laury style risk elicitation, we tried defining the risk parameter in several different ways, including an indicator for very risk averse subjects, an indicator for mildly or very risk averse subjects, a numeric variable which reports how many "safe" choices the subject chose, an indicator for subjects who chose more safe choices than average, an indicator for subjects who reported consistent risk preferences (did not switch back and forth between the risky choices and the safe choices), etc.

Our experimental approach closely follows Eliaz et al. (2008), though our dimensions of variation differ to focus on the effects of information and multi-good demand. In one set of treatments, bidders are informed of the winning price (the second-highest bid) in each phase (referred to as "I" treatments), whereas other treatments do not provide this information (referred to as "NI" treatments). In another set of treatments, bidders draw random values for three goods in each round (multi-good demand – "MG"), while in single-good demand treatments ("SG"), bidders only draw a random value for one good in each round. All of these treatments are tested using a bidder's choice, or right-to-choose, auction ("BC") and a standard sequential good-by-good auction ("GBG"). This 2x2x2 design yields a total of eight treatments.

Values were drawn from a uniform distribution over the support [1, 100]. For SG treatments, three sets of preferred goods (values) were drawn ex ante and used repeatedly for different groups. For MG treatments, we varied the order of the sets of values for different groups to control for ordering effects. Consistent with Eliaz et al. (2008), we did this to ensure that differences in revenue are attributable to differences in behavior rather than differences in the vectors of random variables generated.

Eight sessions (one for each treatment) were executed at the University of Tennessee, Knoxville (UTK) and eight sessions (one for each treatment) were executed at the University of Alaska, Anchorage (UAA) in April 2012. The experimental laboratories at the two universities have similar recruiting procedures, attracting undergraduate students from a variety of disciplines. Four groups of six bidders each occupied the laboratory for each of the sessions held in Tennessee. Due to capacity constraints, two or three groups of six bidders participated in each of the eight treatments in Alaska. There were a total of 324 participants. The sessions lasted about 70 minutes and most participants earned between 15 and 40 U.S. dollars in total.[26] Table 1.9 displays the experimental design.

The experimental sessions proceeded as follows. First, the subjects were asked to participate in a risk elicitation similar to the one popularized by Holt and Laury (2002). Instructions for the risk elicitation were read aloud while subjects followed along with on-screen instructions. The computer program then allowed the subjects to make 10 risk decisions, one of which would be selected at random

[26] This total includes earnings from all 10 auction rounds plus earnings from a risk elicitation.

and paid out at the end of the session.[27] Next, the subjects were given hard copies of the auction instructions and asked to read along while the instructions were read aloud.[28] The subjects were encouraged to ask clarifying questions before the experiment began. The subjects were randomly assigned into groups of 6 and were unaware of the identities of the other 5 participants in their group.

The experiment consisted of a practice round, followed by 10 paid rounds. In each round, there were 3 phases. In BC treatments, each phase was an auction for a right to choose.[29] In GBG treatments, each phase was a standard auction for one of the goods (the goods were labeled "A", "B" and "C"). Bidders were instructed to submit bids ranging from zero to their value. In GBG auctions, the highest possible bid was a subject's value for the good being auctioned. In BC treatments, the highest possible bid was a subject's highest value (in SG treatments, the subject's highest value was also their only value). We did not allow the subjects to overbid in order to decrease the effect of cognitive mistakes. While learning effects have been the focus of other experimental work, we are focused on cleanly identifying the effects of multi-good demand and information. This arrangement also minimized the possibility of bankruptcy. A small percentage of subjects in BC treatments did still go bankrupt due to choosing the wrong good.[30] In these cases, if the subject did not recover from the loss, we paid the subject a show-up fee. Eliminating these subjects from the data does not significantly change the results.

After each auction phase, bidders were informed whether they had won. In BC treatments, all bidders were also informed of the good that was chosen by the winner in their group. In "I" (information) treatments, all bidders were informed of the price of the good sold in their group (the second-highest bid). No subject was ever told the name or ID number of any other subjects in their group so they could not infer that one particular person won more or less often. In SG treatments, subjects whose preferred

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[27] We elicited the risk preferences of the subjects prior to the experiment to ensure that their responses were not affected by their experiences of wins and losses during the experiment. We did not reveal the results of the risk elicitation until the end of the session to avoid any endowment effects.
[28] The instructions and screen shots from the experiment are available upon request.
[29] Note, however, that the last phase was identical to a good-by-good auction for the remaining good.
[30] For example, suppose a subject's values are 80, 60 and 40, the subject bids 51 and wins. For simplicity, further suppose that the second-highest bid (price) is 50. If he chooses the good that he values at 40, he receives negative 10 tokens. If he chooses the good that he values at 60, he receives positive 10 tokens, but this is inferior to choosing the good that he values at 80, which yields positive 30 tokens. Choosing any good other than the most preferred is illogical given our experimental design. However, as mentioned earlier, Harstad (2010) theorizes that a bidder may choose a good that is not his most preferred if he believes the good is a "usual favorite". The bidder's motive is to eliminate the most popular good in hopes of obtaining his most preferred good in a later round for a low price. In our experiment, all values are drawn randomly from a uniform distribution so there is not a "usual favorite". However, it is possible that a few subjects misunderstood the implications of random drawings and wanted to test Harstad's theory as a potential strategy. As stated, this behavior only occurred in a few cases and does not appear to affect our overall results.

good sold in phase 1 or 2 "dropped out" of the auction; they faced a screen that read, "Please wait while the other members of your group bid in Phase …". In the GBG SG treatments (good-by-good auctions where bidders only have positive value for one good), subjects only bid in phases when their preferred good was auctioned. For instance, a subject who preferred good B faced a screen in the first phase that said, "Please wait while good A is auctioned." In MG treatments, all subjects participated in every phase.

Earnings consisted of the subject's value (randomly drawn) minus the price they paid for the good (the second-highest bid). All values and prices were expressed in tokens. In SG treatments, each 8 tokens equaled one dollar; in MG treatments, each 4 tokens was equal to a dollar. The different exchange rates were based on the fact that equilibrium earnings must be less in MG treatments.[31] Earnings were totaled over the 10 rounds. In the final stage of the experiment, the risk elicitation results were revealed and each subject's total earnings were calculated. Subjects were paid in cash and in private.

5.2 Laboratory Results

First, we simply compare the average revenues (sum of prices paid) for each BC treatment to its GBG counterpart. These values are displayed in Table 1.10. BC revenues are significantly higher than GBG revenues, as expected. T-tests reveal no significant revenue differences between any information treatment and its "no information" ("NI") counterpart (i.e. no significant difference between BC – I – SG and BC – NI – SG or between GBG – I – MG and GBG – NI – MG, etc.). Hence, for the following comparisons, we pool information conditions. The difference between single and multi-good demand is significant, as expected (t-test p-values are less than 0.001). This result is a consequence of the fact that more values in MG treatments than SG treatments necessarily decreases the gap between the highest and second-highest values in any phase, thereby raising prices. This also decreases bidder surplus and is the reason for the differing exchange rates between the two treatment groups.

The interesting result lies in the difference in the differences between BC and GBG revenues by type of demand. Put differently, the revenue premium of the bidder's choice mechanism (compared to the benchmark GBG auction) is larger when bidders only have demand for one good. We compare the

[31] In SG treatments, there were 6 random values drawn per group per round. In MG treatments, there were 18 random values drawn per group per round. Due to the increased number of draws, the spread between the highest and second-highest values at any given time in MG treatments was, on average, much less than in an SG treatment. (Recall from the theory that the revenue in MG auctions must be higher than SG auctions, given that the same value for the preferred good. The idea is the same here: values were drawn from the same support for both MG and SG auctions, but since more values were drawn in MG auctions, the demand for each good is essentially higher.) The specific exchange rates of 8 and 4 tokens per dollar were determined based on earnings in a pilot session held prior to the experiment.

BC—GBG difference in the top two rows in Table 10 (SG treatments) to the BC—GBG difference in the bottom two rows (MG treatments). While the BC revenue premium is statistically significant in both cases (p-values = 0.000), the difference is significantly larger for SG treatments. To see this visually, refer to Figure 1.4. The difference in the differences is statistically significant (48.28, (SE = 4.22) for SG and 18.29 (SE = 2.53) for MG). This is consistent with our theoretical prediction that risk averse bidders do not raise their bids as high (over the risk-neutral bid) under multi-good demand as under single-good demand.

The risk elicitation demonstrates that the majority of participants are risk averse; the results are displayed in Figure 1.5. A risk neutral subject would have switched from the lottery to the certainty equivalent at either Row 8 or Row 9 (the two darker shaded columns in the figure). However, we see many subjects choosing the certainty equivalent prior to Row 8, indicating risk aversion.[32]

RESULT 4: While there is no treatment effect associated with withholding price information, there is a significant consequence of multi-good demand. There is a revenue premium for the bidder's choice mechanism regardless of single-good or multi-good demand, but the premium for multi-good demand is significantly smaller. This is consistent with theory.

Due to the fact that bids in multi-good demand treatments are necessarily higher than bids in single-good demand treatments (a result of the larger number of values drawn), we can only compare bidding behavior between the two treatments by using the benchmark GBG auction as a baseline for each treatment, as we have done to analyze revenues. Table 1.11 compares the first phase BC bid for each type of competition alongside the GBG bid for the subject's most preferred good (i.e. if the subject's most preferred good is "A", then this is his first phase bid; if the subject's most preferred good is "B", then this is his second phase bid, etc.). This comparison allows us to analyze each bidder's bid based on his highest value. The first phase BC bids are significantly less than the GBG benchmark for both single and multi-good demand (p-values are 0.047 and 0.001 respectively). This demonstrates that the general bidder's choice model holds for our experiment: bidders shade their bids from their values in the first phase.

The difference in the BC and GBG bids is larger for multi-good demand (3.18) than single-good demand (2.75), though the difference in the differences is not significant. Recall that the theoretical risk

[32] The complete instructions for the risk elicitation and screen shots displaying the ten choices faced by participants are available upon request.

neutral bid is higher for MG than SG given the same value for the most-preferred good (from the theoretical section: $X > R$). On the other hand, risk aversion causes less of an upward force on bids in MG than SG. Hence, we cannot draw any conclusions from this difference and difference comparison.

Table 1.12 provides the BC bids for single and multi-good demand. The data used includes bids where a subject's most preferred good is still available. When bidders only have value for one good (SG treatments), this includes all bids until a bidder drops out.[33] This allows us to see how the bidding path for the most preferred good progresses. Notice that the average highest value decreases from Phase 1 to Phase 2 and again from Phase 2 to Phase 3. This reflects the fact that some bidders drop out of the auction because they either win or their most preferred good is taken by another bidder.

The progression of bids (as a percentage of value) in multi-good demand treatments is significantly flatter than in single-good demand treatments (Phase 1 p-value = 0.00, Phase 2 p-value = 0.04, Phase 3 p-value = 0.04). Again, there are two effects at work: the theoretical bid as a proportion of value is higher (than SG), but the effects of risk aversion should be muted. Overall, we observe that subjects bid very high percentages of their values in multi-good demand; as we have already seen, this ultimately leads to higher revenue than the multi-good benchmark. Thus, subjects must be bidding higher than the risk neutral bid. Average bids in the third phase are slightly below average values for both SG and MG treatments. We find that this is the case in the benchmark GBG auctions as well; we turn to this analysis next.

RESULT 5: Bidding behavior in the lab experiment is generally in line with theory. The bid paths (calculated as bid/value for subjects whose most preferred good is still available) significantly differ between single and multi-good demand.

Table 1.13 provides the theoretical bids for the benchmark treatments (which are the values) alongside the actual bids. Subjects consistently bid a few tokens below their values in the benchmark treatments. Interestingly, this shading is more pronounced under single-good demand than multi-good demand. The average percentage of value that was bid is significantly higher in MG treatments than SG treatments in each phase (p-value = 0.000 for Phase 1, p-value = 0.000 for Phase 2, p-value = 0.004 for

[33] In SG treatments, a bidder drops out when his most preferred good is no longer available. In MG treatments, a bidder continues to bid when his most preferred good is no longer available; at this point, his bid cannot be higher than his second-highest value. For comparison's sake, we limit the MG observations to bidders whose most preferred good is available in the phase of interest.

Phase 3).[34] Multi-good demand has an effect on bidding in the benchmark treatments as well as the bidder's choice treatments. However, this effect is purely behavioral; there is no theoretical foundation for bidding less than value in a second-price good-by-good auction.

In light of this behavioral discovery, we retest revenues to reflect optimal behavior in the benchmark treatments. That is, we compare bidder's choice revenues to the theoretical benchmark revenue; if bidders had behaved according to theory in GBG auctions, would our main result hold? Figure 1.6 displays this new information. We find that our revenue result is, in fact, robust to GBG behavioral biases. The difference between the bidder's choice (BC) revenue and the benchmark (GBG) revenue is significant for both single and multi-good demand. Additionally, the difference in these differences is also significant; the revenue premium is significantly reduced when bidders value more than one good.

In the final part of our analysis, we use econometric methods to demonstrate how risk preferences, variance over values and individual characteristics affect bidding behavior. Our model focuses on the first and second phase BC bids where a subject's most preferred good is available and GBG bids for the most preferred good, allowing us to compare outcomes between persistent and non-persistent competition. We know that no subject has a value of zero for their most preferred good, so a bid of zero is never optimal in our model; we do not need to control for left-hand censoring. It is also never optimal for a subject to bid more than 100% of his value so the fact that the bids are capped at 100% should not cause a bias. Therefore, we use simple linear models with errors clustered at the individual bidder level to analyze bidding behavior. Alevy et al. (2010) use a Tobit model to allow for corner solutions where a subject's optimal bid is zero. In their model, however, they incorporate bids for all available goods, which include goods that may have no value to the bidder. Our use of induced values in a laboratory experiment, on the other hand, allows us to focus on Phase 1 bids (R and X from the theory section), which drive revenues.

Table 1.14 presents the OLS estimates. The baseline for the model is the benchmark GBG auction. We use subjects' bids as a percentage of subjects' highest values as the dependent variable. Since theory predicts a bidder's BC bid should be a fraction of their value, this approach allows us to explore how various characteristics affect bidding behavior. We find that the bidder's choice mechanism

[34] The actual difference in tokens between PC and NPC is also statistically significant for the first two phases (3.72 is a significantly larger difference than 1.31, etc.). We tend to focus on percentage differences, however, because the risk neutral theoretical predictions provide bids in terms of proportion of value.

lowers bids as compared to the benchmark by about 12% of the subject's value for single-good demand and about 13% for multi-good demand (during the first phase).

We also find that subjects increase their bids significantly as the experiment progresses, but at a decreasing rate (the coefficient on "Round" is positive and significant, while the coefficient on "Round^2" is negative and significant). As expected (though contrary to the field study), subjects raise their bids in the second phase if their preferred good is still available; the interaction term for the BC treatment and the second phase has a positive, significant coefficient for single-good demand.[35] This interaction term is not significant for multi-good demand. This is probably due to the fact that the optimal bidding path is flatter for multi-good demand than single-good demand (as long as the most preferred good is available), as seen in Table 1.12. Thus, the effect is more subtle.

Additionally, we find that grade point average has a positive and slightly significant effect on the percentage of value bid under multi-good demand. Contrary to expectation, an indicator for the variance of a subject's values in multi-good demand is not significant. This suggests that subjects may exhibit a threshold bias. It may be the case that bidders perceive *any* positive values for their lesser preferred goods to be the same (versus zero values in SG treatments); i.e. the subject considers that he has a chance to earn surplus in later rounds, but does not consider what that surplus may be. If this is the case, the effects of risk aversion would be muted.

Finally, we also control for risk preferences. We do not expect that risk preference should have an effect in the benchmark, so the fact that this variable is not statistically significant is not a surprise. However, we also interact risk preference with BC; this variable is not significant as well, contrary to expectation. It is possible that the risk elicitation we used was too coarse of a measure to pick up on the differences in risk preference which might affect bidding behavior. The other possibility is that the behavioral bias proposed by Eliaz et al. (2008) could theoretically bias bids, though we argue in the discussion that this is extremely unlikely.[36]

V. Discussion

[35] We do not analyze phase differences for the benchmark because: (i) theoretically, drawing the highest value for good "B" versus good "A" or good "C" should not affect bids and (ii) we see from Table 5 that, in fact, bids in each benchmark treatment are not significantly different between phases.

[36] We also test for endogeneity of risk preference and find that it is not endogenous.

Bidder's choice auctions have been shown to yield higher revenue than simple good-by-good auctions. Theoretically, this is a result of risk aversion, but Eliaz et al. (2008) find evidence to support the bidder's choice premium is partially the result of a behavioral bias, causing subjects to believe they are competing with more people than they actually are. In SG scenarios, this bias is plausible and could theoretically be responsible for the BC revenue premium. However, this bias almost certainly would not affect bidding behavior in MG scenarios because bidders would need to believe that they were competing with people that do not actually exist. Since we do find a revenue premium in our MG treatments, we conclude that the premium is the result of risk aversion, not a behavioral bias.

While the field experiment did not reveal a revenue premium, the laboratory experiment results show that the revenue premium of the bidder's choice mechanism is significantly greater under single-good than multi-good demand. Bidding behavior is generally consistent with the theory and we find that price revelation does not have a significant effect. This suggests that multi-good demand, not information, is probably the reason that our field study finds results that are at odds with previous work.

In conclusion, we find that multi-good demand mutes the revenue superiority of the bidder's choice institution, consistent with the notion that the perceived risk of losing one's most preferred good is softened when there is a chance to win multiple goods. This result implies that bidder's choice auctions should be used in settings where each bidder is likely to strongly prefer one of the goods over the others, though this need not be the same good for every bidder. This conclusion is consistent with Burguet's (2005) result that greater taste diversity leads to greater revenue. In addition, the results explain why our field experiment finds contrasting results to a previous field study conducted by Alevy et al (2010): our field environment is arguably a case of multi-good demand, which mutes the revenue superiority of the mechanism, while the greater taste diversity (closer to single-good demand) that characterizes Alevy et al. 2010 leads the authors to find substantial support for theory.

Future work should include additional field or lab experiments to cleanly distinguish behavioral biases from risk aversion; a more finely tuned and detailed risk elicitation than is typically used may be helpful since the differences in bids may be very small. Interdependent preferences for goods may also be an interesting extension. For example, a prospective landlord who wins an auction for a condo on the seventh floor of a building may subsequently increase his value for another condo on the same floor (i.e. the landlord's preferences for goods depend on the good(s) he has already acquired). This type of preference structure has implications for broadcast spectrum auctions and plausibly many other applications.

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Appendix A

Proof of Proposition 1:

Here, we show that the variance of the second-phase lottery faced by bidders in the simple 2-bidder, 2-good case is larger under single-good demand than multi-good demand.

We use the following formula for the variance of a lottery, where A and B are payoffs and Pr(A) is the probability that outcome A occurs and Pr(B) is the probability that outcome B occurs.

$$Var = (A - EV)^2 \Pr(A) + (B - EV)^2 \Pr(B)$$

Under single-good demand, the variance of the second-phase lottery equals:

$$Var_{SG} = \left(1 - \frac{1}{2}\right)^2 \left(\frac{1}{2}\right) + \left(0 - \frac{1}{2}\right)^2 \left(\frac{1}{2}\right) = \frac{1}{8} + \frac{1}{8} = \frac{1}{4}$$

Under multi-good demand, the variance of the second-phase lottery equals:

$$Var_{MG} = \left(1 - \alpha - \frac{1}{2} + \frac{1}{2}\alpha\right)^2 \left(\frac{1}{2}\right) + \left(0 - \frac{1}{2}\right)^2 \left(\frac{1}{2}\right) = \left(\frac{1}{2} - \frac{1}{2}\alpha\right)^2 \left(\frac{1}{2}\right) + \frac{1}{8}$$

$$Var_{MG} = \left(\frac{1}{4} + \frac{1}{4}\alpha^2 - \frac{1}{4}\alpha - \frac{1}{4}\alpha\right)\left(\frac{1}{2}\right) + \frac{1}{8} = \frac{1}{4} + \frac{1}{8}\alpha^2 - \frac{1}{4}\alpha$$

Since $0 < \alpha < 1$, it must be the case that $\frac{1}{8}\alpha^2 - \frac{1}{4}\alpha < 0$. Therefore, $Var_{SG} > Var_{MG}$.

Appendix B

Tables

Table 1.1: Average Revenues

	Phase 1	Phase 2	Phase 3	Market
BC	78.55 (23.08)	64.69 (26.12)	50.16 (18.30)	193.40 (53.49)
GBG	74.07 (29.96)	55.51 (29.66)	75.27 (40.19)	204.85 (67.96)

Table 1.2: Average Revenues (Using Only Markets with Variation in Most Preferred Good)

	Phase 1	Phase 2	Phase 3	Market
BC	82.67 (23.93)	71.59 (26.62)	51.26 (11.29)	205.52 (53.87)
GBG	71.69 (29.78)	49.77 (21.33)	77.21 (41.14)	198.68 (66.53)

Table 1.3: Average Bids in GBG Auctions and 3rd Phase of BC Auctions

	Hiking	Wine
BC (3rd Phase)	34.46 (20.62)	36.18 (23.47)
GBG	50.75 (41.40)	48.08 (40.65)

Table 1.4: Average Revenues in GBG Auctions and 3rd Phase of BC Auctions

	Hiking	Wine
BC (3rd Phase)	45.92 (11.13)	59.49 (28.07)
GBG	58.93 (21.64)	62.84 (43.97)

Table 1.5: Average Bids for Most Preferred Good in GBG and Phase 1 of BC

	Hiking	Wine	IPod
BC (in phase 1 by 1st preferred good)	54.22 (38.85)	72.06 (38.24)	63.65 (49.27)
GBG (for 1st preferred)	82.67 (53.45)	80.72 (49.77)	85.00 (61.86)

Table 1.6: Change in Bids for BC Auctions when Most Preferred Still Available in Next Phase

	Hiking	Wine	IPod	All
Change from Phase 1 to Phase 2	5.84 (10.21)	2.38 (17.44)	2.96 (19.30)	3.29 (17.45)
Change from Phase 2 to Phase 3	2.83 (3.71)	-23.50 (21.76)	(.) (.)	-7.70 (18.72)
Both Phase Changes	4.33 (7.49)	-6.25 (22.03)	2.96 (19.30)	1.00 (18.09)

Table 1.7: Change in Bids for BC when Most Preferred Still Available by Rank in Initial Period

	Rank = 2	Rank = 3	Rank = 4	Rank = 5
Change from Phase 1 to Phase 2	-8.53 (22.60)	5.73 (13.77)	13.20 (25.95)	5.13 (10.63)
Change from Phase 2 to Phase 3	-4.00 (12.73)	2.00 (5.20)	-31.00 (.)	2.00 (2.65)
Both Phase Changes	-7.63 (20.47)	5.07 (12.63)	5.84 (29.40)	4.27 (9.09)

Table 1.8: Effect of Demographics and Personality Measures on Bids

	Dep. Var = BC Bids	Dep. Var = GBG Bids	Dep. Var = Indicator for Increased Bid
Most Preferred Wine	41.03** (8.73)	49.49** (9.75)	--
Most Preferred Hike	42.73** (14.55)	53.28** (15.29)	--
Most Preferred Ipod	36.76** (7.03)	49.72** (10.44)	--
Second Preferred Wine	14.71** (6.39)	6.49 (8.78)	--
Second Preferred Hike	14.12** (5.84)	17.80** (8.19)	--
Second Preferred Ipod	5.35 (14.03)	31.83** (9.16)	--
Wine	3.82 (8.03)	-4.11 (7.13)	--
Ipod	(omitted)	14.61** (7.66)	--
Risk	-13.64** (6.48)	-7.91 (9.12)	-0.30 (0.52)
Educ Above Average	3.22 (6.78)	7.64 (7.48)	-1.69** (0.50)
Income Above Average	6.45 (6.56)	-3.27 (9.25)	0.74 (0.45)
Iq Quiz	4.05 (3.87)	1.11 (3.37)	0.58** (0.25)
Assert	2.76 (1.89)	-2.39 (1.64)	-0.01 (0.09)
Motivation	0.07 (1.21)	-1.42 (1.56)	0.07 (0.07)
Confidence	-1.29 (1.51)	4.41** (1.99)	-0.23** (0.11)
Efficacy	0.59 (1.74)	-1.95 (1.77)	-0.17* (0.09)
Social	-1.95* (1.14)	-0.88 (1.17)	0.15** (0.07)
constant	25.91** (11.40)	35.95** (12.83)	0.99 (0.79)

One asterisk (*) indicates statistical significance at the 10% level and two asterisks (**) indicates significance at the 5% level. Standard errors are in parentheses. Robust standard errors are reported for regressions in the 1st and 2nd columns. The last column reports the results of a Probit model where the dependent variable indicates an increased bid from the prior period. The sample for this model is restricted to instances where theory suggests bids should increase.

Table 1.9: Experimental Design (Laboratory)

Treatment	Number of UTK groups	Number of UAA groups	Subjects per group	Total subjects
BC – NI – SG	4	3	6	42
BC – I – SG	4	2	6	36
BC – NI – MG	4	3	6	42
BC – I – MG	4	3	6	42
GBG – NI – SG	4	2	6	36
GBG – I – SG	4	3	6	42
GBG – NI – MG	4	3	6	42
GBG – I – MG	4	3	6	42
Total	**32**	**22**	**--**	**324**

Table 1.10: Average Revenues

BC Treatment	Average Revenue (Std. Dev.)	GBG Treatment	Average Revenue (Std. Dev.)
BC – NI – SG	152.41 (36.63)	GBG – NI – SG	105.68 (27.52)
BC – I – SG	146.03 (37.15)	GBG – I – SG	97.34 (33.18)
BC – NI – MG	229.96 (20.22)	GBG – NI – MG	211.37 (22.64)
BC – I – MG	232.20 (19.14)	GBG – I – MG	214.20 (22.60)

Table 1.11: Average Bids by Treatment

	BC – 1st Phase (Std. Err.)	GBG – Most Preferred (Std. Err.)	Difference (Std. Err.)
Single-good Demand	48.94 (0.96)	51.69 (0.99)	2.75 (1.38)
Multi-good Demand	71.06 (0.73)	74.24 (0.64)	3.18 (0.97)

Table 1.12: BC Auctions: Average Values and Bids

	Average Highest Value (Std. Dev.)	Average Actual Bid (Std. Dev.)	Average Bid / Value (Std. Dev.)
SG: Phase 1	54.78 (27.59)	48.94 (26.85)	0.892 (0.20)
SG: Phase 2	50.78 (26.62)	46.29 (25.38)	0.916 (0.17)
SG: Phase 3	42.35 (25.96)	39.42 (24.54)	0.934 (0.14)
MG: Phase 1	75.83 (17.40)	71.06 (21.17)	0.935 (0.17)
MG: Phase 2	72.96 (17.29)	68.49 (20.87)	0.938 (0.18)
MG: Phase 3	69.53 (16.76)	66.55 (18.26)	0.959 (0.13)

The Average Highest Value column provides the average highest value remaining in the phase in question; i.e. the value for subjects whose most preferred good is still available.

Table 1.13: Good-by-Good (Benchmark) Auctions: Average Values and Bids

	Average Value for Most Preferred (Std. Dev.)	Average Bid for Most Preferred (Std. Dev.)	Average Value – Bid (Std. Dev.)	Average Bid / Value (Std. Dev.)
SG: Phase 1	54.82 (30.15)	51.10 (30.24)	3.72 (11.20)	0.927 (0.19)
SG: Phase 2	54.38 (22.56)	51.55 (23.09)	2.83 (6.81)	0.932 (0.17)
SG: Phase 3	55.14 (29.50)	52.42 (29.46)	2.72 (7.38)	0.933 (0.17)
MG: Phase 1	79.65 (14.60)	78.34 (15.02)	1.31 (4.57)	0.984 (0.06)
MG: Phase 2	70.38 (19.50)	69.09 (20.50)	1.30 (6.82)	0.980 (0.10)
MG: Phase 3	77.84 (16.18)	75.62 (18.63)	2.22 (9.93)	0.972 (0.13)

The Average Value for Most Preferred is the mean value for the most preferred good. Since Phase 1 was always an auction for good "A" in the benchmark treatments, the first cell in this table provides the average value for subjects who preferred good "A" in SG treatments. The fourth row down in the first column provides the average highest value for subjects whose most preferred good was "A". This table does not include bids for lesser preferred goods in MG (for purposes of a clean comparison between SG and MG). Note that average values are also average theoretical bids in the GBG auctions.

Table 1.14: Estimates of Bidding Behavior

	Model 1: Single-good Demand	Model 2: Multi-good Demand
	Dependent Variable = Bid / Value	
BC	-.119** (.055)	-.130** (.053)
Round	.024*** (.006)	.014*** (.004)
Round^2	-.001*** (.000)	-.001*** (.000)
BC x Phase 2	.024*** (.008)	.002 (.009)
Risk Preference	-.004 (.005)	-.006 (.005)
BC x Risk	.012 (.008)	.013 (.008)
Variance Indicator	--	.004 (.010)
Age	.001 (.001)	-.002 (.001)
GPA	.012 (.009)	.017* (.009)
Gender	.004 (.018)	-.004 (.014)
Constant	.808*** (.060)	.950*** (.043)
N	2080	2220
F	6.20	4.52
R^2	.036	.047

This table includes bids for the first phase of BC auctions and the second phase of BC auctions when the subject's most preferred good is still available. The table includes bids for GBG auctions for each subject's most preferred good. One asterisk, two asterisks, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

Appendix C

Figures

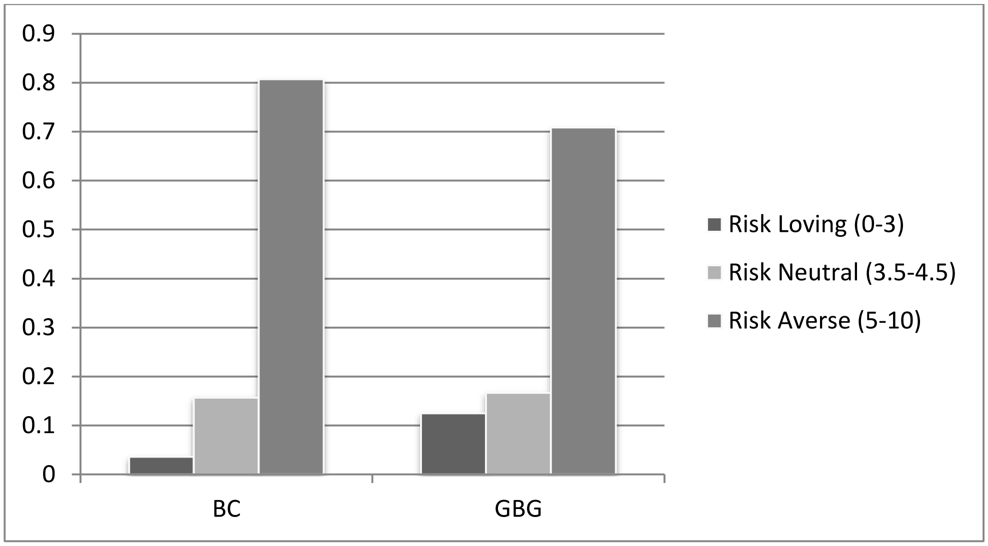

Figure 1.1: Proportions of Participants in Each Risk Preference Group

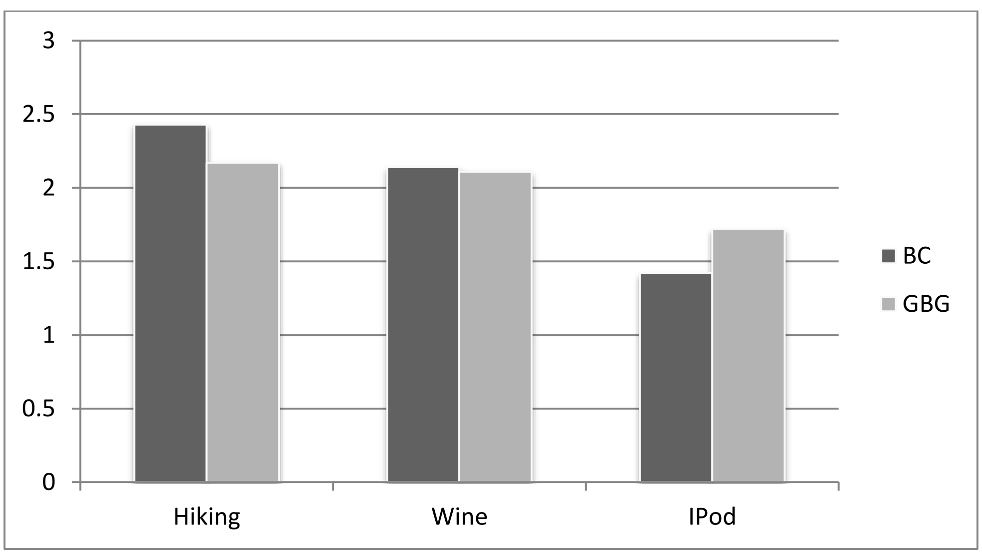

Figure 1.2: Average Rankings for Each Good in Each Auction Format (1 = Most Preferred)

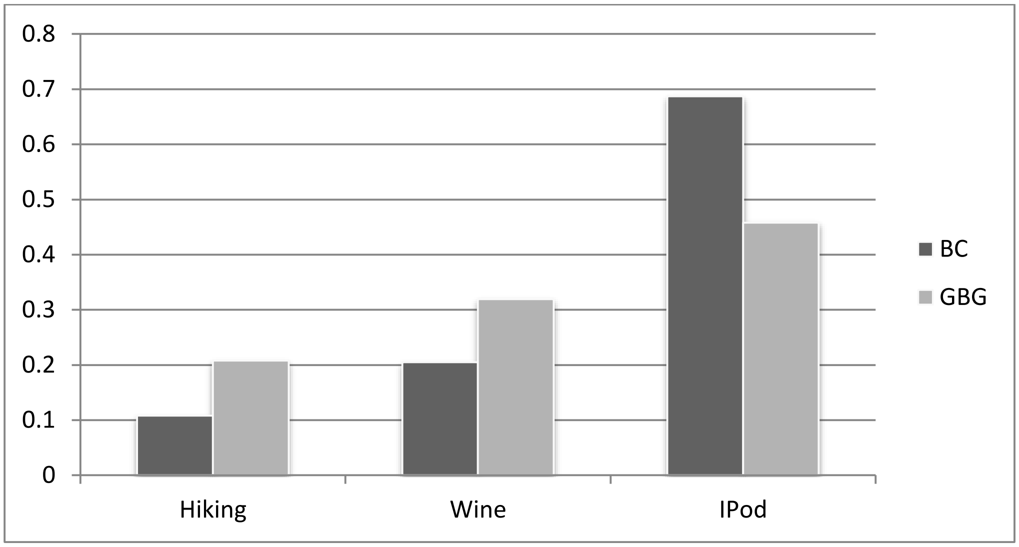

Figure 1.3: Proportions of Participants Who Ranked Each Good as Their Most Preferred

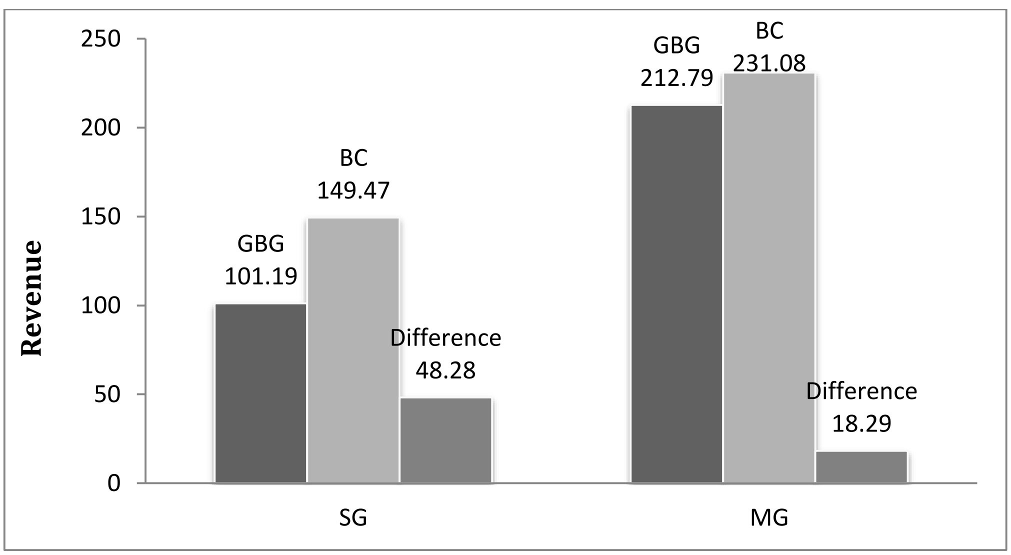

Figure 1.4: Average Revenues

The standard errors for SG treatments are: 2.71 for GBG and 3.23 for BC; the standard error for the difference is 4.22. The standard errors for MG are: 1.91 for GBG and 1.66 for BC; the standard error for the difference is 2.53.

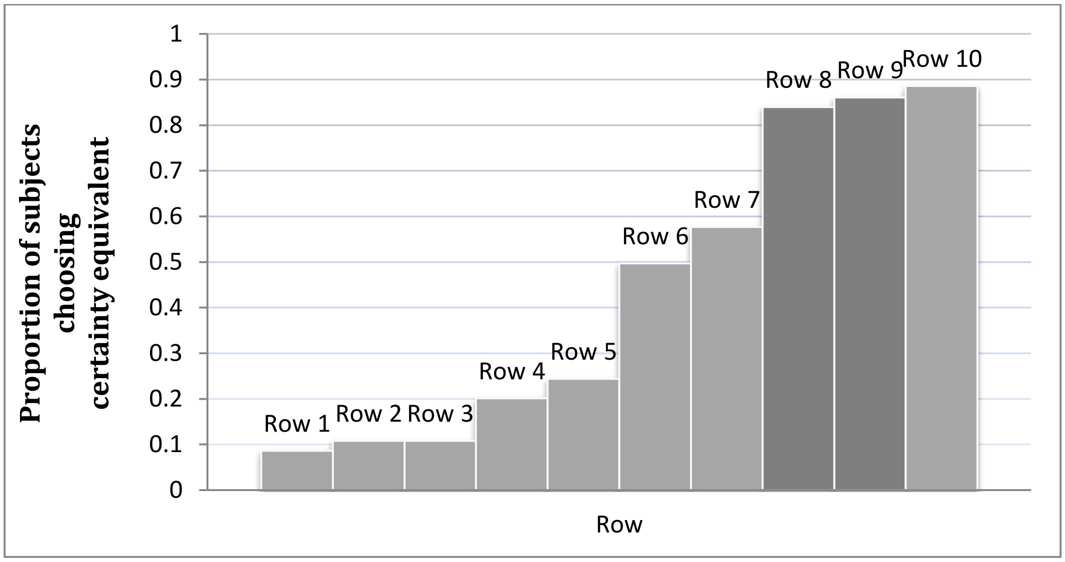

Figure 1.5: Risk Elicitation Results

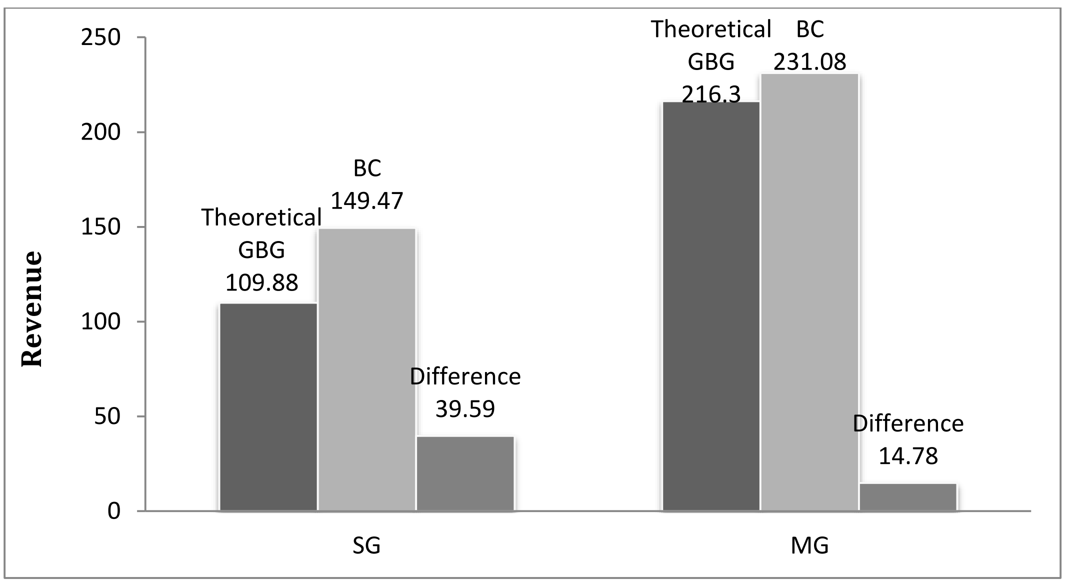

Figure 1.6: Average Revenues Including Theoretical GBG Revenues

The standard errors for SG treatments are: 2.50 for Theoretical GBG and 3.23 for BC; the standard error for the difference is 2.66. The standard errors for MG are: 1.87 for Theoretical GBG and 1.66 for BC; the standard error for the difference is 1.57.

Appendix D

Instructions

This appendix includes the field instructions for the Bidder's choice Auction and the laboratory instructions for the Bidder's choice Auction with Single-good Demand and Full Information. Instructions for other treatments are available upon request.

Field Instructions

Welcome to Jonesie's Auctions. You have the opportunity today to bid in an auction where we will be selling the three bundles of goods displayed on the table in front of you. We will provide you an opportunity to examine each of the items before the bidding begins. We ask that you do not talk with any of the other participants during the session. If you have a question at any time during the session, please raise your hand and a monitor will come to your seat and answer it in private.

Description of the available goods

Good 1: I-Pod and Speakers

- 2 GB I-Pod Nano with 500 song capacity
- JBL On Stage Micro portable music dock for I-Pod

Good 2: Hiking Equipment and Backpack

- REI Ridgeline backpack
- REI Hiker First Aid Kit
- Katadyn Hiker Microfilter

Good 3: Riedel Wine Glasses and Wine

- Set of 4 Riedel Chardonnay Glasses
- One bottle of 2006 Laird Family Estate Carneros Chardonnay
- Set of 4 Riedel Pinot Noir Glasses
- One bottle of DuNah Vineyards Russian River Valley Pinot Noir
- Set of 4 Riedel Cabernet/Merlot Glasses
- One bottle of 2004 Chappallet Napa Valley Cabernet Sauvignon

There are five bidders in this auction which will consist of three phases. Rather than sell the goods one by one, we will sell 'rights to choose' one by one. If in any phase you win one of the rights to choose, you will be able to choose which of the goods remaining at that time you want. To be more precise, in each phase a 'right to choose' is sold to the highest bidder. In the first phase, all five bidders will submit a bid for the first right to choose. The highest of these five bidders wins the first right to choose and selects the good that he or she prefers. At the end of the first phase, every bidder will be informed whether they won the first right to choose and which good was selected by the winning bidder.

Once the winning bidder from the first phase has selected their preferred item, the second phase starts. In the second phase all bidders will submit a new bid for the second right to choose. The highest of these bids wins the second right to choose and selects the good that he or she prefers from amongst the two remaining items. At the end of the second phase, every bidder will be informed whether they won the second right to choose and which good was selected by the winning bidder. In the third and final phase, all bidders will submit a new bid for the remaining item. The highest bidder in the third phase will win the final item.

<u>Auction Rules</u>:

In each phase, you are asked to submit a bid indicating the maximum amount you are willing to pay to acquire the 'right to choose' your most preferred item from the set of available items. Bids may be submitted in intervals as fine as one cent although there is no restriction on the amounts that you can bid. If you do not place a bid, it will be counted as a bid of zero dollars. Once I have received bids from all five bidders, I will order them from highest to lowest to determine the winner in that phase. The price that the winner in each phase pays depends on the bids of the other participants in the market. To be precise, in each phase the individual that submits the highest bid will be awarded the "right to choose" their preferred item for a price equal to the <u>second</u> highest bid submitted for that phase. If you do not submit the highest bid, you will not win the 'right to choose' in that phase and will not be asked to pay anything.

If two (or more) individuals submit the same high bid, then one of these bidders will be randomly selected and awarded the "right to choose" for that phase. In such an instance, the winner pays a price equal to their own bid amount.

<u>Example</u>

If the bids in the first phase are ranked highest to lowest as follows:

$A (bid from bidder A)

$D (bid from bidder D)

$E (bid from bidder E)

$B (bid from bidder B)

$C (bid from bidder C)

Bidder A would win the 'right to choose' his most preferred item from the set of three available items and would pay a price equal the amount of the bid submitted by bidder D.

After Bidder A selected his most preferred item, the bidding process would be repeated with everyone submitting a bid for the 'right to choose' their most preferred of the remaining two items. If the bids in the second phase are ranked highest to lowest as follows:

$E (bid from bidder E)

$C (bid from bidder C)

$F (bid from bidder F)

$B (bid from bidder B)

$A (bid from bidder A)

Bidder E would win the 'right to choose' his most preferred item from the set of two available items and would pay a price equal the amount of the bid submitted by bidder C.

Once Bidder E selected her most preferred good, the bidding process would be repeated one final time with bidders submitting a bid for the final item.

Example

Before you submit your actual bids, I would like you to work through an example. Consider an auction where the following bids were submitted in the first phase. We want you to determine who will win the auction and how much they will pay to obtain the good.

Bidder 1's First Bid = 1103¥

Bidder 2's First Bid = 850¥

Bidder 3's First Bid =1200¥

Bidder 4's First Bid = 250¥

Bidder 5's First Bid = 475¥

Take the two highest bids and order them from highest to lowest:

Highest Bid ________________ 2nd Highest Bid _________________

Now, determine which bidder has won the first 'right to choose' and the amount that he or she will have to pay. Fill in those numbers here.

Winning Bidder _____________ Amount Paid ___________________

To assure that you understand how this auction mechanism operates, I will check your work after you complete this example. Please raise your hand once you have completed the example.

Final Transaction:

The winners in each phase will be required to pay me (cash or check) for the items that they have selected at the end of the session. Once I have received payment, the respective item will be awarded to the winning bidder.

I understand that you may not have anticipated the need to bring cash or your checkbook with you for this experiment. In the case that you do not have the necessary cash (or a check) to pay for the items, we will provide you with a stamped envelope in which to mail the payment. Upon receipt of your cash or check, I will send you the items that you won. All postage will be paid by Jonesie's Auctions for items mailed to the winners.

Note that while this is a real auction for the items displayed on the table in front of you, I plan to use data on the bids in this auction for economic research. I guarantee to sell all three of the items to the winners of this five-bidder auction, whatever the final auction prices turn out to be. Your bids represent binding commitments to purchase the items you win at the prices specified by the auction outcomes.

Good luck – we now invite you to spend a few minutes examining the goods on the table at the front of the room. Once you have examined the items, please return to your seats. Once everyone has been seated, we will ask you to write your bid for the first phase on the sheet provided.

Lab Instructions

Welcome to this experiment on economic decision-making! This experiment consists of 10 rounds plus 1 practice round. At the start of the session, you will be randomly assigned to a group of 6 people and you will remain in this same group for all ten rounds. Importantly, you will not know the identity of the other five participants in your group and the other participants in your group will not know your identity. You will earn tokens in the experiment by purchasing a good you value in a market. At the end of the experiment your tokens will be exchanged for dollars. Each 8 tokens is equal to 1 dollar. Your total earnings in the experiment will equal the sum of your earnings in all 10 rounds.

Values of the Goods

In each group, 3 goods will be available for sale in each round: good A, good B, and good C. Each participant will have a positive value for only one of the goods in each round. Values for this good are randomly determined and will lie between 1 and 100 tokens. That is each number between 1 and 100 is equally likely to be assigned as your value. The other goods have no value (=0 tokens) to the participant. Each participant will receive a different value for his or her preferred good. The value of this good for each participant does not depend on the values of the preferred goods for the other participants. You will have the opportunity to earn money by purchasing your preferred good at a price less than your assigned value.

At the start of each round, you will be informed of which good you prefer and how much you value it. You will not know the preferred goods or the values of the other participants and the other participants will not know your preferred good or value. Among the 5 other participants in your group, there will be one other participant who prefers the same good as you do and his or her value is also determined randomly from the interval between 1 and 100.

Which good a participant prefers changes (randomly) from round to round. This implies that the person who prefers the same good as you will also change from round to round. Each participant will receive a new value for the preferred good in each round. The value for a preferred good in one round does not depend on the value for the preferred good in any other round.

Sale of the Goods

Rather than sell the goods one by one, the market will sell "rights to choose" one by one. If in any phase you win one of the rights to choose, you will be able to choose which of remaining goods you wish to purchase. To be more precise, in each phase a right to choose is sold to the highest bidder. In the first phase, all six bidders will submit a bid for the first right to choose. The highest of these six bidders wins the first right to choose and selects the good that he or she prefers. At the end of the first phase, every bidder will be informed whether they won the first right to choose and which good was selected by the winning bidder.

Once the winning bidder from the first phase has selected their preferred item, the second phase starts. In the second phase the remaining bidders (whose preferred goods are still unsold) will submit new bids for the second right to choose. The highest bidder wins the second right to choose and selects the good that he or she prefers from amongst the two remaining goods. At the end of the second phase, every bidder will be informed whether they won the second right to choose and which good was selected by the winning bidder. In the third and final phase, the remaining bidders (whose preferred good is still unsold) will submit new bids for the remaining good. The highest bidder in the third phase will win the final good. This process will be repeated in each of the ten rounds.

<u>Prices of the Goods</u>

In each phase, you will be asked to submit a bid indicating the maximum amount you are willing to pay to acquire the "right to choose" your most preferred good from the set of available goods. You may submit any number up to your value for your most preferred good. The price that the winner in each phase pays depends on the bids of the other participants in the market. To be precise, in each phase, the individual that submits the highest bid will be awarded the right to choose their preferred good for a price equal to the second-highest bid submitted for that phase. The profit to the bidder from winning will be equal to his or her value minus the price he or she pays, so profit = (value – price). At the end of each phase, the price paid by the winning bidder will be announced to all six members of the group. If you do not submit the highest bid, you will not win the right to choose in that phase and you will not pay anything.

If two (or more) individuals submit the same high bid, then one of these bidders will be randomly selected and awarded the right to choose for that phase. In such an instance, the winner pays a price equal to their own bid amount.

<u>Example</u>

Suppose the bids in the first phase are ranked highest to lowest as follows:

\$A (bid from bidder A)
\$D (bid from bidder D)
\$E (bid from bidder E)

\$B (bid from bidder B)
\$C (bid from bidder C)
\$F (bid from bidder F)

Bidder A would win the right to choose his most preferred good from the set of three available goods and would pay a price equal the amount of the bid submitted by bidder D. After Bidder A selects his most preferred good, the bidding process would be repeated with the remaining bidders (whose preferred goods are still unsold) submitting a bid for the right to choose their most preferred of the remaining two items.

Final Payout

At the end of the experiment, your total tokens earned will be displayed on your screen. You will be asked to fill out a short, anonymous survey and then you will be paid in private. If you have any questions at any time, please raise your hand.