Auctions: A Survey of Experimental Research*

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Introduction

The first question faced in writing this survey is how to organize it and what to include. There have been hundreds of papers reporting experimental work on auctions since the 1995 survey published in the first Handbook of Experimental Economics (Kagel, 1995) so that it is quite impossible, and not very useful, to cover them all. Early theoretical and experimental research on auctions was restricted to simple environments with a fixed and commonly known number of bidders, each demanding a single unit. Accordingly, the 1995 survey focused on the Revenue Equivalence Theorem with respect to independent-private-value (IPV) auctions, with research on common value auctions largely restricted to demonstrating the overwhelming presence of a *winner's curse*.

The present survey takes up where the other one left off. Section I reviews work since then on single-unit IPV auctions. Much of this research continues to be concerned with bidding above the risk neutral Nash equilibrium (RNNE) in first-price sealed bid (FPSB) auctions, work that is covered in Sections 1.1 and 1.2. Empirical economists have developed techniques for analyzing field data on auctions that are designed to uncover the underlying distribution of bidder values. Section 1.3 looks at an econometric analysis designed to investigate the validity of these techniques using experimental data where, unlike in field data, the underlying distribution of bidder values is known and can be compared to the implied probability distribution. Recent work on second-price sealed bid (SPSB) auctions is reported in section 1.4. Section 1.5 reviews work on auctions with asymmetric valuation structures, where *weak* and *strong* bidders compete against each other. Section 1.6 reviews work on procurement auctions (where the low bid wins), dealing with some of the practices that are peculiar to that environment. Experiments investigating the role of cash balances and outside earnings on bids are reported in Section 1.7. Section 1.8 visits an important methodological issue related to analyzing experimental outcomes in auctions and other repeated trial settings.

Section II reviews work on single-unit common value (CV) auctions. Sections 2.1-2.3 review studies investigating some of the important comparative static predictions of the theory; the ability of English auctions to raise revenue compared to FPSB auctions, the effect of a bidder with superior information (an insider) on auction revenue, and bidding in almost common-value auctions (where one bidder has a small private value advantage for the item). Section 2.4 looks at results from the closely related "takeover" game, with a focus on sorting out between recent theories designed to explain the winner's curse. Section 2.5 ties up some loose ends: Examining the behavior of super experienced bidders (e.g., is the persistent bidding above the RNNE a best response to rivals who are bidding more aggressively?), bidding in auctions with both common and private value elements for all bidders, the role of selection bias, demographic and ability effects on the presence of a winner's curse (e.g.; do "smarter" subjects bid closer to Nash prediction and/or make more money?), and the extent to which the winner's curse extends beyond the lab to field settings.

Section III takes up multi-unit demand auctions – auctions in which bidders demand more than a single unit of the items being sold. Much of the work here has been spurred by the Federal Communications Commission's sale of spectrum (air wave) rights, beginning in the early 1990s, and the explosion of theoretical and applied research that followed (as well as the widespread application of auctions for the sale of government owned property rights that followed). Section 3.1 looks at bidding in uniform price and Vickrey auctions for substitute goods. The experiments here are concerned with the issue of *demand reduction* in the uniform price auctions, and the ability of the Vickrey mechanism to correct for this. Section 3.2 extends the study of multi-unit demand Vickrey auctions to different ways of implementing the Vickrey auction – dynamic versus static mechanisms. Multi-unit demand auctions with synergies are covered in Section 3.3, with sequential multi-unit demand auctions covered in Section 3.4. Mechanism design studies that deal primarily with the thorny issues associated with package bidding are covered in Chapter xx.

Section IV deals with several issues that do not fit in neatly elsewhere: collusion, an ever present concern in auctions (Section 4.1), selling multiple units simultaneously to bidders who demand only a single unit (Section 4.2), Internet auction practices (Section 4.3), and entry in auctions (Section 4.4).

The literature is much more extensive and less focused this time around than in the 1995 survey. The good news is that it covers a lot of new ground. The bad news is that we cannot hope to cover all of the good papers out there. Our hope is that we have surveyed enough of the more important developments in enough detail for both the novice and experienced reader to benefit from the survey, and that we have established synthesis in some areas, while not leaving out too much of importance.

I. Single-Unit Private Value Auctions

Initial experimental research on auctions focused on the independent private values (IPV) model, with particular focus on the Revenue Equivalence Theorem (RET). In the IPV model each bidder privately observes their own valuation (known with certainty), bidders' valuations are drawn independently from the same commonly known distribution function, and the number of bidders is known. Under the RET (Myerson, 1981, Riley and Samuelson, 1981) the four main auction formats – first- and second-price sealed-bid auctions, English and Dutch auctions – yield the same average revenue assuming the same number of risk-neutral bidders and the same reserve price.[1] Further, FPSB and Dutch auctions, as well as SPSB and English auctions, are theoretically isomorphic to each other, yielding not just the same ex-ante expected revenue but also the same revenue (price) in any realization of bidders' signals. These two isomorphisms are particularly attractive as they do not depend on risk neutrality (as does the more general RET), which makes for more robust tests of the theory's predictions.

An experimental session typically consists of several auction periods under a given auction institution. Subjects' valuations are determined randomly prior to each auction with valuations being independent draws (iid) from the same distribution, typically a uniform distribution. In each period the high bidder earns a profit equal to his value less the auction price; other bidders earn zero profit. Bids are commonly restricted to be nonnegative and rounded to the nearest penny. Theory does not specify what information feedback bidders ought to get after each auction, which usually differ between experimenters, and which will be shown to impact bidding.

At the time of the 1995 survey it was clear that both the RET as well as the strategic equivalence between each of the two pairs of auction formats failed. Further, there were persistent reports of significant bidding above the risk neutral Nash equilibrium (RNNE) benchmark in FPSB auctions, initial explanations of which focused on risk aversion. This

[1] The Dutch auction starts with a high price which is lowered until a bidder accepts at that price. In English auctions price starts low and increases until only one bidder remains active, paying the price at which the next to last bidder dropped out. In a first- (second-) price sealed-bid auction the high bidder wins the item and pays the highest (second-highest) bid.

explanation generated considerable controversy among experimenters (see the December 1992 issue of the *American Economic Review).* Sorting out between explanations for bidding above the RNNE in FPSB auctions has preoccupied a number of later papers as well, several of which are reviewed first.

1.1 Bidding Above the RNNE in First-Price Private Value Auctions

Isaac and James (2000a) compare estimates of risk preferences from FPSB auctions to the Becker-DeGroot-Marshak (BDM) procedure for comparably risky choices.[2] Aggregate measures of risk preferences under the two procedures showed that bidders were risk averse (RA) in the FPSB auction but risk neutral, or moderately risk loving, under the BDM procedure. The latter may result from subjects' failure to understand and follow the dominant strategy of truthful revelation under BDM (much like what is reported in SPSB auctions; see Section 1.4 below). In any case, what is more damaging to the risk aversion argument, is that the if those who are most risk averse in the auction tend to be most risk averse under BDM, then the Spearman rank order correlation coefficient between individual subject estimates of risk preferences should be positively related under the two institutions. However, as Figure 1 shows, if anything the there is a modest *negative* relationship indicating those counted as most RA in FPSB auction, tend to be least RA under BDM. Although it is well known from the psychology literature that different elicitation procedures commonly yield somewhat different quantitative responses (see Camerer, 1995, pp. 657-61; Mellers and Cooke, 1996), a negative relationship between the two measures is *not* what one would expect. Under the circumstances, while one can still maintain a hypothesis of RA in the FPSB auctions, an equally compelling alternative hypothesis is confusion of one sort or another in the FPSB auctions, with those who are most confused under BDM procedures being most confused in the auctions.[3]

[Insert Fig 1 here]

[2] These experiments use computerized rivals who bid according to the RNNE bidding strategy in the first-price sealed bid auctions. This permits isolating the risk preferences of individual human bidders in each auction market.

[3] James (2007) shows that with experience, risk preference estimates from the buying and selling versions of the BDM procedure converge in the vicinity of risk neutrality, but nowhere near the estimates from FPSB auctions. Engel (2009) compares risk preferences measured in FPSB auctions (with human rivals) to measures using the Holt-Laury (2002) elicitation procedure, reporting much closer correspondence between the two than Isaac and James do.

Dorsey and Razzolini (2003; DR) look at IPV auctions in which a single human bidder competes in a series of FPSB auctions with three simulated buyers who bid according to the RNNE. They compare bids in this setting to an equivalent lottery procedure in which the same subjects essentially pick their preferred probability of winning against their computerized rivals, with expected profits conditional on winning being computed for them for each probability level chosen. Mean lottery-equivalent bids are compared to mean auction bids over the relevant range of valuations. As shown in Figure 2, mean bids are essentially the same between the two procedures over the interval [0, 750], the first three quarters of the uniform distribution from which valuations were drawn. In the remaining interval the lottery equivalent bids are consistently *lower* than the auction bids, suggesting that probability miscalculations (how close rivals' valuations are to your own) play some role in bidding above the RNNE at higher valuations. DR also compared bids in FPSB auctions, where subjects are told the probability of winning the auction for each possible valuation, with the lottery equivalent procedure. In this case bids under the two procedures overlapped over the entire range of valuations, which supports their probability miscalculation hypothesis. Finally, note in Figure 2 the humped back nature of the deviations from the RNNE over the range of possible valuations, with mean bids essentially equal to the RNNE over lower valuations, above the RNNE (with the difference growing) for middle valuations, with these differences decreasing over the upper 25% of valuations, only to fall below the RNNE at the very highest valuations. We will return to this point later. Armantier and Treich (2009) study the same issues with similar manipulations, reaching even stronger conclusions that biased probabilistic beliefs are the primary driving force behind bidding above the RNNE, with risk aversion playing a lesser role than previously believed.[4]

[Insert Figure 2 here]

Neugebauer and Selten (2006; NS) compare different information feedback treatments in a series of FPSB auctions against computerized rivals. They focus on three

[4] Elbittar (2009) looks at FPSB auctions with two bidders who know the rank of their valuation. Estimating bid functions assuming constant relative risk aversion, both low and high value subjects bid as if they are significantly *less* risk averse after information about their ranking is released. That is, information about relative rankings seems to alleviate the strategic uncertainty associated with FPSB auctions, inducing both higher and lower ranked subjects to bid lower relative to their valuations, which certainly seems counter-intuitive for the lower valued bidder.

types of information feedback: (i) no information about bids of computerized rivals, just telling bidders if they won the auction or not along with profits earned if they won, (ii) adding information about the bid of the highest computerized rival when they did not win (i.e., the market price, which is the feedback usually employed in experiments), and (iii) adding information about the highest computer's bid in case of winning the auction. They look at differences between actual bids and the RNNE bid in the first auction period and averaged over the entire set of 100 auctions, and do this with different numbers of computerized rivals. The number of subjects bidding above the RNNE in the *first auction period* is reasonably small under all three treatments – 22% - with minimal differences between the three treatments. However, averaged over all auctions, there was significant movement towards bidding above the RNNE in all three treatments, with the largest increase in treatment (ii); 75% of all subjects bidding above the RNNE, with an average estimated risk tolerance parameter (r_i) of 0.78, where 1-r_i is the Arrow-Pratt measure of constant relative risk aversion. In contrast, under treatments (i) and (iii) 41% and 48% of subjects bid above the RNNE, with an average estimated *r* of 1.25 and 1.17 respectively (i.e., on average subjects act as if they are risk loving). NS use "learning direction theory" to explain the changes in bidding over time under the different feedback conditions.[5]

Goeree, Holt and Palfrey (2002) (GHP) report a series of FPSB auctions with two bidders with a limited number (6) of discrete values (requiring discrete bids as well).

[5] There is considerable variation in the extent of bidding above the RNNE relative to the number of computerized rivals under the different treatments: more than 50% bidding above the RNNE under all three treatments with 3 and 4 computer rivals, but less than 33% with 9 computer rivals in treatments (i) and (iii) (67% in treatment ii). Ockenfels and Selten (2005; OS) report similar results from a series of FPSB auctions with two human bidders under treatment conditions (ii) and (iii); With experience average bids are consistently higher under treatment (ii). Similar results are reported with four human bidders in Isaac and Walker (1985; IW). In both OS and IW there is a clear tendency for the bid ratio (bid/value) to *increase* more often following a lost income earning opportunity than for it to *decrease* following "money left on the table" in case of winning under treatment (iii). OS argue that since the impulse to decrease bids is not present in treatment (ii), this accounts for the bid ratio increasing more with experience (bidders act as if they are more risk averse) than in treatment (iii). They go on to attribute the greater responsiveness to lost income earning opportunities to a social comparison process along the lines developed in Bolton and Ockenfels (2000) and Fehr and Schmidt (1999) (see Cooper and Kagel, 2008; Chapter xx for a review of the other regarding preference literature). However, the fact that responses to treatments (ii) and (iii) are the same with computerized as well as human rivals would seem to argue against a social comparison process. Finally note that Cason and Friedman (1997, 1999) report similar asymmetric responses to lost income earning opportunities as opposed to leaving money on the table in two-sided SB auctions.

They employ a low and high values treatment with the same RNNE bid in both treatments, but with the cost of bidding above (below) the RNNE being higher in the low (high) values treatment. They employ discrete values in order to estimate a quantal response equilibrium (QRE). They find bidding above the RNNE in both treatments, with an estimated Arrow-Pratt measure of constant relative risk aversion (CRRA) under the QRE of approximately 0.50 in both cases. They compare their QRE model with risk aversion to (i) a non-linear probability weighting model and (ii) a joy of winning model. The non-linear probability weighting model fits the data as well as the QRE with risk aversion but has one additional parameter, and does not overweight (underweight) small (large) probabilities and underweighting of large probabilities as one would expect. Joy of winning adds nothing to the QRE estimates with risk aversion, while a pure joy of winning model fits the pooled data quite well, although not as well as the QRE with risk aversion.

GHP take on the Rabin (2000) critique that estimates of risk aversion from laboratory experiments do not plausibly scale up to larger gambles, so that given the levels of risk aversion reported subjects would (implausibly) avoid very attractive large gambles. Their response to this critique is that the relevant argument in subjects' utility function is gains and losses from particular gambles and/or is defined over a smaller time interval (e.g., within the experimental session itself) as opposed to changes in wealth. On this point, also see Cox and Sadiraj (2006).

Cason (1995) investigates SB emission trading auctions where both constant absolute risk aversion and CRRA requires bidding *below* the RNNE. In auctions with all human bidders, 75% of the subjects bid *above* the RNNE. Replacing the human competitors with robots, the number of subjects consistently bidding above the RNNE dropped to 50%.[6]

1.2 *Bidding Above the RNNE and Regret Theory*

Rabin (2000) points out that alternatives to expected utility theory would seem to provide a more plausible account of the substantial risk aversion over modest stakes observed in experiments without requiring ridiculous levels of risk aversion over large stakes. Filiz and Ozbay (2007; FO) explore the implications of one such model, regret

[6] See Kagel and Levin (1993) for similar prediction and results in third-price SB auctions.

theory (Loomes and Sugden, 1982; Bell, 1982) in an experiment looking at bidding in FPSB auctions.[7] In their analysis they note that the information bidders receive at the end of the auction may generate one of two types of regret: (1) "Losers' regret" if a losing bidder could have won the item with a higher bid and earned positive profit and (2) "Winner's regret" if a winning bidder could have earned more by bidding less (money left on the table). They first demonstrate that loser's regret by itself will generate bidding above the RNNE and that winner's regret, by itself, will generate bidding below the RNNE. To isolate the effect of these two factors, and to judge their relative strength, they conduct a series of one-shot, FPSB auctions in which following completion of the auction (i) losers learn the winning bid but the winner learns nothing about others' bids (Losers' regret), (ii) winners learn the second highest bid but losers learn nothing about the winner's bid (Winner's regret), and (iii) a control treatment in which bidders learn nothing about others' bids (No regret).

They run one-shot as opposed to repeated auctions on the grounds that their theory relies on bidders anticipating future regret in terms of their current decisions, while repeated auctions introduce the possibility of regret from outcomes in previous rounds. To gather sufficient data they solicit bids for 10 possible valuations from each bidder, and use the *average* bid (across bidders in several auctions) at each of these valuations as the dependent variable in estimating linear bid functions.[8] The estimated slope of the bid function in the control treatment (no information provided) is 0.79, just within the 95% confidence interval for the RNNE value of 0.75 in auctions with four bidders. The slope estimated from the winner's regret treatment is just below this (0.77), but is not significantly different from the no information treatment. However, the slope of the loser's regret treatment is 0.87, which is significantly higher than the no information treatment. Although averaging bids across subjects with the same valuations does not bias the estimated slope coefficients, it no doubt biases the standard errors of the

[7] See Engelbrecht-Wiggans (1989) for an earlier discussion of the potential effect of regret on bids in first-price private value auctions.
[8] Linear bid functions were estimated with no intercept. There were four bidders in each auction.

estimates downward as it removes any *between-subject* variation in bids. Thus, the statistical significance of their results is suspect.[9]

Engelbrecht-Wiggans and Katok (2008, 2009) (EK) report two experimental tests of regret theory with human bidders competing against two computerized rivals. The primary variation between the two papers consists of the number of auctions bidders receive feedback from. When subjects receive feedback on 1000 auctions evenly divided between each of five valuations, the predictions from regret theory are supported across the board, although it takes some time before bidding under the winner's regret treatment drops below that of the no regret (no feedback) treatment (EK, 2008). Results are considerably more mixed when subjects decisions affect only a single auction and they only receive feedback for that one auction (EK, 2009). .[10]

The NS experiment discussed in Section 1.1 also has implications for regret theory as their treatment (i) corresponds to a no regret treatment, with treatment (ii) corresponding to FO's losers' regret. For bidders competing against three or four computer rivals (the treatments that come closest to FO and EK) NS find 50% of their subjects bidding above the RNNE in the first auction of their no regret treatment versus 9.1% in their losers' regret treatment, which does *not* match FO's results. Averaged over all auctions they find essentially the same number of subjects bidding above the RNNE in the no regret and loser regret treatments which is qualitatively consistent with EK.

To sum up: The design and execution of experiments to explain bidding above the RNNE in FPSB auctions on account of regret theory is quite innovative. However, the statistical significance of FO's results are suspect, NS fails to replicate their results, and EK's results suggest that the impact of regret is sensitive to the level of feedback subjects get regarding auction outcomes.[11] Nevertheless, the idea that losers' regret is

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[9] FO also report the results of a survey in which subjects were asked to rate the intensity of emotions they would feel after they got the relevant information. They find that losers' regret is substantially more intense than the regret in the other two treatments. FO go on to show that winners' regret has no role to play in second-price, English and Dutch auctions, but that loser's regret can impact Dutch auctions.

[10] They also have an interesting test for CRRA in which they report earnings back to bidders aggregated over 10 auctions, as opposed to auction by auction as is typically done. Under CRRA aggregated earnings should lead to less overbidding relative to the RNNE compared to knowing earnings following each auction. Their test provides *no* support for CRRA.

[11] Hayashi and Yoshimoto (2012) construct a structural model of bidder behavior in sealed-bid auctions which nests risk-aversion and regret-aversion. Applying the model to two sets of experimental data, they conclude that bidders exhibit weak risk-aversion (close to risk neutrality) and strong regret-aversion.

greater than winner's regret receives support from studies showing that subjects tend to increase their bid to value ratio more often in response to losing out on an income earning opportunity compared to leaving money on the table (Ockenfels and Selten, 2005, Cason and Friedman, 1997, 1999).

One important methodological point these experiments emphasize is that results from earlier experiments can be, and often are, reinterpreted in light of new and different theoretical perspectives. This in turn calls for new experiments to see if the insights from the new perspective are satisfied in the data. On this score there is still more work to be done on anticipated regret if it is to explain bidding in private value auctions.[12]

1.3 *Using Experimental Data to Corroborate Maintained Hypotheses Empirical Applications to Field Data*

Bajari and Hortacsu (2005) (BH) use experimental data from FPSB auctions with three and six bidders to non-parametrically estimate bid functions. The primary purpose of their paper is to determine whether structural models of first-price auctions as applied to field data can generate reasonable estimates of bidders' private information.[13] The latter is an essential element of what econometricians hope to recover in examining field data. In using experimental data the econometrician has at his disposal bidders' actual valuations against which to judge the accuracy of the recovery process, data that is not available in field applications. Further, unlike with field data, there is no question that one is dealing with an IPV auction as opposed to say a common value, or affiliated private value, auction which should reduce the possibility of specification errors.

The results are also of interest to experimenters as BH test between four competing models: (i) the RNNE, (ii) Nash equilibrium bidding but with (homogenous) CRRA bidders, (iii) an adaptive learning model in which bidders maximize their expected utility based on beliefs about the distribution of bids (formed on the basis of previous auction outcomes), and (iv) QRE with CRRA bidders. Their results show that Nash bidding with risk aversion provides the best overall fit to the data.[14] Further, they are unable to reject a null hypothesis that the actual and estimated distribution of bidder

[12] One unanswered question that might be worth exploring is what does regret theory have to say about bids relative to the RNNE in third-price auctions (KL, 1993) or in Cason's (1995) emission trading auctions.
[13] For a similar exercise with respect to common value auctions see Armantier (2002).
[14] The RNNE model provides a reasonably good fit to the data in auctions with six bidders, but risk aversion is necessary to explain bidding in auctions with three bidders.

valuations is the same under this specification. In reaching this last conclusion they need to trim the upper bound of the support from which valuations are drawn (corresponding to the top 5% of all bids) as there is a negative correlation between bids and values over this part of the support. This is consistent with DR's results, reported in Section 1.1 above, that at the highest private valuations bids actually drop below the RNNE reference point. QRE with risk aversion provides results similar to those of the Nash model with risk aversion, but does not correctly pin down the lower end of the support from which valuations are drawn.

In short, this whole exercise represents a novel use of experimental data. It also illustrates the potential for complementarities between experimental and "real" data. On this score also see Sections 1.7 and 2.5.3 below for applications of applied econometric techniques employed in analyzing field data to better understand experimental outcomes.

1.4 Second-Price Private Value Auctions

The 1995 survey covered research showing a breakdown in the strategic equivalence between second-price and English clock auctions, primarily as a result of bidding above value in second-price auctions as opposed to sincere bidding (bid equal to value) in the clock auctions. Since then there have been several experiments designed to better understand why subjects overbid in second-price auctions, as well as why subjects do so much better in English clock auctions. We review these below.

Shogren, Parkhurst, and McIntosh (2006) (SPM) report bids from SPSB auctions conducted under a tournament structure so that bidder earnings depend on the total points earned over 20 auction trials with a tournament payoff structure: the player with the most total points earned $120, the second most earned $80, and so on, with the three lowest earning $5 each. They compare bidding in the tournament to bidding in a series of 20 standard SPSB auctions. Each auction had a total of 10 bidders who were repeatedly matched with each other as part of the tournament structure.[15]

Deviations from sincere bidding were much smaller in the tournament than in the standard SPSB auctions with the difference between bids and values (bid – value) averaging 6.28 (63.51) in the standard auctions versus 0.96 (4.14) in the tournament

[15] In each auction bidders got to see if they won the auction and how much they earned, with no one seeing what anyone else bid or earned.

(standard deviations are in parentheses). However, there were relatively small differences in the frequency with which the highest value bidder won the auction averaging 55.0% in the tournament versus 42.5% in the standard auctions, with similar results for the frequency with which the highest and second highest value bidders won (72.5% in the tournament versus 70.0% in the standard auctions). SPM conjecture that the superior performance in the tournaments results from the fact that the typical mistake of bidding above value has a much greater adverse effect on outcomes given the tournament pay structure. However, under a tournament structure there is clear motivation for losing bidders to bid above value as this reduces the winner's profits, which may help in terms of winning the tournament, so that it is far from clear that SPM's explanation for the difference is correct.[16]

Garratt, Walker and Wooders (2012) (GWW) conduct a SPSB auction using subjects who regularly participate in eBay auctions for Morgan ("Golden Age") silver dollars. Arguably these subjects have considerable field experience given the similarity between eBay and second-price auctions. (But there are significant differences; see Roth and Ockenfels, 2002, reported in section 4.3 below.) GWW invited these bidders to participate in a standard SPSB auction with induced valuations from a support comparable to the range of values that Morgan silver dollars sell for. There were five bidders in each auction. After bidding once in a presumably one-shot auction, subjects were invited back for a second-round of bids, conducted as a control against possible skepticism that payoffs in round one might not be for "real."

[Insert Fig 3 here]

Figure 3 shows bids and valuations from their experiment. Looking at these they conclude that "… despite having substantial experience with auctions in the field, eBay subjects do not value bid." (p. 7). GWW compare the frequency of sincere bidding to Kagel and Levin's (1993; KL93) experiment, employing the same criteria that any bid within five cents of a subject's value is counted as sincere. They find essentially the same frequency of sincere bidding, 21.2% versus 27.0% in KL. However, there is substantially more under bidding than over bidding in their data: 41.3% (37.5%)

[16] Consider the last round of a two round tournament with valuations from the interval [0, 10], where bidder 1 has a lead of four points and gets a signal of 5. Bidding 8 dominates sincere bidding as it assures winning the tournament.

underbidding (overbidding) in GWW versus 5.7% (67.2%) in KL. GWW are able, at least qualitatively, to resolve this discrepancy after they break their data down into eBay only buyers versus eBay sometime sellers, as sellers tend to underbid much more often than buyers do (50.9% versus 29.5%). There is a corresponding discrepancy in the frequency of overbidding, 45.5% for buyers versus 32.1% for sellers, with both sets of differences statistically significant at the 10% level using a non-parametric Mann-Whitney test.[17]

The fact that frequent sellers underbid as opposed to those with no selling experience tending to overbid has certain parallels to Burns (1985) study comparing professional wool buyers to students in a continuous double auction market. In that experiment the students performed much better than the wool buyers (earning more money with more efficient outcomes), in large measure because the wool buyers ignored subtle differences between the laboratory experiment and the wool market. The connection here is that people who sell on eBay will typically only buy if the price is below their value, as otherwise they cannot profit from resale, and one cannot expect them to ignore these habits when put into a new situation. This is consistent with the psychology literature which suggests that in deductive reasoning processes people typically employ short-cuts, developing mental models of situations and reasoning about them in the context of the model (Johnson-Laird, 1999). Thus, it is easy to see how Burns' wool buyers might behave in ways that are more appropriate to their customary environment which was similar to, but not exactly the same, as the laboratory environment. Similarly, it is easy to see how e-Bay sellers, who make a living by buying low and selling high, might deviate from sincere bidding by bidding less than their induced values, while buyers, as is typical of standard laboratory subjects, bid above their induced values. In short, there is no particular reason to think that experienced professionals will perform much better than student subjects when placed in a laboratory

[17] The difference in overbidding between buyers and sellers is significant at the 5% level in a regression analysis. Subjects were told that they could lose part, or all of, their $15 participation fee in case they won the auction with the second-highest bid above their value. GWW's results have been cited several times as demonstrating that the tendency to overbid in SPSB auctions disappears for experienced bidders. It is hard to see how this conclusion could be reached once one looks at the detailed data, or the aggregate data conditional on bidders' eBay experience.

setting, unless there are *strong and relevant* similarities between the field setting they are familiar with and the laboratory environment.[18]

Andreoni, Che, and Kim (2007; ACK) report the highest rate of sincere bidding in SPSB auctions we are aware of – 77.3% overall (85.5% in the last 10 periods) – in auctions with four bidders and a uniform distribution of valuations. They find that sincere bidding drops substantially, largely replaced by overbidding, when subjects know their rivals resale values. They attribute this result to spite.[19] While spite might explain overbidding when rivals valuations are known, this does not provide a credible explanation for overbidding absent this information, as there is minimal overbidding in English clock auctions, which are strategically equivalent, and in which spite (as well as joy of winning) should play just as strong a role.

Cooper and Fang (2008; CF) look at bidding in a series of two player second-price auctions with bidders valuations drawn from an approximate normal distribution. Their primary treatment variable consists of noisy information about rival's valuations, which in some cases is provided exogenously, and in other cases can be purchased. In the control treatment, with no information about rival's valuations, just under 40% of all bids are sincere, with overbidding accounting for most of the deviations. Unlike ACK, with exogenously provided information about rival's valuations the rate of sincere bidding increases, especially with less noisy information. The probability of overbidding is reduced in response to costly mistakes (overbidding that causes subjects to lose money), with the apparent stability of bidding above value resulting from the infrequency of costly mistakes.

CF also find that subjects tend to buy costly information about rivals valuations (since the game has a dominant strategy, at least from a game theoretic perspective this involves throwing money away), with these purchases diminishing over time. There is

[18] On this score also see Dyer, Kagel, and Levin (1989; DKL) along with Dyer and Kagel (1996; DK). Also see Fréchette (2010) for a survey of differences in laboratory behavior between professionals and students.

[19] ACK employ an (augmented) dual market technique with subjects bidding in each of three markets with the same valuations. In the first market bidders only have information about the common distribution from which values were drawn. In the second market precise information about one other bidder's value is provided and in the third market information about all other bidders' values is provided. ACK also explore the impact of information about rivals' values in first-price auctions where the theory makes clear predictions, which are largely satisfied, at least qualitatively.

considerable heterogeneity in these purchases with subjects who overbid the most buying information more often. This suggests a split in the population between more "rational" types who neither overbid nor pay to buy essentially worthless information, and less rational types who commit both types of mistakes.

Georganas, Levin, and McGee (2010) look at the effect of penalties for deviations from sincere bidding. This involves multiplying any realized losses by a factor β, where β is at times greater than 1, equal to 1 or less than 1. These penalties have no impact on the dominant strategy. Although Ss fail to discover the dominant strategy, they respond "sensibly" to changes in the value of β, getting closer to the sincere bidding when $\beta = 20$, and further away when $\beta = 0.1$ (see Figure 4). The impact of the change in β is immediate and occurs even though bidders do not typically lose money when deviating from sincere bidding. These responses are consistent with the notion that subjects bid above value in SPSB auctions out of the mistaken notion that it increases the likelihood of winning with minimal adverse income effects, as winners pay the second-highest bid (see Kagel, Harstad, and Levin, 1987). In terms of this argument, what changing β does is to alter the potential cost of such wins, which in turn alters bids in the expected direction. Although joy of winning can also explain bidding above value (with changes in β impacting the cost of doing so), joy still cannot explain why bidding above value is so limited in English clock auctions when $\beta = 1$, whereas it is so prevalent in the SPSB auctions.

[Insert Fig 4 here]

1.5 Asymmetric Private Value Auctions

While much of the auction literature has focused on bidders that are *ex-ante* symmetric, in many auctions it is commonly known that one or more bidders (the *strong* bidders) are likely to have higher valuations for the auctioned item than the other (*weak*) bidders. This extension of the private values model raises interesting theoretical questions (see Maskin and Riley, 2000) that have been explored in a handful of experimental studies reviewed below.

Pezanis-Christou (2002) investigates a model with two risk- neutral bidders ($i = 1$, 2) each demanding a single unit. Bidders values are independent draws from a uniform distribution, with support [0, 100] for the strong bidder and support [-100, 100] or [-300, 100] for the weak bidder, so that the underlying support for the strong bidder first-order stochastically dominates (FOSD) the weak bidder. Negative bids are not allowed, with the weak bidder not allowed to bid when receiving a negative value. Each session consisted of either 60 or 72 auctions in which subjects' type changing between auctions, along with changes in the support for weak bidders' values.

FPSB and SPSB auctions were run. Key comparative static predictions investigated are: (i) In the FP auctions the strong types bid less aggressively than weak types for the same private valuation, (ii) Efficiency is greater in the SPSB auctions, and (iii) Expected revenue is higher in the SP auctions. The intuition underlying (iii) is that since there is a positive probability that weak bidder will not bid (as a result of a negative value), strong bidders in the FP auctions maximize their expected earnings by placing very low bids ("low balling") when they get low values. In contrast, sincere bidding remains a dominant strategy in the SP auction, resulting in higher revenue on average. Both the frequency of low-balling and the revenue differences should be greater when the weak bidder has a greater likelihood of drawing a negative value (with support [-300, 100]).

As predicted, strong bidders shave their bids more than weak bidders do in the FP auctions under both treatments; where bid shaving is defined as the ratio $\varepsilon_i = (v_i - b_i)/v_i$ where v_i is bidder i's value. And they shave more when weak bidders draws are from [-300, 100]. About 46% of all SP bids were sincere, which is substantially larger than in previous experiments, with 40% of bids above value. However, SP revenues were close to their predicted level, indicating that whatever overbidding there was had to be relatively small.

As predicted, the SP auctions have higher efficiency averaging 97% versus 95% with weak bidders support [-100, 100] and 99% versus 96% with support [-300, 100].[20] However, contrary to the theory, average revenue was greater in the FP auctions in both cases. Although average revenue in the SPSB auctions was approximately equal to its predicted value, revenue in the FP auctions was well above the RNNE prediction. Pezanis-Christou attributes this failure of the theory to bidders' difficulty in recognizing the profitable opportunities from low-balling in the FP auctions. However, he does not

[20] Efficiency is measured by the ratio of the [winner's value]/[highest value] * 100.

attribute this to risk aversion as (i) with the weak bidders draws from the interval [-300, 100] the revenue ranking is not affected by risk aversion, (ii) simulations assuming both bidders are extremely risk averse cannot account for the reversal of the revenue ranking with weak bidders draws from the interval [-100, 100], and (iii) the extent to which strong types bid above the RNNE in the FPSB auctions was decreasing over time, suggesting that subjects were employing an adaptive bidding strategy as opposed to a static, fully-optimizing one.[21]

Güth, Ivanova-Stenzel and Wolfstetter (2005; GISW) conduct an experiment in which bidders values were drawn from a *uniform* distribution with support [50, 150] for weak types versus [50, 200] for strong types, running both first- and second-price sealed bid auctions. As predicted under the RNNE, efficiency is consistently higher in the SP auctions averaging 98%, 99%, and 99% versus 97%, 97%, and 98% over the three phases of the experiment.[22] Although the theory predicts that weak bidders' payoffs will be higher in the FP auction, and strong bidders' payoffs higher in the SP auction, both types' average payoffs are significantly higher in SP auctions. Bids are close to predicted levels in the SP auctions (sincere bidding), but as typically reported, are substantially higher than the RNNE in the FP auctions. The latter accounts for the failure of weak bidders' payoffs to be higher in FP auctions.

A closer look at bid patterns shows that strong bidders in FP auctions generally obey first-order rationality, as there are few bids above 150, the maximum possible valuation for weak bidders. Further, weak bidders shave their bids less than strong bidders at higher valuations ($v \approx 100$). Although, this satisfies a key qualitative prediction of the theory, the pattern differs from the predicted one as the differences in bid shaving between weak and strong bidders does not increase monotonically over higher valuations, and the differences are not nearly as large as the theory predicts. When given a choice, both weak and strong bidders overwhelming chose the second-price auction, consistent with the significantly higher payoffs for both types under this format.

[21] Note, however, that the revenue reversal remains even after looking at bidding in the last 30 auctions, where learning should have tended to stabilize.
[22] No statistical tests are reported for this.

Chernomaz (2012) studies asymmetries resulting from two otherwise symmetric bidders merging to submit a single bid based on the highest of their private valuations.[23] This s*trong* bidder competes against a single w*eak* bidder. Each bidder draws a private value from a common uniform distribution, but by virtue of using the higher of their two private values, the value distribution for the strong bidder FOSD the weak bidder. Subjects participate in a series of FPSB auctions under each of three treatments: (i) They bid as separate entities based on their private values in an auction with three bidders. (ii) "Merged" firms let each subject bid separately, with no communication, based on the higher of their two valuations. (iii) Merged firms submit a single agreed upon bid after they have the opportunity to communicate via an instant messaging system. Subjects' roles as weak or strong bidders remain fixed throughout a session, as do the pairings for the "merged" firm. The dual market technique is employed so that in each auction bids under all three treatments are based on the same valuations with the market to be paid off on determined randomly.

Between treatment predictions consist of the following: In equilibrium, the strong type bids less than the weak type with the same valuation, resulting in less efficient allocations compared to the symmetric (three bidder) auctions. Following the "merger", both weak and strong types bid lower than in the symmetric (three bidder) auctions. As a result, revenue decreases and bidders' profits increase, with the weak bidder getting a larger absolute increase than the strong bidders after splitting their earnings. This last result has implications for the incentive to merge and bid jointly in a fully blown model where joint bidding is determined endogenously.[24]

The experimental results show bidding above the RNNE in both the symmetric and asymmetric auctions. Strong types bid less aggressively than in the symmetric auctions, although the difference is not as large as the theory predicts. Weak types bid the same, or slightly higher, than in the symmetric auctions. Chernomaz shows that this difference can be partly accounted for by the greater incentive strong types have to

[23] There are a couple of different ways to think about what's going on here. The firms have merged so that the bidder with the higher private value is the firm's value. Alternatively, there is a consortium of bidders who bid jointly and agree to allocate the item to the bidder with the highest value, along with some agreed upon device for splitting the profits. All of this is in the background, as in order to simplify the experimental design, which "merged" firm bids is determined by the experimenter, with profits split equally in case of a joint bid.

[24] This result is similar to results from horizontal-mergers in a Cournot oligopoly (Levin, 1990).

reduce bids. Contrary to the RNNE prediction, efficiency is *higher* with joint bidding than in the symmetric benchmark case. This can be explained by the reduction from three to two bidders, so that any inherent noise in bids is less disruptive to efficiency in the two bidder case, as bidders' valuations are further apart on average than in the three bidder case.[25] Strong bidders benefit from joint bidding at least as much as the weak bidders (even after accounting for splitting their profits), indicating that the incentive to bid jointly is stronger than predicted. Finally, there are essentially no differences in bids when members of the "merged" firm bid individually versus bidding jointly. But for some unknown reason, weak bidders tend to submit higher bids when the "merged" firm bids jointly.

Goeree and Offerman (2004; GO) explore the revenue raising properties of the Amsterdam auction when bidders have asymmetric valuations.[26] The Amsterdam auction has two stages: Stage one consists of an English clock auction until all but two bidders have dropped out. The price at which the last bidder dropped is called the bottom price and serves as a reserve price in stage two. Stage two consists of either a first- or second-price SB auction. Further, and this is the unique element, in the second phase both bidders receive a premium which is a proportion of the difference between the lowest stage two bid and the bottom price. With asymmetric valuations, the Amsterdam auction provides endogenously determined incentives for weak bidders compete against stronger rivals. GO compare both a FP and SP Amsterdam auction with a FPSB, an English clock auction and Myerson's (1981) optimal auction design. Treatments consist of symmetric valuations and weakly asymmetric and strongly asymmetric valuations, with four bidders in all auctions (three weak and one strong bidder in the asymmetric auctions).

The FPSB auction generates significantly more revenue than the other auction formats with symmetric valuations (including the optimal auction) as subjects bid well

[25] This is partly an artifact of how efficiency is typically measured when comparing efficiency between different auction structures. One solution is to normalize efficiency measures by the difference from random bidding in each case.

[26] The Amsterdam auction has been used to sell real estate in the Dutch capital for centuries. Premium auctions of this sort are regularly employed in Europe for a variety of items.

above the RNNE.[27] In the weakly asymmetric case the FPSB, the Amsterdam FP and the Optimal auction all raise significantly more revenue than the other two formats (with the FPSB ahead by a nose). In the strongly asymmetric case the Amsterdam auction raises significantly more revenue than the FPSB and the English auction, with the Amsterdam SP raising 10% more revenue than the Amsterdam FP, and only slightly less revenue (7%) than the Optimal auction. English auctions consistently have the highest efficiency but with strong asymmetries, absent some sort of positive incentives for weak bidders, strongly discourages participation as weak bidders (correctly) anticipate that they have little chance of winning (Klemperer, 2002).[28]

Summing Up: Tests of revenue predictions in asymmetric private value auctions are confounded by the fact that subjects tend to bid well above the RNNE in FPSB auctions but bid close to the dominant strategy in SPSB auctions with only two bidders. Bid functions tend to move in the right direction, at least qualitatively, strong bidders tend to bid less than weak bidders for comparable valuations in FPSB auctions. Efficiency tends to be lower in FP compared to SP auctions which is the same result reported for symmetric FP and SP auctions (reviewed in Kagel, 1995). One secondary result of these experiments is that they show closer conformity to sincere bidding in SPSB auctions with two bidders than typically found with larger numbers of bidders. With strong asymmetries, the Amsterdam auction raises more revenue than a FPSB auction, and generates almost as much revenue as Myerson's optimal auction design, but requires much less information on the part of the auctioneer than the optimal auction.[29]

1.6 Sequential Auctions

[27] Net revenues are reported for the Amsterdam auctions, defined as the winner's payment less the premiums paid to the stage two bidders. The premium was set at 0.3 in the experiment.

[28] Hu, Offerman and Onderstal (2011) compare the collusive properties of FPSB and English clock auctions to that of the Amsterdam SP auction. Corns and Schotter (1999), in a proof of principle experiment, demonstrate that proper price preference rules in favor of historically disadvantaged bidders can both increase their representation *and reduce* procurement costs. Ayers and Cramton (1996) report the results of what amounts to a "natural experiment" on the revenue raising effects of price preferences in one of the Federal Government's air wave rights auctions.

[29] Given asymmetric valuations, with weak types bidding more aggressively than strong types, it is natural to think of auctions with resale opportunities, which has motivated a growing theoretical literature (see Hafalir and Krishna, 2008; also Haile, 2003 and Garratt and Troeger, 2006). These models have started to become explored experimentally (Georganas and Kagel, 2011; Lange et al, 2011; Pagnozzi and Saral, 2014).

Experimental research on single unit demand sequential auctions has been devoted to exploring the declining-price anomaly reported in field data: Prices of homogenous auctioned items decrease systematically over the course of selling multiple items (Ashenfelter, 1989, Ashenfelter and Genesove, 1992). Declining prices are an anomaly because economic intuition suggests that prices of identical items sold in a sequence at the same time and place should be the same when each bidder demands a single item. Weber (1983) proves this to be the case for risk neutral bidders. Further, although intuition suggests that risk aversion may cause prices to decline, McAfee and Vincent (1993) demonstrate that this can only be guaranteed if buyers' have strictly increasing absolute risk aversion, a questionable assumption. One advantage of controlled laboratory experiments on this topic is that one can insure that bidders have single unit demands, which is not assured when looking at field data. This is important since with multiple unit demands, there are circumstances under which decreasing prices would be expected to occur.

Keser and Olson (1996; KO) report the first sequential auction experiment with unit demands with paid subjects.[30] Each auction consisted of eight bidders with known supply of four units bidding in a sequence of FPSB auctions. Each bidder made a bid for the first unit, with the highest bidder receiving that unit at the price bid. The winning bidder was no longer permitted to bid, with the auction continuing with new bids solicited for a second unit. This process was repeated for all four units. Prices of units sold were announced following the sale of each unit. Values were iid from a uniform distribution. Four sessions with 20 auction periods each were conducted with subjects not permitted to bid above their values.

The symmetric RNNE bid function for unit *l* under this design with support [0, 1] is

$$b^l(v)=\frac{n-k}{n-l-1}(v),$$

[30] In an earlier paper, Burns (1985) compared bidding in a sequential auction between wool buyers and students in which both groups were motivated "by a desire to succeed in their chosen field." Both groups started out with declining average prices, with the students eventually converging to constant average prices. In contrast, the wool buyers continued to have declining average prices throughout the session. Burns attributed the latter to rules of thumb relevant to field settings but not the more austere conditions of her experimental markets.

where *v* is the bidder's valuation, *n* is the number of bidders and *k* the number of units sold, so that bids on later units are substantially closer to bidders' values than earlier units. However, expected prices remain constant as bidders with higher values get units earlier than those with lower values.

Table 1 reports realized and predicted prices for each of the four units. There is some variation in predicted prices as a consequence of the random draws used in the experiment. Both average and median realized prices decline for later units consistent with the declining price anomaly. Further, prices were higher than the RNNE for all four units, only more so for early units. Overall, average efficiency was 98% compared to close to 85% based on randomly allocating units among the six highest value bidders. KO classify individual bidders as risk averse if the number of bids above the RNNE benchmark is greater than the number of bids below it. By this measure, 84% and 81% of all subjects were risk averse with respect to unit 1 and 2 bids, with these percentages decreasing to 72% and 53% for bids on units 3 and 4.[31]

[Insert Table 1 here]

We are aware of two replications of the KO experiment. In Salmon and Wilson (2008) sold two units in auctions were four bidders for up to 20 periods using an English clock procedure. This was used as a control treatment for the second-chance offer auctions discussed in Section 4.3 below. They report average prices of 335 for the first unit sold versus 273 for the second, compared to the equilibrium prediction of 270 for both units.

Neugebauer and Pezanis-Christou (2007; NPC) report a series of FP sequential auctions with eight bidders and four units supplied. Values were iid from a uniform distribution with support [0, 100], with winning prices announced following each unit sold. One major difference from the KO experiment is the number of auctions in a session – 100 here as opposed to 20 in KO.[32] NPC measure efficiency in terms of the proportion of allocations to bidders whose value ranking was lower than the order in which units were offered – yielding an average aggregate efficiency of 72%.

[31] KO report two other treatments designed to represent the impact of agents bidding on behalf of principals, with agents penalized for failure to obtain items.

[32] NPC also have treatments with uncertain supply, where the RNNE is predicted to result in decreasing prices.

Misallocations were greater for units 1 and 2 than 3 and 4, indicating that the highest value bidders had adopted a "wait and see" strategy regarding sales of early units, giving bidders with lower values a chance to win these early units. One consequence of this is that average prices were approximately constant across units, ranging from a high of 51.7 on unit 1 to a low of 49.5 on the unit 4. So that in this case the "right" result for prices is achieved for the wrong reason – systematic deviations from the predicted order in which units were sold with lower valued bidders tending to buy earlier units. One side note here: Like KO average prices were decreasing across units in the first 20 auctions in NPC, the total number of auctions in KO's sessions, as it took some experience for higher valued bidders to learn the benefits of the wait and see strategy.

Summary: Multiple unit sequential auctions typically exhibit the decreasing price anomaly observed in field settings. Observing decreasing prices in the laboratory suggests that its presence in field settings cannot be solely attributed to supply or value uncertainty, the presence of buyers' agents in the bidding pool, or other factors that may contribute to the phenomena in less structured field settings. These results establish an important connection between laboratory and field settings. What's missing with respect to this line of research are direct comparisons of single-unit sequential auctions with, for example, simultaneous or uniform price auctions in terms of the relative impact on revenue and efficiency in order to get some idea of which auction mechanism is likely to perform best in field settings.

1.7 Procurement Auctions

In procurement auctions the lowest bid wins, but this is not what differentiates them from the buyers' auctions (high bid wins) discussed so far. Rather, many business-to-business (B2B) auctions allow for nonbinding (buyer-determined) auctions in which the buyer does not commit to award the contract to the lowest bidder. Rather, the buyer reserves the right to select the winner based on bid (price) and "quality." Quality is typically treated as exogenous and consists of factors that cannot be easily quantified, such as reputation and past relationships, so that no explicit scoring rule is announced in advance.[33] Research on these types of auctions, which are quite common for firms

[33] For an experiment in which sellers can vary quality characteristics and compete on that dimension in addition to price see Chen-Ritzo et al. (2005).

purchasing goods and services in B2B auctions (Jap, 2002), is just beginning, the results of which are reported on below.

Engelbrecht-Wiggans, Haruvy, and Katok (2007; EWHK) address the question of under what circumstances does a buyer-determined (BD) mechanism increases the buyer's surplus as opposed to a price-determined (PD) mechanism where the buyer commits to awarding the contract to the lowest bidder. They consider an IPV auction in which quality $Q = C + \gamma X$ where C (cost) is uniformly distributed on (0, 100), X is uniformly distributed on (0, 1), and γ is a constant, so that C and Q are positively correlated. This specification turns a two dimensional problem in terms of seller's costs and quality into a one dimensional problem in which each seller knows their own Q_i as do buyers, prior to the start of the auction. Each seller bids a price $B(C_i, Q_i)$ with the buyer selecting the seller with the highest score $Q_i - B(C_i, Q_i)$. Under the RNNE, FPSB and SPSB auctions generate the same expected buyer surplus, with the superiority of the BD mechanism varying as a function of the number of competitors (N) and the extent to which cost is correlated with quality (γ). Three treatments are studied: (1) N = 2 and γ = 100 so that average buyers' surplus is greater under BD than under PD, (2) N = 2 and γ = 300 so that buyers' surplus is greater under PD than BD, and (3) N = 4 and γ = 300 so that average buyers' surplus is greater under BD. FPSB auctions are employed throughout.

Aggregate results comparing buyer surplus confirm these comparative static predictions, with stronger results for experienced than inexperienced bidders. Efficiency, defined as the frequency with which the highest scoring bidder win's the auction, is consistently higher under BD than under PD, but consistently lower than the point prediction under BD (between 81-89% versus 100% predicted). One important shortcoming of this experiment relative to the target environment is that both buyers and sellers know Q_i with certainty prior to the start of the auction, which is almost certainly not the case in most field settings. There are, however, problems in establishing clear analytic predictions when Q_i is uncertain or is not known by other bidders. Nevertheless, both the analytic and experimental results serve to disabuse practitioners of the common notion that buyer-determined auctions will always give them the best of both possible worlds: the intense price-based competition of price-based auctions and the ability to account for subjective quality characteristics as in more traditional approaches to procurement.

Haruvy and Katok (2013; HK) consider BD auctions with and without information about *other* bidders'quality, using both FPSB and English auctions. They use the same experimental set-up as in EWHK focusing on the treatment with $\gamma = 300$ and $N = 4$. With full information, each bidder knows all other bidder's qualities (Q) as well as whether their own Q is the highest. Under private information bidders only know their own Q. Given the IPV assumption, under the RNNE expected buyer surplus is the same under full-information in the English auction and with private information in the FPSB auction (as in the RET). Further, as with standard English auctions, bidders have a dominant strategy to bid down to their cost of production before exiting the auction. Analytic results are not available for English auctions with private information regarding Q or in FPSB auctions with full information regarding Qs. However, numerical analysis based on linear approximations of the relevant bid functions and the draws employed in the experiment show that: (i) Efficiency is lowest in the FPSB auctions with full information, near 100% in the English auctions with private information, and 100% in the other two cases, and (ii) Predicted buyer surplus is lowest in the English auction with private information regarding Q, highest under the FPSB auction with full information, with expected surplus under the other two treatments falling approximately half way between the other two cases.

Results show that realized buyer surplus is quite close to predicted surplus in the English auctions with full-information, but significantly *higher* than predicted in the other three treatments, with the highest surplus achieved in the FPSB auction with private information. The latter corresponds to the standard FPSB auction results in which bids typically exceed the RNNE (in this case, are below the RNNE), so that buyer surplus is higher in the FPSB auctions. The present result no doubt rests on many of the same factors underlying this result in standard auctions. Actual buyer surplus under English auctions with private information about quality is significantly higher than under English auctions with public information about quality. This provides support for the idea that English auctions with information on bid ranks, as opposed to precise bid information, often employed in BD auctions, is surplus enhancing.[34] Efficiencies hover in the mid eighties in all four treatments, with little difference between any of the four cases.[35]

Shachat and Swarthout (2010; SS) compare a FPSB auction with an English auction with bid credits that can, potentially, implement Myerson's (1981) optimal auction design. In this experiment sellers' costs and quality are independently determined draws so that cost and quality may be negatively correlated. As in the experiments reported on above, both sellers and the buyer know each firm's quality prior to bidding, with buyers selecting the firm with the greatest difference between quality and cost. Buyer subjects determine the bid credits. All auctions involve two bidders. Bid functions for the FPSB auctions are nonlinear, which typically cause more problems for bidders than the usual linear bid functions. The English auctions have the usual weakly dominant strategy of remaining active until price reaches costs, after accounting for bid credits in this case.

Under the Nash equilibrium the FPSB auctions are predicted to be more efficient, with average winning quality, seller profit and social surplus a bit higher as well. The tradeoff is that in the English auctions with optimal bid credits average auction prices will be lower and average buyer surplus will be higher than in the FPSB auctions. Contrary to these predictions, efficiency is higher and *both* buyers and sellers earn greater surpluses under the English auction (while buyers tend to be too generous with their bid credits). This is the result of closer conformity to theoretical predictions in the English auctions compared to the FPSB auctions (a pattern reported in almost all experiments comparing the two auction institutions). The experiment suffers from the fact that bid credits as well as the auction mechanism both change between the two treatments so that one cannot distinguish which of these two factors is driving the results.

In BD auctions, the buyer knows the quality of their incumbent supplier but have yet to fully screen potential competitors who are invited to participate in the auction, as

[34] See Elmaghraby, Katok, and Santamaria (2010) for a BD experiment comparing rank feedback with price feedback in BD auctions.

[35] In the English auctions with public information there is jump bidding (a bid that is greater than the minimum bid increment). As a result losing bidders sometimes stop short of their cost and winning bidders overshoot the second-best bid. Jump bidding tends to lower efficiency, but the two effects tend to cancel each other out with respect to buyer surplus.

full screening is costly.[36] Wan, Beil and Katok (2012; WBK) look at the strategic impact of (full) post-auction screening on incumbent's bids in a stylized model with one incumbent whose quality is known and one potential new supplier whose quality is unknown. There is also asymmetry in the incumbent and entrant's costs, with the former potentially a bit more expensive than the latter. Qualification costs are known and are *added* to the entrant's costs, reflecting the cost of switching. There is common knowledge regarding the probability that the entrant will meet qualification requirements. Behavior is studied within the context of an English auction with the focus on incumbents' behavior.

Potential entrants have a dominant strategy to bid truthfully and are replaced by computers. Three types of equilibria are studied: (1) Incumbents do not compete, bidding the maximum (reserve) price, (2) Incumbents compete down to their costs, and (3) Incumbents bid somewhere in between these two extremes (but above their cost). WBK employ a restricted treatment in which either case (1) or (2) above holds with incumbents restricted to playing one or the other of the two equilibrium outcomes, and an unrestricted treatment in which all three possibilities are present and incumbents are free to compete down to whatever price level they wish.[37] The motivation for the restricted treatment is that there are relatively low profits, along with a complicated piecewise linear bidding strategy, for case (3).[38]

The comparative static predictions of the restricted treatment are satisfied qualitatively in the data. For example, with low qualification costs and a low probability of qualifying, the incumbent should bid the reserve price 100% of the time regardless of whether it has low or high costs, and subjects do so 85% of the time. And with high qualifying costs and the same low probability of qualifying, the incumbent should always compete with low costs and bid the reserve at high costs, with this comparative static prediction satisfied qualitatively as well. However, the point predictions are very far off

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[36] One of the services provided by the company conducting the auction is to identify potentially qualified suppliers. But it is not uncommon in BD auctions for there to be an extended period after the auction has finished where buyers do a thorough screening of low bidders before awarding the contract.

[37] In the restricted treatment the incumbent seller makes a bid and then the clock auction is played out. That is, there are no repeated decisions regarding continuing to bid or dropping out, which would be expected to enhance the learning process.

[38] There is also a treatment looking at buyers' choice of a BD or PD auction, which will not be discussed here.

in this case as incumbents bid the reserve 63% of the time at low costs (as opposed to 0% predicted) and bid the reserve 85% of the time with high costs (with 100% predicted). Further, with high costs of qualifying and high probability of qualifying the predicted outcome is for always entering at low costs and not entering at high costs, with the respective entry probabilities being 20% at low costs versus 40% at high costs, changes in the right direction but well away from the point prediction. Winning rates and contract prices are quite close to aggregate predicted values for the unrestricted treatment, but mask a good deal of variability in bid patterns relative to those predicted for any given cost realization. In spite of the noise in the experimental outcomes, this paper begins to capture some of the key strategic considerations which are at the heart of what is different about BD auctions: There are real switching costs to contracting with new suppliers so that incumbent bidders face strategic issues in determining how hard to compete given uncertainties about these switching costs and entrants' costs of production.

There are a number of issues in BD auctions that have yet to be explored. One important issue is the effect of BD auctions on longer term relationships between buyers and their suppliers, as the latter are generally unhappy about participating in these auctions and claim that they can harm longer term relationships, with negative effects on longer run costs and quality. Unfortunately, this is one issue which more than likely needs to be looked at in field data. However, what is know from experiments studying incomplete contracts (and other regarding behavior in general) is that this may well be the case. But then the question is one of long run benefits versus costs. A second issue concerns uncertainty buyers and sellers have regarding sellers' quality characteristics, as it is rare for these factors to be explicitly quantified before the auction takes place. As such it would seem important to have a good idea of the extent to which buyers employ BD or PD auctions in field settings, the types of auctions employed (FPSB or English), as well as some characterization of the economic conditions that appear to favor one type of auction over the other, to help guide what kinds of experiments to conduct.

1.8 Cash Balance Effects and the Role of Outside Earnings

In the typical auction experiment subjects bid in a series of auctions with payoffs following each auction period. As a consequence bidders' cash balances will vary over the course of the auction which, for a variety of reasons, may impact bidding; e.g., if subjects are risk averse or have earnings targets or earning aspirations that they bring to the experiment. Further, since these cash balances are endogenous, absent proper instruments they cannot simply be included as a right hand side variable in estimating bid functions since this will result in biased estimates for the variables of interest.

Ham, Kagel and Lehrer (2005; HKL) investigate cash balance effects in the context of a FPSB auction with affiliated private values (see Kagel, Harstad and Levin, 1987).[39] HKL introduce exogenous variation in cash balances by simultaneously enrolling subjects in a lottery which has both positive and negative payoffs (with positive expected value). In this way they create their own instrumental variable to study the effects of cash balances on bids. Instrumental variables for endogenously varying cash balances consisted of a number of exogenous variables (e.g., ranking of bidders' values) produced during the experiment. They also varied the number of bidders in each auction with either 4 or 6 bidders competing in an experimental session in a between groups design.

Their results show a small, but statistically significant, negative cash balance effect on bids; i.e., the larger cash balances are the lower subjects bid, other things equal. The quantitative effect of cash balances on the bid factor (the difference between a bidders value and what they bid) is to increase it from \$1.76 to \$2.36 in auctions with 4 bidders, and from \$1.27 to \$1.70 with 6 bidders (evaluated at the mean value for cash balances). KHL also estimate a time trend variable ($1/t$ where t is the number of auction periods) to capture any learning/adjustments on the part of bidders, which shows that, other things equal, bid factors decrease over time. This is consistent with NS's result (section 1.1 above) that bids tend to increase with experience and feedback regarding auction outcomes.

HKL estimate the impact of not including cash balances in the bid function. It biases the time trend coefficient downward – so that there is less of an increase in bids over time. In addition, since in auctions with larger numbers of bidders, subjects have lower earnings and smaller increases in their cash balances (holding the support from

[39] The advantage of affiliated private values is that except for end point effects, bidders do not know if they have a high or low signal value. This is valuable since in IPV auctions bidders with low valuations know they have little chance of winning the auction which result in a number of "throw away" bids. The affiliated private values model largely eliminates such bids except near the end points of the underlying distribution, as with affiliation bidders do not know if they have a relatively high or low value.

which values are drawn constant), the impact of increased numbers of bidders is biased upwards (as with larger N and a constant support bidders earn smaller profits).

HKL attribute the negative cash balance effect to target income earnings and/or income aspirations on bidding. They conjecture that the mechanism underlying this effect is that subjects, who are recruited for the experiment with the promise of cash earnings, enter the auction with some target income earnings in mind and quickly recognize that they must win an auction to realize these earnings, which promotes higher bids at first. However, as cash balances accumulate, bidders come closer to their target earnings which motivates them to take a chance on a bigger score by lowering their bids, even though this reduces their chances of winning. This effect is partly offset by the feedback regarding lost profit opportunities, which induces more aggressive bidding over time. This conjecture concerning the mechanism behind the cash balance effect remains to be investigated directly. However, it does receive indirect support from at least one independent study.

Turocy and Watson (2012) (TW) report an experiment comparing bids in a first-price IPV auction using the typical resale value frame compared to having an "outside price" frame. With resale values, the typical experimental design, bidders values are specified as resale values (the auction winner gets the difference between their resale value and the bid; all other bidders earn zero profits for that auction). With outside prices each bidder draws an iid outside price comparable to drawing resale values. Subjects then bid for the item with the high bidder's earnings equal to the max of the support from which values are drawn minus the winning bid; with all other bidders earning the difference between the max of the support minus their outside price.[40]

The outside price treatment does two things: (i) it frames the problem differently as winning now involves an opportunity cost (what you would have earned by not winning given your outside price) and (ii) everyone is assured of earning a profit in each auction period. TW find that bids are consistently lower in the outside price treatment than in the standard resale value treatment; winning bids averaged 3.77 in the resale frame vs 3.40 in outside price frame but still well above the RNNE ($3.03). TW attribute

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[40] In the resale value case, payments are made each period. But in the outside price frame, in order to keep the expenses comparable, they are paid for *n* randomly determined auctions.

the lower bidding under the outside option exclusively to the first factor as a result of differences , which they attribute to differences between losers and winner's regret (always getting a payoff reduces loser's regret). This is quite similar to HKL's conjecture, since with everyone assured of earning a profit this should help eliminate anxieties about achieving a reasonable level of positive earnings regardless of whether they win or lose the auction.

1.9 An Unresolved Methodological Issue

In reviewing the auction literature one does not have to look very far to identify two distinctly different ways of treating the data from different experimental sessions. One approach (one we have usually followed) is to enroll a relatively large number of subjects into each experimental session and to run several auctions simultaneously, randomly remixing subjects between groups in each auction. In reporting aggregate auction data (e.g., average revenue), we have pooled the data (after, perhaps allowing for a learning period) and conducted either parametric, or non-parametric, statistical tests for treatment effects. In reporting more disaggregated data (e.g., estimating bid functions for treatment effects) the data are treated as a time series-cross sectional data set, with regression estimates based on (standard) random effect models with subject as the random effect, thereby accounting for obvious serial dependency in individual bid patterns (e.g., some subjects consistently bid well above the RNNE in FPSB auctions, others less so).

A second approach is to take the subjects within a given experimental session and put them into subgroups randomly rematching within the subgroups as opposed to over the entire sample population. For example, in a study of FPSB auctions with four bidders, with 16 subjects in each session, the investigator would form two 8 subject subgroups and randomly mix between them (as opposed to mixing over all 16 subjects in the session). The motivation for this is to obtain two "independent" sets of observations per session (the data for each 8 person subgroup) instead of only one independent group (the data for the 16 subjects in the session as a whole). The data analysis then proceeds on the basis of the aggregate behavior of these "independent" groups. The concern here is that in randomly rotating among all 16 bidders in the session, the repeated interactions between subjects this generates session level effects that will dominate the data. This practice eschews the use of appropriate panel data techniques to correct for dependencies across and between subjects within a given experimental session, as well as to control for potential session level effects.

There are several important and unresolved issues in choosing between these two procedures. In both cases experimenters are trying to squeeze as much data as they can from a limited subject-payment budget, as well as the time and energy devoted to conducting experiments. With the reader fully aware of our own biases on this matter we note the following: First, advocates of repeated matching of the same smaller subset of subjects (i) often implicitly deceive subjects as they commonly do not report the rotation rule employed to subjects and (ii) if subjects are as sensitive to repeated matching effects as proponents of this technique assume, it seems plausible that repeated play within a small subset might generate super-game effects that will contaminate the data (whereas the models employed commonly assume one-shot games). Second, and more importantly, there have been a few experiments which have devoted time and effort to determine the severity of possible session level effects from random rematching for the group as a whole. More often than not these studies find no differences, e.g. Cooper et al. (1993; footnote 13, p. 1308), Duffy and Ochs (2009). Also see Walker et al. (1987) and Brosig and Reiβ (2007) who find no differences when comparing bids in auctions with all human bidders versus humans bidding against computers who follow the RNNE bidding strategy.

More generally we think experimenters should treat this "independence" issue as an empirical one rather than a doctrinal one determined on the basis of prior beliefs. In this respect experimenters need to be sensitive to potential session level effects and to employ appropriate econometric techniques (see, for example, Frechette, 2012) as well as the old inter-ocular eyeball technique in looking for, and adjusting for, possible session level effects.

II Single Unit Common Value Auctions

In common value auctions (CVA) the value of the item is the same to all bidders. What makes CVAs interesting is that although bidders don't know the true common-value they receive signals (estimates**)** that are correlated (affiliated) with that value. Mineral rights auctions (e.g., outer continental shelf - OCS - oil lease auctions), are usually modeled as a

CVA. There is a common value element to most auctions. Bidders for a painting may purchase it for their own pleasure, a private value element, but also for investment and eventual resale, the common value element.

Experimental research on CVAs has focused on the “winner's curse.” Although all bidders obtain unbiased estimates of the item's value, they typically win in cases where they have (one of) the highest signal value(s). Unless this adverse selection problem is accounted for, it will result in winning bids that are systematically too high, earning below normal or negative profits - a disequilibrium phenomenon. Oil companies claim they fell prey to the winner's curse in early OCS lease sales, with similar claims made in a variety of other settings (e.g., free agency markets for professional athletes and corporate takeovers). Economists are naturally skeptical of such claims as they involve out-of-equilibrium play. Experiments reviewed in Kagel’s (1995) survey clearly showed the presence of a winner’s curse for inexperienced bidders under a variety of circumstances, and with different experimental subjects: average undergraduate or MBA students (Bazerman and Samuelson, 1983; Kagel and Levin, 1986), extremely bright (Cal Tech) undergraduates (Lind and Plott, 1991), experienced professionals in a laboratory setting (Dyer et al, 1989), and auctions in which it is common knowledge that one bidder knows, with certainty, the value of the item (Kagel and Levin, 1999). Papers reviewed there also dealt with several alternative explanations for the winner’s curse – limited liability for losses (Hansen and Lott, 1991, Kagel and Levin, 1991, Lind and Plott, 1991) and joy of winning (Holt and Sherman, 1994).

We pick up the story here with experiments investigating the ability of English auctions to raise revenue compared to FPSB auctions and the effects of an insider who has better information than rival bidders, with the focus on the comparative static predictions of the model in these cases. We look at behavior of very experienced bidders who have overcome the worst effects of the WC, bidding in “almost” CV auctions where one bidder values the item more than others (with this being common knowledge), and bidding in auctions with both private and common value elements for *all* bidders. New results on the closely related “takeover” game are reported with the focus on sorting out between different explanations for the winner’s curse (WC). We report on the impact of demographic and ability variables on the likelihood of falling prey to the WC, and what the lab results may or may not tell us with respect to behavior in field settings.

The auctions reported on here, unless otherwise noted, use the following experimental design: The common value, x_o is the same for all bidders and is chosen randomly from a *uniform* distribution with support $[\underline{v}, \overline{v}]$. Each bidder *i* receives a private information signal, x_i, about the unknown value of the item based on an iid from a uniform distribution with support $[x_o - \varepsilon, x_o + \varepsilon]$.

2.1 English Auctions

Levin, Kagel, and Richard (1996; LKR) implement an irrevocable exit, ascending-price (English clock) auction. Prices start at $\underline{v}$, the lowest possible value for x_o, and increase continuously. Bidders are counted as actively bidding until they drop out of the auction and are not permitted to reenter after that.[41] The last bidder earns a profit equal to x_o less the price at which the last bidder dropped out. Bidders observe the prices at which their rivals drop out of the bidding. The irrevocable exit procedure, in conjunction with the public posting of drop-out prices, insures that in equilibrium bidders can infer their rivals' signal values from the drop-out prices.

The analysis focuses on signals in the interval $\underline{v} + \varepsilon \leq x \leq \overline{v} - \varepsilon$. In a symmetric RNNE the bidder who holds the lowest signal value (x_L) drops out of the auction once the price reaches x_L.[42] This drop out price reveals x_L to the remaining bidders. Given the *uniform* distribution of signal values around x_o, and the fact that in a symmetric equilibrium any remaining bidder j wins only when she holds the highest signal, each bidder j ought to use $(x_L + x_j)/2$ (a sufficient statistic for x_o) as their drop out price in the symmetric RNNE. Drop out prices other than x_L contain no additional information and should be ignored. Expected profits in the English auction are reduced by about 50%

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[41] Prices started at $\underline{v}$ as any other price rule would reveal information about x_o. Prices increased by smaller and smaller increments as bidders dropped out, with brief pauses following each drop out.

[42] The intuition behind this is roughly as follows: Given symmetry, the low signal holder knows that those remaining in the auction have higher signal values so that his estimate of x_o is higher than x_L. But the low signal holder can't profit from this additional information since not dropping at x_L pushes the price up, so that winning at a higher price, when others drop at equilibrium prices, assures the low bidder negative expected profit.

compared to a FPSB auction when more than two bidders are competing, so that the English auction is predicted to raise significantly more revenue compared to a FP auction.

Earlier experimental results from FP auctions with x_L *publicly announced* (Kagel and Levin, 1986;KL, 1986) showed that when bidders suffered from a winner's curse (WC), announcing x_L *lowered* revenue (contrary to the theory's prediction) as bidders with higher signal values recognized that they were overestimating the common value. However, once bidders had adjusted to the WC, and were making reasonable profits relative to the RNNE benchmark, revealing x_L increased revenue via the linkage principle as the theory predicted. The key difference between LKR's English clock auctions and these earlier FPSB auctions is that information dissemination is endogenous in the clock auctions rather than exogenous, when x_L is publicly announced. As such higher signal holders must be able to recognize and process the relevant information, and low signal holders must recognize the futility of remaining active once the price exceeds their signal value in order for the results to generalize.

[Insert Table 2 here]

Table 2 shows averages of predicted and actual changes in revenue between English and FP auctions for inexperienced bidders with the results classified by the number of bidders.[43] Average revenue is predicted to be higher in the English auctions in all cases for the set of signal values actually drawn, with significantly higher average revenue predicted for $n = 4$ for all values of ε and for $n = 7$ with $\varepsilon = \$12$.[44] However, for these inexperienced bidders, with the exception of $n = 4$ and $\varepsilon = \$24$, actual revenue is *lower* in the English auctions, with significantly lower average revenue for $n = 4$ and 7 with $\varepsilon = \$6$ ($p < 0.05$) and for $n = 7$ and $\varepsilon = \$12$ ($p < 0.10$).

These perverse revenue effects in terms of Nash equilibrium bidding theory are associated with negative average profits in both the FP and English auctions (see Table 2). The negative average profits indicate that inexperienced bidders suffered from a WC in both FP and English auctions, but that the curse was relatively stronger in the FP

[43] Common-value auctions involve pure surplus transfers so that revenue differences are calculated as: $[\pi_E - \pi_F]$ where π_E and π_F correspond to profits in English and FP auctions, respectively. This effectively normalizes for sampling variability in x_o by subtracting it from the price.

[44] One-tailed t-tests are conducted for predicted revenue increases since the symmetric RNNE makes unambiguous predictions regarding revenue. Two-tailed t-tests are used for determining statistical significance of actual revenue changes since the presence of a WC promotes lower revenue in English auctions.

auctions. These results serve to generalize those reported for FP auctions with x_L publicly announced (KL, 1986). However, the generalization is not complete as average profits in the English auctions were negative compared to positive average profits in the FP auctions with x_L publicly announced. This suggests that information dissemination in the English auction is noisier than with x_L publicly announced. This probably results from two factors: (i) in the English auction bidders may not completely recognize the relationship between the first drop-out price and x_L and (ii) there is some out of equilibrium play with low signal holders dropping out sometimes above and sometimes below their signal value. [45]

For more experienced bidders, English auctions raised average revenue with n = 4, with a statistically significant increase for ε = $18 (see Table 3). However, for n = 7, there was essentially no difference in revenue between the FP and English auctions. The significant increase in average revenue in English auctions with n = 4 was associated with the elimination of the worst effects of the WC in the FP auctions, as bidders earned a substantial share (more than 50%) of predicted profit. In contrast, with n = 7 bidders earned a relatively low share (21%) of predicted profits in the FP auctions, indicating substantially stronger residual traces of a WC, and highlighting the importance of largely eliminating the WC in order for English auctions to raise revenue as the theory predicts.

[Insert Table 3 here]

LKR develop an econometric model to characterize how bidders process information in the English auctions. As noted, the Nash bidding model predicts that bidders with higher signal values will average their own signal value with the first drop-out price observed, ignoring all intermediate drop-out prices. What they found, however, is that bidders placed weight on their own signal and the immediate past drop out price, ostensibly ignoring x_L and any earlier drop out prices. Further, as more bidders dropped out, subjects placed less and less weight on their own signal and more weight on the last drop-out price. This pattern, although inconsistent with the Nash model, is consistent with bidders acting "as if" they were averaging their own signal with the signal values

[45] To further investigate this question Kagel and Levin (unpublished data) conducted some additional sessions with inexperienced bidders in which x_L was publicly announced prior to bidding in the English auctions. In auctions with 6 bidders and ε = $12, average profits in the standard English auction were -$1.55, with average profits in auctions with x_L announced of $1.56 (t = 1.46, d. f. = 30, p < .10, 1-tailed test).

underlying the drop out prices of *all* earlier bidders. They attribute the adoption of this signal averaging rule to the fact that (i) it is easy and quite natural to use and (ii) it yields results quite similar to the Nash rule without requiring that bidders explicitly recognize the adverse selection effect of winning the auction and/or knowing anything about sufficient statistics. One unanswered question raised by this analysis is if the signal-averaging rule would still be used with distribution functions where it leads to markedly different outcomes from the Nash equilibrium. In this case bidders would have more opportunity to recognize and respond to the profit opportunities inherent in abandoning the signal-averaging rule.

2.2 Auctions with Insider Information

The standard CVA model assumes that all bidders are *ex-ante* symmetric with respect to the quality of their signals (estimates) regarding the common-value. It is quite natural to ask how robust the equilibrium is to the insertion of one bidder, an *insider*, who is better informed than the other bidders, *outsiders*. The easiest place to start this analysis is to assume that it is commonly-known that there is a single insider with a better, more precise, estimate of the true value (at the extreme, an insider who knows the true value).

Evaluating auction performance with an insider compared to the symmetric baseline depends quite critically on the baseline chosen. Wilson (1967) employed a symmetric baseline in which all bidders have *only* public information so the seller extracts the entire surplus in the resulting mixed strategy equilibrium (also see Hausch, 1987 and Hendricks et al., 1994 for similar models). Introducing an insider into this environment reduces the seller's revenue, as the insider can, and does, bid below the true value, earning positive profits. Since *ex-post* efficiency is not an issue in a pure common-value model, the insider's gains must be the seller's loss. We are unaware of any experiments that have investigated these predictions of the Wilson-type model.

In contrast Kagel and Levin (1999; KL 1999) used the symmetric bidding model characterized in Section 2.1 as their baseline. Their "insider" treatment consisted of a single bidder who knows the true value with certainty, with all other bidders aware of this fact. "Outsiders" continued to draw signal values as in the symmetric bidding model. They did this to see if the presence of an insider who knows the true value would help bidders recognize the adverse selection effect conditional on winning thereby mitigating, or possibly even eliminating, the WC. Although this hypothesis failed (inexperienced outsiders suffered from as strong a WC as inexperienced bidders with symmetric information), the experiment led to a very surprising and significant discovery: With more experienced subjects who had learned to overcome the worst effects of the WC, earning substantial positive profits in FPSB auctions with symmetric information, the introduction of an insider actually *increased* seller's revenues, as opposed to the decrease predicted in a Wilson-type model. Table 4 reports these results.

[Insert Table 4 here]

This surprising outcome, particularly given the theoretical results from Wilson-type models, might have led some skeptics to dismiss this new finding, arguing that "in laboratory experiments anything can happen." However, a further examination of the model revealed that the data are consistent with the model's predictions and to the discovery of the mechanism underlying this effect. Unlike in Wilson-type models, in KL's symmetric information benchmark model all bidders have private information, so in equilibrium bidders make positive profits. As a result the introduction of a perfectly informed insider eliminates those baseline cases where the winning bidder makes very large profits, as the insider bids closer to the true value, on average, than bidders in the symmetric information baseline. (Evidence for this can be seen in the much smaller variance in average profits between asymmetric versus symmetric information setups reported in Table 3.) Further, unlike the early Wilson-type models, both insiders and outsiders earn positive average profits in equilibrium, as both agents have *private* information (insiders do not know the outsiders' private information signals). What the two types of models do have in common is that conditional on winning, insiders make much larger average profits compared to outsiders as they have superior information.[46]

KL (1999) argue that many "real world" cases are more realistically modeled with outsiders having some proprietary information and not just public information. In these circumstances, it may well be the case that the introduction of a single well-informed insider increases average sellers' revenue, and that both insiders and outsiders earn

[46] There is no analytic solution, or even readily calculated numerical solutions, to the system of differential equations that characterizes the Nash equilibrium in KL (1999). However, see Campbell and Levin (2006) for a model which solves for the Nash equilibrium analytically, in which the introduction of an insider may raise revenue as well.

economic rents. This potential for an insider to raise average revenue in a CVA had not been recognized in the literature prior to this.

2.3 Common Value Auctions with an Advantaged Bidder

The standard CVA model assumes that all bidders have exactly the same value for the item. But how robust, theoretically and in practice, are the properties and performance of auctions to slight departures from this assumption? In many common value auctions it is common knowledge that one (or more) bidder(s) (*advantaged* bidders) get an extra payoff relative to the other (*regular*) bidders; e.g., in the FCC regional air wave rights auctions, Pacific Telephone was widely believed to place a higher value on the West Coast regional area than their potential rivals because of their familiarity with the region and their existing customer base (Klemperer, 1998). Economic theory suggests that with two bidders and a SPSB or English auction even the tiniest private value advantage can have an "explosive" effect on auction outcomes, with the advantaged bidder always winning and earning very high profits (sharply reduced revenue) (Bikchandani, 1988; Klemperer, 1998). However, the question of whether or not these predictions will emerge depends critically on bidder behavior. It is here where experiments can help sort out when, where and why we ought to be concerned about such explosive effects.

Avery and Kagel (1997; AK) investigated the explosive effect of a small private value advantage in a SP "wallet-game" auction. Two bidders bid in a SPSB auction for the value of a wallet with two cells, where each of them privately observes the content of only one of the cells. Let x_1 and x_2, represent the privately observed signals by the first and second bidder respectively. The value of winning the wallet for these bidders is: $V_1 = x_1 + x_2 = V_2$. Bidding twice their observed signal, $b(x_i) = 2x_i$, $i = 1, 2$ is both a unique symmetric equilibrium as well as an *ex-post* equilibrium in which bidders have no regret.[47] Further, it is distribution free and independent of risk preferences.

With a private value advantage, the valuation of the advantaged bidder (say bidder 1) becomes: $V_1 = x_1 + x_2 + \Delta$ (or $V_1 = x_1 + x_2 + \Delta x_1$, in the multiplicative form) where $\Delta > 0$, is presumed small. Essentially what the private-value advantage does is to destroy the symmetric equilibrium of the SP auction. In the resulting asymmetric

[47] The winner earns $x_{High} + x_{Low}$ and pays $2x_{Low}$ for a net gain of $x_{High} - x_{Low} > 0$. However, if the loser wins she earns $x_{High} + x_{Low}$ and pays $2x_{High}$ for a net gain of $x_{Low} - x_{High} < 0$. Thus, even after learning both signals, no one regrets the outcome (given the equilibrium strategy of the other bidder).

equilibrium the private-value advantage has a "snowball" effect resulting in the advantaged bidder winning all the time, bidding too high for the disadvantaged bidder to profitably unseat him. This does not happen in a FPSB auction but does in a SP auction as the high bidder does not have to pay what he bids.

In the experiment, the effect of the Δ value advantage on bids and prices was proportional rather than explosive as, controlling for signal values, the difference in bids between advantaged and disadvantaged bidders was closer to the private value advantage of $1 than to the $3 difference predicted under the explosive effect. In effect, both advantaged and disadvantaged bidders were bidding closer to the naïve expected value of the item conditional on their signal value, with the advantaged bidder simply adding their private value advantage to their estimate. AK explore a number of alternative explanations for this outcome. None fit as well as the naïve behavioral model in which advantaged bidders simply add their private value advantage to their estimate of the common value.

Rose and Levin (2008; RL) investigate the effect of a private value advantage in the two-person wallet game, this time using an English clock auction. The key motivation for this experiment is that in virtually all experimental work behavior is much closer to equilibrium predictions in English clock auctions compared to sealed-bid auctions (KHL, 1987; LKR; KL, 1999). As such there is a clear need to explore the model in an English auction before concluding that small asymmetries do not matter very much, particularly since English auctions are far more common than SPSB auctions. RL do not find any evidence of the explosive effect either, with players clearly suffering from the winner's curse in both the symmetric and asymmetric auctions, as evidenced by the frequency with which they lost money. When tested against the data, the Nash equilibrium model and the expected value hypothesis (naïve expectations) are both rejected, although the expected value hypothesis provides a better fit than the Nash model.

Rose and Kagel (2008; RK) explore the effects of a private value advantage in an English clock auction under the same single structure employed in LKR. They employ twice-experienced subjects who have come to earn relatively large positive profits in FPSB auctions. This is important since virtually all research in CVAs shows that when bidders suffer from an obvious WC, as they did in the control treatments in AK and RL, the comparative static predictions of the Nash model fail to hold. However, once bidders have learned to overcome the worst effects of the WC, the theory's comparative static predictions tend to hold.[48]

Here too bidders' responses to the private value advantage are closer to proportional than explosive as advantaged bidders won only slightly more often than would be expected based on chance factors alone. Further, there are no significant differences in revenue between the pure CVAs and almost CVAs. RK show that the same behavioral model employed in AK, with advantaged bidders simply adding their private value advantage to their estimate of the common value, better organizes the data than does the Nash model with its explosive outcome. From a broader perspective these results demonstrate that adjustment to equilibrium under a trial and error learning process (which seems to be how subjects learn to overcome the WC in FPSB auctions; see KL, 1986) provides no assurance that after near equilibrium behavior is achieved, the comparative static predictions of the theory will be satisfied.

Takeover battles for control of a company when bidders already have stakes/shares (toeholds) in the target company are quite similar to almost CVAs.[49] Consider the wallet game when each of the two bidders for the firm has an i.i.d. signal and where the common value of the firm is the sum of the two signals. In addition every bidder already owns a share Q_j, j = 1, 2, of the target firm. In this setup the (relative) ratio of the shares, $Q_j/(Q_1+Q_2)$ has a dramatic impact on the predicted outcome as (i) the probability of winning the auction by bidder j is $Q_j/(Q_1+Q_2)$, (ii) increasing a bidder's share, Q, makes that bidder more aggressive and (iii) increasing a bidder's toehold increases her profits regardless of her signal. Thus, although the equilibrium does not lead to the explosive outcome when both bidders have positive toeholds, behavior is quite sensitive to even small disparities in the relative size of bidders' shares. This is quite surprising as it predicts the same equilibrium outcome regardless of the absolute size of the toeholds as long as the relative ratio is the same; e. g., the same outcome is predicted

[48] In employing an English clock auction with four bidders RK are also able to address Klemperer's concerns regarding the use of ascending price auctions on bidders' reluctance to enter the bidding process. Regular bidders were not deterred from bidding.
[49] The discussion here, as well as the experiment that follows is based on Bulow et al. (1999).

when bidders 1 and 2 hold 20% and 10% shares as when they hold 0.2% and 0.1% shares!

Georganas and Nagel (2011) explore the predictions of the toehold model using an English clock auction. They find that larger toeholds raise the probability of winning and the profits of their owners as the theory predicts, and that revenue tends to fall the larger the discrepancy between the shares of the two players' toeholds. However, as in the almost CVA, these results are not nearly as dramatic as the theory predicts. The paper concludes that laboratory subjects do not respond to small toeholds or to small disparities in toeholds to the extent that the theory predicts.

Summary: The results of all four experiments reported on here agree that contrary to what theory predicts, a private value advantage leads to proportionate as opposed to explosive effects in almost common value SPSB and English auctions. This is true even with experienced bidders who earn a respectable share of RNNE profits in pure CVAs so that they have overcome the worst effects of the WC. The apparent reason for these failures is that bidders do not fully appreciate the adverse selection effect conditional on winning, which is exacerbated for regular bidders when facing an advantaged rival. As such, the behavioral mechanism underlying the explosive effect is not present, and there are no forces at work to replace it.

This leaves us quite skeptical of finding similar effects outside the lab *under the conditions the theory specifies.* Indeed, it would seem to require very sophisticated bidders for the explosive effect to be realized under these conditions. As such we would expect that bidders outside the laboratory would employ alternative strategies available to them in the less structured environment they operate in to press their private value advantage. PacTel appears to have done something like this in the FCC major trading area (MTA) sale of broadband personal communication licenses for Los Angeles and San Francisco. PacTel, which held a substantial private value advantage, publicly announced their intentions to top their opponents bids, while obviously having the resources and a sufficiently large private value advantage to make such an announcement credible (see Cramton, 1997), a strategy that lies outside the formal theory. As a side note, PacTel got the licenses in question but they were only partially successful in obtaining rock bottom prices, as there was rivalrous bidding based on the personalities of the leading bidders, another element left out of the formal theory. Further, as Cramton (1997) notes, there may also be some incentive under these circumstances for predatory bidding on the part of rivals that would work against the revenue reducing forces implied by the explosive effect and indeed seem to have been at play in the MTA broadband sales.

2.4 New Results in the Takeover Game: Theory and Experiments

The systematic overbidding resulting in a WC for inexperienced bidders has attracted the attention of theorists in efforts to explain the WC within a generalized Nash bidding model that permit a more relaxed belief system. Eyster and Rabin (2005; ER) generalize the Nash model by introducing the notion of a "cursed equilibrium" in which bidders correctly predict, and best respond to, the *distribution* of others' bids, but do not correctly perceive how these other bids depend on other bidders' signals. This model rationalizes deviations from the standard Nash equilibrium depending on the degree of "cursedness" bidders suffer from.

Crawford and Iriberri (2007; CI) rationalize the WC within the context of a level-*k* reasoning model. Roughly, they allow different levels of "sophistication" where they define a level-0 player as a bidder who picks randomly from the allowable set of actions, with more sophisticated players best responding to all other players being one level less sophisticated than they are (so level-1 best responds to level-0, and level-2 best responds to level-1). The remarkable thing about this approach is that (i) a combination of level-1 and level-2 players explains the high frequency of WC for inexperienced bidders in FPSB auctions and (ii) the estimated frequencies of the two player types closely matches the frequencies reported in a variety of other, unrelated, experiments (having (i) without (ii) would simply be an exercise in data fitting).[50] Both the ER and CI models apply to CVAs and the closely related "take over" game.

Nash equilibrium bidding in CVAs requires complicated calculations of best responding to other bidders actions, involving both beliefs about others rationality and strategic uncertainty. To circumvent these complications Charness and Levin (2009; CL) employ a modified version of the takeover game turning it into an individual decision

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[50] As CI note, their model can*not* explain the winner's curse in SP CVAs or the persistent overbidding in FP private value auctions. Nevertheless, this paper is important because it shows a totally unanticipated result for FP CVAs. The failure to explain overbidding in SP CVAs can be rationalized by the fact that subjects simply do not understand SP auctions very well, whether private or common value.

making problem where avoiding the WC does not depend on beliefs about other bidders' actions. In the takeover game (first studied in Samuelson and Bazerman, 1985) there are two players, a buyer (the acquiring firm) and a seller (the target firm). The buyer knows that the target's value, V_S, is a random variable uniformly distributed in the interval [$0, $100]. The value of the target firm to the buyer, V_B, is $V_B = 1.5V_S$. The buyer does not know V_S when placing their bid, but knows that the seller does and that the seller employs the dominant strategy of only accepting offers that are greater than, or equal to V_S. In spite of the simplicity of this game, which abstracts from many of the complications embodied in a multi-player auction context, subjects still suffer from not recognizing the adverse selection effect conditional on winning and succumb to the WC, bidding somewhere between the unconditional expected value to the seller of 50 and the unconditional expected value to the acquirer of 75 (as opposed to the optimal bid of zero; see Kagel, 1995; and KL, 2002 for summaries of results from these experiments).

CL transform the game into an individual-choice task where subjects make a bid and then choose one of 100 'cards' numbered {0, 1, 2,…, 99}, that are displayed face-down on the computer screen. The same rules apply as in the takeover game in that if the card chosen is less than or equal to the bid, players receive 150% of the current value of the card less their bid, and zero otherwise. However, there are no other human agents whose behavior bidders need to establish beliefs for, either in the sense of ER or CI.[51]

CL find average bids to be 38.9, which is lower than the 50-75 average typically reported when the game is framed in terms of sellers accepting or rejecting bids. Further, there is a higher proportion of very low bids in the 0-9 range (around 25%) than typically reported.

To further simplify choices, CL modify the game even further, employing just two possible card values, 0 or 99. This treatment circumvents the need to use Baye's law to construct posterior beliefs, as well as the need to recognize the implications of the firm's values being drawn from a uniform distribution. Now, without any calculations, it should be clear that 0 dominates any bid except for 99. Further, in choosing between 0 and 99 the choice of 99 involves a rather unattractive gamble between a positive profit of

[51] Also see Tor and Bazerman (2003) who argue that the WC in the takeover game results from buyers ignoring sellers' cognitive processes.

49.5 or a negative profit of 99, with both outcomes equally likely, for an expected profit of *negative* 24.25.

[Insert Figure 5 here]

Figure 5 reports the results from this last treatment under two sets of instructions, with one providing more detail than the other. While there are relatively few bids other than 0 and 99, 47% of all bids are 99. Since the latter may reflect a need for some "action" as opposed to always bidding zero, CL further modify the game so that the card values are either 20 or 119. Now, bidding 20 yields positive expected profit. This results in an even further reduction in the frequency of non-optimal bids to 30%.[52] Finally, CL have subjects choose between lotteries whose payoffs are equivalent to the 0-99 and 20-119 treatments to rule out risk loving as a possible explanation for non-optimal bids.

CL note that taken literally, converting the takeover game to an individual choice problem rules out both the ER and CI models as an explanation for the winner's curse, since there are no other players whose actions must be taken into account. However, assuming that subjects still frame the situation as a two-player game, with the computer as the second player, results from the two-card treatments are inconsistent with both models as they predict all bids will be 0 (in the 0 or 99 treatment) or 20 (in the 20 or 99 treatment). CL conclude that the fundamental problem underlying the winner's curse is the failure to fully account for payoffs contingent on winning the auction.

One possible limitation of CL's results is that in transforming the problem into an individual choice task, this still leaves open the possibility that models which incorporate best response behavior, but allow for inconsistent beliefs, may explain the WC in auctions. To address this issueIvanov, Levin and Niederle (2010) employ a SPSB CV auction called the *maximal game* in which two players receive an iid signal, with the common value of the item equal to the highest signal drawn. The maximal game is dominant solvable in two iterations, so that overbidding (the WC) can only be rationalized by cursed (or *k*-level) beliefs if a bidder believes that others are using dominated strategies (in this case bidding *below* their signal values). They investigate this by (i) exogenously disallowing underbidding and (ii) by having subjects bid against

[52] There is little change over time in the frequency of 0 bids or bids of 20 in the 0-99 and 20-99 treatments respectively. Further, it does not appear that many subjects consistently bid 0 or 20 in these treatments.

their own bid from previous auctions. Neither of these two treatments eliminates the WC. There is minimal tendency toward downward correction of bids in both treatments as well. These results, together with CL, strongly suggest that the WC in laboratory experiments represents a more fundamental departure from Nash equilibrium bidding than simple inconsistency of beliefs. Quantal response equilibrium, which relaxes the requirement for strict best responding, is at odds with their data as well.

2.5 Additional Common Value Auction Results

2.5.1 Super Experienced Bidders: Kagel and Richard (2001; KR) investigate bidding for super-experienced bidders - subjects who had participated in at least two, and up to four, prior CVA sessions. These super-experienced bidders had learned to overcome the worst effects of the WC in FPSB auctions, rarely bidding above the expected value conditional on winning. However, they still earned less than 50% of the Nash profits (at a cost of between $2.50 - $3.50 per auction, conditional on winning). KR examine a number of elements that might be responsible for the continued shortfall relative to the RNNE benchmark.

They first look at the bid function itself, which is quite complicated over the full support from which signals are drawn, to see if it is for the shortfall in profits relative to the RNNE benchmark. They find that bidders use sensible piecewise linear bid functions rather than the more complicated Nash bid function. But simulations show that there exists a symmetric rule of thumb equilibria (RTE) (in which bidders are restricted to using piecewise linear bid functions of the sort estimated) in which profits are equal to or *greater* than the RNNE benchmark. As such, bidders' inability to account for the complexities of the Nash bid function cannot account for the marked reduction in their earnings. KR also show that subjects are *not* best responding to bids in excess of the RTE as large sample estimates of best responding requires a piecewise linear bid function very close to the symmetric RTE benchmark. Losses relative to best responding averaged 20% and 44% in auctions with 4 and 7 bidders, respectively. Thus, very experienced bidders still suffer from a WC, albeit one that is much less pronounced and more subtle than the negative average profits inexperienced bidders suffer from.

KR suggest two primary reasons for these continuing losses relative to the RNNE and the RTE benchmarks. First, best responses are highly variable in small samples of the sort that bidders would have seen, sometimes pointing in the wrong direction (bid higher than best responding based on large sample estimates) and sometimes implying overly passive bidding (bid below x - ε). This makes best responding far more problematic than the large sample estimates suggest, and could lead bidders to simply ignore any feedback once consistently positive profit levels were achieved. Second, large sample best responses require winning half as many auctions as were actually won. This involves a rather dramatic change in bidding, assuming that bidders are able to identify this fact, so that here too subjects may be reluctant to deviate from a rule of thumb that has proved capable of generating acceptable profit levels (compared to their inexperienced selves) in such a high variance environment.

2.5.2 Auctions with Both Common and Private Value Elements: One of the simplifications in standard auction theory is that bidders are dealing with either a pure common value *or* a pure private value environment. However, most real world auctions have both private and common value elements. For example, bidders for oil leases may have a single estimate for the common-value of the oil in the ground that is affiliated with other bidders' estimates and, in addition, have an idiosyncratic cost of extracting the oil and delivering it for refining. The theoretical difficulty with multiple signals for all bidders is how to combine them into a single statistic that can be mapped into a bid.[53] Goeree and Offerman (2003) develop one such model, and investigate it experimentally (Goeree and Offerman, 2002; GO).[54]

GO employ a series of FPSB auctions, the main objectives of which are to evaluate those factors their model predicts will raise efficiency and revenue. These consist of (i) reducing the variance in the signals for the CV component, which ought to make the auction more efficient as it moves the environment closer to a pure private value auction, (ii) increasing the number of bidders which, in their model, reduces the weight bidders place on the CV component of their signal, thereby increasing efficiency, and (iii) releasing public information that reduces the importance of the CV element, thereby increasing revenue as in a pure CVA and improving efficiency as well. In all treatments, both the

[53] This section is clearly related to that of common value auctions with an advantaged bidder. However, in this case bidders have two independent signals, one for the common value and one for the private value.
[54] In their formulation the common value component depends on the *average* of bidders common value signals.

"rational" bid function in which bidders fully account for a potential WC, and a naive bid function in which bidders fail to do so, predict the *same* winner as they are both functions of the same summary statistic, so there is no efficiency loss in their design due to a WC.

[Insert Figure 6 here]

GO report that the winner's curse is alive and well in their experiment as bids lie in between the naïve and Nash benchmarks (see Figure 6) even for experienced bidders, and lie closer to the naïve benchmark the less important a bidder's private value is relative to the common value.[55] The WC serves primarily to raise revenue and reduce bidders' profits, with realized efficiency roughly at the level predicted under the RNNE. The latter occurs because (i) almost all bidders suffer from a WC and (ii) the degree of suffering is roughly the same across bidders, so that the private value element of a bidder's signal serves to dictate who wins the auction. As predicted, efficiency increases the smaller the variance in the signals for the CV component and with increases in the number of bidders. Ignoring their low variance treatment, with its minimal scope for a WC, public information regarding the CV component increases bidders' profits in four out of five treatments, consistent with the comparative static prediction of the naive bidding model and the results reported in KL (1986).

2.5.3 Selection Bias, Demographic, and Ability Effects: The transition from inexperienced bidders suffering persistent losses to experienced bidders earning respectable profits in CVA experiments is characterized by large numbers of bidders going bankrupt, with these bankrupt bidders much less likely to return as experienced subjects. Further, the WC involves a judgmental error – the failure to account for the adverse selection effect conditional on winning – so that it joins a growing literature suggesting that limited cognitive abilities might help to explain many of the observed deviations from full rationality reported in experiments. Casari, Ham and Kagel (2007; CHK) conduct an experiment designed to better understand the process whereby experienced bidders learn to avoid the WC, as well as the impact of cognitive ability and demographic effects on learning to overcome the WC. Cognitive ability is measured by Scholastic Aptitude and American College Test (SAT/ACT) scores collected from university records. University

[55] Bankrupt bidders from inexperienced subject sessions were *not* invited back for experienced sessions. This generates potential selection effects discussed in the next subsection.

records also provided information regarding college major, grade point average (GPA), and gender.

Subjects participated in two sessions approximately one week apart. To better understand the learning process, starting cash balances were randomly varied across bidders, with additional random shocks generated via a lottery with positive expected value (similar to the HKL experiment reported in section 1.6 above). Further, some sessions followed standard experimental procedures inviting all subjects back for additional sessions without any special inducements to return, while others recruited subjects who were committed to returning and were provided strong incentives to do so in the form of relatively large show-up fees (to be paid at the end of session two), with half of session one's earnings withheld until completion of session two. In this way CHK hoped to distinguish between learning via market selection effects (less able bidders going bankrupt, exiting the market and not returning for subsequent experimental sessions) versus individual bidders learning to avoid the WC.

CHK report a number of substantive as well as methodological results: First, not surprisingly, ability as measured by SAT/ACT scores matter in terms of avoiding the WC. However, the nature of these ability effects are different from what one might expect as (i) composite SAT/ACT scores were consistently more significant than either math or verbal scores alone and (ii) the biggest and most consistent impact was that subjects with *below* median scores were more susceptible to the WC, as opposed to those with very high scores doing exceptionally well. Second, there were clear demographic effects as inexperienced women were much more susceptible to the WC than men, even after controlling for ability and college major, factors that are not typically controlled for in investigating gender effects in experiments.[56] However, women learned faster than men so that this difference disappeared with experienced bidders. Economics and business majors were much more susceptible to the WC than other majors, and continued to earn lower profits even as experienced bidders controlling for SAT/ACT scores and gender. Controlling for selection effects, bidders are capable of substantial individual learning, even those subjects who start out being most susceptible to the WC. However, more able bidders were more likely to return as experienced subjects, with this factor

[56] Similar gender effects are identified by Charness and Levin (2009) in the closely related takeover game.

dominating learning between weeks one and two for those sessions that did not employ special inducements to get subjects to return. As such previous studies that have not controlled for selection effects are likely to have substantially overestimated the amount of individual subject learning that occurs when moving from inexperienced to experienced bidders.

CHK also find that standard econometric estimators for dealing with selection effects in field data do not identify them in their data, in spite of having a relatively large sample by experimental standards and well identified econometric models. However, the different experimental treatments built into the experimental design serve to identify, measure, and verify these effects. The latter is not surprising, since at least as far back as Fisher (1935) statisticians have understood that experimental design could permit the identification of casual effects.

As to why economics and business majors were more susceptible to the winner's curse, CHK suggest that this is more than likely a personality effect, with business and economics students by nature more aggressive in business-type transactions. An alternative hypothesis, that 'little knowledge is a dangerous thing,' is rejected on the grounds that subjects were drawn primarily from introductory economics classes which do not cover issues like the WC. The gender effect is much more difficult to explain. Two known factors that immediately come to mind, that women tend to be more risk averse than men and that men tend to be overrepresented in the upper tail of mathematical reasoning, fail as (i) risk aversion cannot explain succumbing to the WC since it involves earning *negative* expected profits and (ii) the estimated bid functions show that mathematical ability does *not* play a critical role in succumbing to the WC (and was controlled for in the statistical analysis). CHK conjecture that the greater susceptibility of women to the WC may reflect a relative lack of experience with strategic interactions compared to men, perhaps as a result of women shying away from competition more than men (Niederle and Vesterlund, 2007; see Chapter xx as well). This relative lack of familiarity might induce more aggressive bidding as a consequence of the failure to fully think through its implications.

Remark: CHK also compared their sample population to the university population from which their sample was drawn. The most interesting result here is that 20.2% of their sample were in the top 5% (of the national average) with respect to composite SAT/ACT scores (versus 4.9% for the university), with less than 8.9% scoring below the median (versus 20.9% for the university), indicating that much brighter students enrolled in their experiment. These results suggest that subjects who voluntarily enroll in economics experiments more than likely over represent high ability students.

2.5.4 Is the Winner's Curse Confined to College Sophomores? One inevitable question raised by laboratory experiments is whether the behavior reported is confined to the typical population of convenience, undergraduate students, as opposed to "real people" in field settings. Kagel's (1995) survey addressed this question in two ways: First, it reported a number of striking similarities between anomalous field data and the experimental outcomes that could be directly attributed to the WC.[57] Second, results from a laboratory experiment comparing experienced bidders from the construction industry with student subjects showed both suffered from a strong WC (Dyer, Kagel and Levin, 1989). Follow up research suggested two key factors, which are not mutually exclusive, behind the executives performance in the lab and their apparent success in the field (Dyer and Kagel, 1996; DK): One is that the executives had learned a set of situation-specific rules of thumb which permit them to avoid the WC in the field, but which could not be applied in the laboratory, such as their specialized experience with a given branch of the construction industry, or familiarity with the architect responsible for supervising the work. Second, the bidding environment created in the experiment, which is based on theoretical work, is not fully representative of the environment encountered in the construction industry; e.g., repeated play elements present in the field typically permit bidders to pull winning bids that are clearly too low relative to the expected cost of the project, and to do so without penalty.

Harrison and List (2008; HL) report results that appear to be at odds with the contactor results. In their experiment they compare bids by sports card dealers with non-dealers in a laboratory type setting under the symmetric information structure employed in KL (1986) (each bidder gets a random signal from the interval $[x_o - \varepsilon, x_o + \varepsilon]$) as well as the asymmetric information structure employed in KL (1999) (one bidder knows the true value, x_o, with certainty while all other bidders get a signal drawn from the interval $[x_o - \varepsilon, x_o + \varepsilon]$). Subjects bid in a single auction after having participated in at least 10

[57] To be sure there are alternative explanations for the field data (see KL, 1986), but the WC is a much more straightforward explanation than the alternatives offered.

practice auctions, with examples run until subjects were confident with the rules of the auction. Treatments included two different values of ε ($6 and $12) and two different levels of competition – auctions with 4 and 7 bidders.[58]

Their results show that with symmetric information dealers rarely suffer from a WC, while non-dealers do, with these differences statistically significant at conventional levels. Further, there are significant differences in the estimated bid function between dealers and non-dealers, with much of the difference resulting from the sharper discounting of bids relative to value with ε = $6 for dealers.[59] In contrast, in the asymmetric information laboratory treatment HL are unable to reject a null hypothesis that dealers in their role as outsiders bid differently from non-dealers, with dealers suffering from a non-negligible frequency of the WC (in 25%-30% of all auctions).

HL interpret their results as follows: The absence of a WC with symmetric information is consistent with the notion that dealers have experience in comparable settings. Further, since this experience is generated in the field and not in the lab, it supports the notion that "… context-specific experience does appear to carry over to comparable settings, at least with these types of auctions." (HL, p. 839) However, once dealers are taken out of their comfort zone, bidding as outsiders in the asymmetric information auctions, a role HL argue dealers rarely occupy in field settings, they look very much like the student subjects. At a minimum HLs results provide additional evidence for very limited learning generalizability: Dealers having adapted to adverse selection effects in field settings with symmetric information do not recognize the heightened adverse selection effect when an insider is present, succumbing to the WC. This is consistent with the psychology literature on learning generalizability which indicates that learning transfer, unless specifically taught for, does *not* generalize easily

[58] Subjects were not provided with any starting capital balances or participation fees to cover potential losses. Rather a second experiment, not announced until the first experiment was completed, was used to insure that subjects went home with positive earnings. Given the potential impact of limited liability for losses on bids (Kagel and Levin, 1991), failure to announce in advance how potential losses would be covered is problematic at best.

[59] Shaving of bids relative to signal values averaged 40% (82%) for non-dealers versus 93% (88%) for dealers with ε = $6 ($12).

across different domains, and the more different the domains the harder to obtain positive learning transfer.[60]

Given the limited learning generalizability identified in HLs data, in conjunction with the psychology literature on the subject and DKLs results with construction contractors we offer the following alternative explanation of HL's results: It may well rest on a heuristic that travels well as HL claim, but one that is *not* related to the WC. Rather it rests on a heuristic that adventitiously protects dealers from the WC in the symmetric information case. Namely dealers are in the habit of buying low and selling high; e.g., List and Lucking-Reiley (2000) show that dealers bid just under $50 for cards with a retail value of $70 in a Vickrey auction (also see GWW, 2004). Applying such large discount factors could very well protect dealers from a winner's curse. In contrast non-dealers, who buy for own use, would not be in the habit of applying such a large discount factor. We are not sure how to sort out their explanation from ours. However, we would note that, to the extent dealers have experience with buying and selling objects with a significant CV component (as there are established markets and prices for sports cards and sports memorabilia) there is little scope for any kind of an adverse selection effect for dealers, as elaborated on below.

Remark: HL also report a treatment in which subjects bid to purchase an unopened package of L*eaf* sports cards, packages containing 10 cards of unknown value, and an *established* retail price of between $9-$10. They argue that this represents a CVA, which we agree with. However, it is *not* one in which there is any scope for a WC since the cards have an established market value; i.e., there is no scope for an adverse selection effect based on different estimates of value that anyone but a very poorly informed buyer might have. As such, this exercise is comparable to auctioning off a $10 bill. Plots of bid distributions bear this out as there is not a single bid above $10 for dealers and only a handful of bids above $10 for non-dealers.

HL also make a number of broader and related claims, at least one of which deserves further discussion. They claim that the absence of a WC among dealers in both the *Leaf* trading card treatment and in the more abstract laboratory treatment with symmetric information is "… consistent with the conclusion that *dealers in the field do not fall prey to the winner's curse providing tentative support for the hypothesis that naturally occurring markets are not in disequilibrium because of the WC*" (HL, p. 823-24, italics in the original). Here, we would remind the reader that the term "winner's curse" was initially coined by three petroleum geologists (Capen, Clapp and Campbell,

[60] For a good primer from the psychology literature on learning generalizability see Salomon and Perkins (1989). Or as the Noble laureate Richard Feynman (2005, p. 39) put it: "I don't know what's the matter with people: they don't learn by understanding; they learn by some other way - by rote, or something. Their knowledge is so fragile."

1971) reporting on results from early outer continental shelf (OCS) oil lease auctions in an effort to explain low (or below normal) returns on these leases. The debate that this assertion set off for OCS leases, as well as similar claims in other settings, is what originally motivated experimental work investigating the WC.[61] The fact that these experiments showed that the WC is alive and well, persistent and robust, indicate that it is likely to exist *at least in the start up phase* of auction markets with a strong CV element. Finally, let us assume, that HL are correct that in relatively settled markets with very experienced bidders survivors no longer fall prey to the WC. To us this is similar to arguing that in a population ravaged by an infectious disease the disease no longer exists since the survivors have developed immunity to it. This does not, however, imply that should a significant variation of the disease strike the surviving population that they will be able to do any better than the original population. The auction analogy is that market participants who no longer show symptoms of a WC will not necessarily exhibit equilibrium responses to significant changes in the environment, such as increased numbers of rivals, the introduction of an insider with better information about the common value, or an almost CV element.

III. Multi-Unit Demand Auctions

Theoretical and experimental research up to 1995 focused almost entirely on auctions where each bidder demands a single unit of a homogenous commodity. Not much changes in the theory if there are multiple units for sale as long as individual bidders continue to demand a single unit. However, in auctions where bidders demand multiple units, outcomes can change rather dramatically. The FCC air wave right (spectrum) auctions in the 90's provided the main incentive to better understand auctions where bidders demand multiple units, raising a host of new issues, many of which are of public policy importance. (The extensive use of Internet auctions also has played a major role in stimulating auction research; see Section 4.3 below.) Where and how can one design efficient multi-unit demand auctions? Are efficient multi-unit demand auctions very different from optimal (revenue maximizing) auctions? Multi-unit demand auctions also call attention to a much richer strategic environment where bidders may exercise demand reduction, bidding "passively" on some units in order to obtain other units at low prices. They also call attention to the difficult case of complements, with strong synergies generated as a consequence of winning multiple units, and the potential role of package bidding to help achieve more efficient outcomes.

[61] For example, auctions for book publication rights (Dessauer, 1981), professional baseball's free agency market (Cassing and Douglas, 1980; Blecherman and Camerer, 1998), corporate takeover battles (Roll, 1986), and real estate auctions (Ashenfelter and Genesove, 1992).

In looking at multi-unit demand auctions we need to distinguish between small scale, traditional laboratory experiments designed to investigate some of the new theoretical/behavioral issues identified in the literature as opposed to market design issues. In the latter the laboratory serves as a "wind tunnel" for comparing different mechanisms for specific public policy purposes. There are limited numbers of comparable market design experiments against which to evaluate results (and often not much emphasis on the behavioral mechanisms behind the results reported). We will review the more traditional small scale experiments that focus on behavioral issues, with market design issues covered in Roth (Chapter xx, this volume).

3.1 Auctions with Homogeneous Goods - Uniform-Price and Vickrey Auctions

In multiple-unit, uniform-price (UP) auctions items are allocated to the high bidders at a price equal to the highest rejected bid. With bidders demanding multiple units, if the goods are substitutes, bidders have an incentive to reduce demand in an effort to obtain more favorable prices on the items actually won (Ausubel and Cramton, 1996; Engelbrecht-Wiggans and Kahn, 1998). The argument for demand reduction is essentially the same as a monopsonist who takes account of the fact that with increased demand, the price they pay will increase as well. Cramton (1997) argues that the first nationwide FCC spectrum auctions could be best modeled as UP auctions of this sort.

Kagel and Levin (2001; KL, 2001) experimentally investigate the sensitivity of bidders to these demand reduction possibilities, comparing behavior under a sealed-bid uniform-price (SBUP) auction with an English clock auction in which bidders receive information regarding rivals' drop-out prices as the auction progresses. They study behavior in the simplest possible setting while still preserving the essential strategic elements of more complicated auctions: A human subject with flat demand for two units of a homogeneous commodity competes against different numbers of rivals demanding a single unit of the commodity, with the role of single unit buyers played by computers whose bids are equal to their private value (the dominant strategy).

With IPV draws from a uniform distribution, and supply of two units, the equilibrium prediction for the "large" (human) bidder is to bid her value on unit 1 and to bid sufficiently low on unit 2 so as to not affect the market price.[62] This holds irrespective of the value of the item, the number of computer rivals, or whether a SB or English auction format is used. For the SB auctions this requires bidding zero on the second unit, which is far from transparent. In contrast, the optimal bidding strategy in the clock auctions requires dropping out on the second unit at a price $p \in [0, v_2]$ where v_2 is the drop-out price of the second highest computer rival. This has exactly the same consequences as dropping out at 0, but the feedback information provided by rivals dropping out, and the flexibility in the dropping rule, makes the optimal bidding strategy substantially more transparent.[63]

Results from this experiment showed clear evidence of demand reduction in the UP auctions, but with substantially more demand reduction in the English auctions: 30.8% of all unit 2 bids were pivotal (higher than v_2, thereby setting the market price) in the sealed-bid auctions compared to 11.4% in the clock auctions.[64] However, there were even more striking differences between the two auction formats as: (i) There was a much higher frequency of bidding above value on the first (and even the second) unit in the SB auctions (comparable to the results for SPSB auctions) and (ii) there were relatively few bids at 0 in the SB auctions, required to insure not being pivotal. Figures 7 and 8 illustrate these differences between the two UP formats with five computer rivals.

[Insert Figs 7 and 8 here]

KL show that the primary basis for the superior performance of the clock auction over the SB version results from the feedback information regarding the computer's drop

[62] With bidders having the same value for two units we refer to the higher bid as the bid on unit 1 and the lower bid to the bid on unit 2.

[63] For example, assume a support for values of between [0, 100] with the values for both units for the human bidder, v_h, of 90. Suppose that h has no formal understanding of the optimal bidding strategy and decides to remain active as long as $p \leq v_h$. Suppose that v_2 drops out at 50. Now h has two options, drop at 50 and earn an instant profit of 40 or remain active in an effort to win both units. In the latter case there are two events to consider (i) the highest computer rival (v_1) drops prior to $p = v_h$ in which case h's expected profit is 40 (as 70 is the expected drop price for v_1) or (ii) $v_1 \geq v_h \geq 90$ in which case h's expected profit is zero. Thus, dropping at $p = v_2$ dominates waiting and trying to win two units. This is not to say that these calculations are trivial but they are far more transparent than the ex ante calculations underlying the optimal bidding strategy in the SB auctions. Further, if h remains active once $p > v_2$ it should be increasingly transparent that she is competing against herself, which should lead to dropping out before the price is equal to v_h, which might help promote learning over time.

[64] Results are pooled over auctions with 3 and 5 computer rivals. All data are for the last 12 auctions in a session. Subjects were never told that the computers were following a dominant strategy, just that they would drop out at their randomly drawn values.

out prices. They did this in two ways. First, they conducted a clock version of the auction in which there was no feedback, with the auction ending when the last bidder dropped out. In this case the clock was of no help to bidders as there was massive overbidding on both units, quite similar to what was found in the SB auctions. They also conducted a UPSB auction in which v_2 was posted in a prominent place on bidders' computer screens. Subjects were not told how to use the information, just what it was and that it had been suggested that the information might prove helpful in determining how to bid. This treatment went a long way to moving the SB outcomes closer to the clock results as (i) it essentially eliminated the overbidding on unit 1 and (ii) resulted in a level of demand reduction closer to the one reported for the clock auctions.

KL also compared outcomes in the uniform-price auctions to a dynamic Vickrey/Ausubel auction (Ausubel, 2004). This dynamic version of the Vickrey auction with drop-out information provided employs a "clinching" metaphor from sports leagues to characterize prices paid.[65] It generates sincere (value) bidding in iterated deletion of dominated strategies and, under KL's demand structure, raises more revenue than the UP auctions. Results from the Ausubel auctions are shown in Figure 9, where outcomes are reasonably close to sincere bidding.

[Insert Figure 9 here]

Using bidders' actual earnings relative to predicted earnings as a measure of how close bidders were to optimal outcomes, KL establish a clear ranking for the three auction institutions studied: the UPSB auctions are furthest from the maximum predicted (only 13.6% of all subjects averaging within 5% of maximum possible profits), the UP clock auction with feedback is next (46.5% of all subjects averaging within 5% of maximum possible profits), with the Ausubel auction closest to the maximum (85.2% of all subjects averaging within 5% of maximum possible profits).[66] KL conclude that like the UP

[65] Clinching works as follows: With 2 objects for sale, suppose at a given price, *p*, the human bidder (*h*) still demands two units, but the aggregate demand of all *other* bidders has dropped from 2 to1. Then, in the language of team sports, bidder *h* has clinched a unit no matter how the auction proceeds. As such, at that moment, *h* is awarded one unit at the clinching price, *p*. The auction continues with the supply reduced from 2 to 1 and *h*'s demand reduced to one unit. This process repeats itself until all units are allocated. In this way the auction sequentially implements the Vickrey rule that each bidder pays the amount of the $k^{\mathbf{th}}$ highest rejected bid, other than his own, for the k^{th}t unit won.

[66] Given the use of computer rivals, actual profit relative to predicted profit provides a suitable metric for comparing outcomes across institutions. Z statistics using individual subjects as the unit of observation show all three of these differences to be statistically significant at better than the 1% level.

clock auction with feedback, the Ausubel auction benefits from the clock procedure with feedback to prevent overbidding. However, unlike the uniform price clock auction, the Ausubel auction encourages non-strategic bidding (full demand revelation), something that bidders are inclined to do even in the uniform-price auctions. Thus, the closer to optimal performance observed in the Ausubel auction partly results from an institution that accommodates itself to bidders' natural tendencies, rather than any adjustments on bidders' part to the strategic requirements of the institution.

Remark: KL's UPSB auction included explicit advice against subjects bidding above their values, along with examples as to how this could lead to losses. The motivation for this was to speed up equilibrium outcomes on unit 1 bids, a "nuisance" factor in terms of KL's primary interest in demand reduction on unit 2 bids. Referees criticized these procedures as biasing the SB auctions too strongly in favor of equilibrium outcomes, in response to which additional sessions were run dropping the advice. As anticipated the primary impact was to reduce the frequency of unit 1 bids above value, with essentially no impact on the overall frequency of demand reduction. The point of this remark is that by the turn of the century with experiments firmly entrenched in the economist's tool kit, and behavioral economics making its way onto the stage, referees and editors of a major journal were concerned with biasing procedures in *favor* of the theory. From our personal experience this reflects a significant (and welcome) shift from earlier referees (and journal) biases in favor of experimental outcomes *supporting* a theory, with little regard, in some cases, to procedures that favored the theory.

There have been a number of subsequent experiments using all human bidders investigating demand reduction in UP auctions. List and Lucking-Reiley (2000; LLR) look at demand reduction in a field experiment with subjects bidding for sports cards in a UPSB auction. Each auction had two subjects bidding for two identical units with supply of two units (subjects participated in a single auction). Since LLR do not know bidders' value for the sports cards, they employed a parallel series of SB Vickrey auctions (in which sincere bidding is a dominant strategy) as the reference point against which to evaluate demand reduction in the UP auctions. Their design also has an equilibrium in which subjects bid their value on both units (Ausubel and Cramton, 1996), but argue against this equilibrium on the grounds that it is a knife edge case, so that any small reduction in value for the second unit, which is likely to be present, would eliminate it.

They employed two types of sports cards – one with low ($3) and one with high ($70) book value – and conducted separate auctions for dealers and non-dealers.

LLR find that unit 2 bids are systematically lower in the UP compared to the Vickrey auctions, with these differences statistically significant for the high valued cards for both dealers and non-dealers: $41.77 versus $30.60 for dealers, $28.82 versus $16.62 for non-dealers. They also found that unit 1 bids were consistently higher in the UP auctions, with these differences statistically significant for the higher valued sports cards. This stands in marked contrast to the sincere bidding predicted for unit 1bids in both cases.

Porter and Vragov (2006) replicate the LLR experiment, only with induced values and adding a UP clock auction to the mix. Sessions consisted of 30 auctions, with new randomly drawn valuations and auction partners in each auction. There is supply of two units with two bidders each demanding two units, sometimes with different values, sometimes with the same values. In the latter case they have the same multiple (symmetric) Nash equilibrium problem as LLR.

Their results largely replicate those reported so far. First, for the UPSB auctions there is rather massive overbidding with respect to unit 1 bids and relatively large scale demand reduction with respect to unit 2 bids (see Figure 10). For the clock auctions unit 2 prices are close to their starting price and well below prices in the sealed-bid auctions, consistent with strong demand reduction. Their SB Vickrey auctions exhibited substantial bidding above value for both units (see Figure 11), consistent with the results reported for SPSB auctions.

[Insert Figures 10 and 11 here]

Engelmann and Grimm (2009) (EG) also investigate bidding for two homogenous items in auctions with two bidders each with flat demand for both units. They look at demand reduction in both UP clock and SB auctions, and compare outcomes with a dynamic Vickrey (Ausubel) auction and a static Vickrey auction.[67] Their experimental design is hampered by the fact that subject pairings remain fixed over the full set of 10

[67] EG also report on discriminatory auctions with this design. One of their most interesting results in this case involves submitting different bids on the two items (bid spreading), where bidders should submit equal bids for both items. In this case, 58% of unit 2 bids are below the RNNE without any discernable time trend, which is inconsistent with risk aversion (Grimm and Englemann, 2005). Kagel and Levin (2005) also report bid spreading where it should not occur in multi-unit demand auctions with synergies.

auctions in each treatment, which leads to scattered efforts to promote collusive outcomes. However, after factoring out these collusive efforts, their primary results are well in line with those reported in KL: (1) there is more demand reduction in the UP clock auctions than in the UPSB auctions, (2) there is close to sincere bidding in the Ausubel auction, and (3) there is a higher frequency of bidding above value on unit 1 bids in the UPSB auction than in the UP clock auction or the Ausubel auction. Based on this last result, they note that contrary to the theory, the UPSB auction generates higher revenue but lower efficiency than the Ausubel auction, so that there might be a tradeoff between these competing objectives for a government seller, a point that KL (2001) noted as well. Like LLR they find more overbidding on unit 1 in the UPSB auctions than in the static Vickrey auction. The one inconsistency with earlier results is that they find surprisingly little learning within and across auction formats, in contrast to the modest learning reported in KL.

Remark: The one anomalous finding in these experiments is that unit 1 bids in the UPSB auctions exceed those in the SB Vickrey auction. Levin (2005) argues that with two bidders each demanding two units with supply of two units there is a very appealing low revenue (implicitly collusive) Nash equilibrium that is also an *ex-post* equilibrium in which both bidders bid above their private value on unit 1 and zero on their unit 2 bids. Although bidding above value on unit 1 involves a weakly dominated strategy, this alternative equilibrium is attractive on a number of grounds: 1. It is an *ex-post* equilibrium so it is distribution free; 2. The equilibrium has *no-regret,* so there is less incentive to correct actions than the one focused on in the papers employing this design; 3. It allows a wide range of bidding (any high bid on the first unit will work) so it is easier to coordinate on; 4. It has a more equitable distribution of payoffs which is favorable to maintaining collusion. Engelbrecht-Wiggans, List and Reiley (2005; EWLR), in their response to Levin's comment, argue that (i) the data in LLR are inconsistent with the beliefs underlying this alternative equilibrium, as it depends on both agents bidding zero on unit 2, while nearly three-fourths of all unit 2 bids were strictly positive in their experiment[68], and (ii) there is a similar equilibrium in weakly dominated strategies for their SB Vickrey auctions resulting in incentives to bid above value there as well. The alternative equilibrium identified in Levin (2005) collapses once there are three or more bidders (with two units supplied) and/or with a positive reserve price. EWLR (2006) report an experiment of this sort with three or five bidders, the results of which show that unit 1 bids in the UP auction are statistically indistinguishable from the Vickrey auction.

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[68] However, bidding zero on unit 2 is also possible in LLR's equilibrium since the underlying distribution of values is unknown and bidding errors can, at least partially, account for positive bids on unit 2, since deviations from Levin's proposed equilibrium can only be positive.

Summing Up: UPSB and clock auctions with homogenous goods generate demand reduction as the theory predicts. But there is substantially more demand reduction and closer to equilibrium bidding in clock auctions. The key mechanism behind this difference appears to be the feedback provided by other bidders' drop-out prices in the clock auction (KL, 2001). Ausubel's version of the dynamic Vickrey auction eliminates much of this demand reduction, with close to equilibrium outcomes (sincere bidding) as well. The SB Vickrey auction generates overbidding relative to induced values, as do unit 1 bids in the UPSB auctions, consistent with the results typically reported for SPSB auctions. All of these results hold up both with simulated (computer) bidders and with all human bidders. More generally, these results support the notion that bidding is closer to equilibrium predictions in dynamic auctions with feedback as opposed to SB versions of the same auction mechanism.

3.2 More on Multi-Unit Demand Vickrey Auctions

The 1995 survey summarized research showing that sincere bidding emerges quickly for most bidders in single-unit English clock auctions in contrast to the persistent overbidding in SPSB auctions. In auctions where bidders demand a single unit, the clock auction and SPSB auctions are strategically equivalent, with both yielding sincere bidding in weakly dominated strategies. In multi-unit demand auctions where bidders have weakly diminishing marginal valuations, the SB Vickrey auction and the dynamic Ausubel auction with drop-out prices reported are no longer strategically equivalent. Rather the SB Vickrey auction generates sincere bidding in weakly dominated strategies whereas the Ausubel auction requires iterated deletion of dominated strategies, a weaker solution concept.[69] Nevertheless, the research summarized in this section shows that the Ausubel auction with drop-out information generates outcomes much closer to sincere bidding than either the SB Vickrey auction or an Ausubel auction with no drop-out information provided (the latter is strategically equivalent to the SB Vickrey auction). While this may not be surprising from a behavioral perspective, it is surprising from a mechanism design perspective which typically calls for employing a mechanism with the

[69] While the first solution requires agents' rationality alone the later must add the requirement of common-knowledge of rationality, a far from trivial addition. Thus, the first solution concept is much more robust and desirable from a mechanism design standpoint.

strongest possible solution concept. This suggests a possible tradeoff between the simplicity and transparency of a mechanism and the strength of its solution concept when agents are not fully rational or are still learning. This has important implications for the market design literature. In addition to summarizing these results, we report results from studies that have looked at generalized versions of the SB Vickrey auction suitable for dealing with synergies between items.

Kagel, Kinross and Levin (2001; KKL) investigate different versions of the Vickrey auction in which a human bidder with flat demand for two units competes against computer rivals each demanding a single unit. They compared outcomes in a SB Vickrey auction with bidding in the dynamic Vickrey/Ausubel auction with drop-out information provided (hereafter referred to as the Ausubel auction). As anticipated, in the static Vickrey auction there was a high frequency of bidding above value for both units, with bidding above value on unit 1 more severe than unit 2. Comparing these results with those for the Ausubel auction, it's clear that the Ausubel auction comes closer to sincere bidding than the Vickrey auction, resulting in significant improvements in efficiency (but lower revenue) than in SB Vickrey auctions than in the Ausubel auction.[70]

One weakness with the KKL experiment is that with computers bidding their value, it only takes a single round of deletion of dominated strategies by the human bidder to achieve sincere bidding. With all human bidders it requires several more rounds of deletion of dominated strategies to arrive at sincere bidding. As such it is quite natural to ask whether the results with computerized rivals will extend to auction environment with all human bidders. Kagel and Levin (2009) address this question, looking at all three auction formats with four (human) bidders, each demanding two units and with supply of 2 or 3 units. Bidders' valuations were iid from a common uniform distribution. The results essentially replicate those reported in KKL as (i) there is substantially more sincere bidding in the Ausubel auction than in the other two auction formats and (ii) there is massive overbidding relative to valuations in the SB Vickrey auctions resulting in a relatively high frequency of negative profits conditional on winning. Finally, note that it is the ascending prices in the Ausubel auction in

[70] Average efficiencies were 97.5% and 97.9% in the sealed-bid auctions with three and five computer rivals, compared to 99.1% and 99.3% in the Ausubel auctions. Although these differences are small, they are statistically significant in both cases.

conjunction with the provision of dropout information that underlies *both* the greater transparency of the auction rules and the weakening of the solution concept.[71]

Manelli, Sefton, and Wilner (2006) compare a SB Vickrey auction with the Ausubel auction for the private values case, reporting overbidding in the Vickrey auction and closer to sincere bidding in the Ausubel auctions.[72] EG also compare the SB Vickrey auction with the Ausubel auction, reporting little difference between the two auction formats, including rather limited bidding above value on unit 1 bids in the SB auctions. The latter is at odds with results reported for the other multi-unit SB Vickrey auctions reported in this section, as well as Porter and Vragov's (2006) results reported in the previous section. The best explanation we have to offer for this difference is sampling variability or subject pool effects, as EG's experiment involved Swiss and German university students whereas the other studies reported on this issue involved U. S. university students.[73]

In concluding this section, we briefly review results from studies looking at generalized versions of the SB Vickrey auction with complementarities between items, the Vickrey-Clarke-Groves (VCG) mechanism (Vickrey, 1961, Clarke, 1971, and Groves, 1973). These are package auctions that permit XOR bids, with bidders bidding for as many packages as they wish, but only winning on one of their bids; e.g., in the simple case of two items, A and B, with values V_A, V_B and V_{AB} (where V_{AB} is the value of getting *both* A and B with $V_{AB} > (V_A + V_B)$) with XOR bids agents are permitted to bid for A alone, for B alone, and for the package containing both A and B, but can win only *one* of the packages bid on. The VCG mechanism is designed to produce sincere bidding and maximum efficiency, using suitably generalized Vickrey pricing rules to allocate items. There are a number of technical issues associated with implementing the VCG

[71] The drop-out information enriches the strategy space relative to the SB Vickrey auction by allowing bidders to have strategies that are contingent upon other players' drop-out prices. This enrichment also opens the door to different kinds of "misbehavior."

[72] The primary focus of this paper is on comparing the advantages of the Ausubel auction to the static Vickrey auction in the presence of a significant *common-value* component.

[73] A closely related experiment that deserves mention here is Kagel, Pevnitskaya, and Ye (2007) who compare the Ausubel auction to the strategically equivalent *survivor auction* in which the Ausubel auction is essentially implemented through a series of SB auctions. In spite of the similarity in structure and information feedback between the two auction formats, the Ausubel auction achieves significantly higher levels of sincere bidding and efficiency than the survivor auction to begin with, so that only with experience does the survivor auction comes close to the performance of the Ausubel auction.

mechanism, as well as potential tradeoffs between efficiency and seller revenue that are of concern in using it, discussion of which goes well beyond the scope of the present review (see Ausubel and Milgrom 2006). Rather, our primary interest is to report the results of an experiment applying the SB version of the VCG mechanism.

The experiment with the most complicated demand structure investigating the SB VCG mechanism is Chen and Takeuchi (2010) (CT). In each auction bidders compete for four items, resulting in a total of 15 possible packages to bid on. Human subjects compete against two computer bidders who bid sincerely in one treatment and randomly in another, under two different information conditions - with and without information on how the computers were bidding. Sincere bidding is a weakly dominant strategy regardless of what the computers do or the information provided about their bidding strategy. Subjects participated in 10 auctions under each treatment condition.[74] The auction interface automatically computed the value of each of the 15 possible packages so that bidding on all packages was relatively easy.

Optimal bidding in this case requires subjects to bid their value on *all* 15 packages. Subjects consistently failed to do so, with the average frequency of bidding on possible packages going from a low of 65%-66% for single item packages to a high of 83%-86% for combinations of items (83% for the package with all four items). This confirms one of the potential concerns with the VCG mechanism (and package bidding mechanisms in general), the complexity associated with formulating bids for all possible packages of interest. Conditional on making a bid, subjects generally underbid with 57% classified as under-bidders, 32% as sincere bidders, and 12% over-bidders. Losing bidders were significantly more likely to increase the number of packages they bid on as well as their bid to value ratio in the next auction, with winning bidders decreasing their bid to value ratio (albeit, to a smaller degree than losing bidders). These bid changes indicate that the dominant strategy is not transparent, with subjects adjusting their behavior according to a trial and error learning process.[75]

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[74] CT also compared the static VCG mechanism to an ascending price (iBEA) mechanism.

[75] Isaac and James (2000b) and Morgan (2002) study a SB VCG auction with two items and synergies, involving only three possible packages to bid on. Subjects bid on almost all possible packages in both studies.

Remark: The studies reported here have been concerned with behavioral issues within a market design context. In a market design experiment it is perfectly reasonable for the instructions and working examples to point out the benefits of different bidding strategies in describing how the underlying mechanism works, and what it's supposed to do, and should be considered part of the mechanism. Whether or not this would completely clear up the problems with the SB Vickrey mechanism identified here is problematic as (1) KL (2001) report substantial bidding above value on unit 1 in UPSB auctions with instructions intended to dissuade subjects from doing so and (2) Kagel, Lien, and Milgrom (2010) (reported on in section 3.3) show that subjects bid on only a small percentage of profitable packages early on even though they were informed of the benefits of doing so. The key point here is that one part of market design is to identify mechanisms that are aligned closely with agents' natural tendencies in order to come closer to achieving a desired outcome.

3.3 Auctions with Synergies

Most of the work in this area has been concerned with market design issues, particularly with respect to those raised in the FCC spectrum auctions. Here we cover several small-scale experiments concerned with underlying behavioral issues in the presence of synergies.

Kagel and Levin (2005; KL, 2005) look at a simple model of auctions with synergies comparing UP clock auctions to SB auctions. Their experimental design is similar to KL (2001) for the case of substitute goods - humans demanding two units of a commodity compete against computer rivals each demanding a single (and bidding their value – the dominant strategy for single-unit buyers). The standalone values for *h*, the human bidder, are the same (v_h), but winning both units generates synergies equal $3v_h$. The UP auction creates incentives for demand reduction for the "large" bidder similar to those discussed in section 3.1. However, there is an opposing incentive to bid aggressively to capture the synergy bonus, which becomes stronger at higher valuations. The net effect of these two competing forces is as follows: (1) at lower valuations, the demand reduction force dominates so that *h* bids zero on unit 2 (drastic demand reduction), (2) at the highest valuations the synergy force dominates so that *h* "goes for it," bidding high enough to insure winning both units, and (3) at middle valuations the two forces are at peak tension, with *h* bidding above the stand-alone value of both units (but short of "going for it") in the SB auction and "going for it," conditional on rivals' observed drop-out prices, in the clock auction. In both cases *h* faces an *exposure* problem for these middle valuations; the possibility of winning a single unit at a price above its standalone value and earning negative profits. Depending on the size of the potential loss, and risk preferences, bidders may refrain from suitably aggressive bidding, resulting in inefficient outcomes and relatively low revenue.

KL look at bidding in auctions with three and five compute rivals. Given the complexity of the auction environment, they employed a limited number of values for the human bidder designed to span the strategy space and to induce maximum differences in behavior between the SB and clock auctions, while providing bidders with considerable experience at each value.[76] The lowest v_h, \$3.00, calls for complete demand reduction in both SB and clock auctions. The highest v_h, \$5.10, requires "going for it," and insures a *secure* (minimum) profit in each auction. The two middle values make different predictions between SB and clock auctions: With v_h = \$4.00, in the SB auction *h* should bid the same on both units at prices modestly above their standalone values. The clock auction also requires bidding above value on both units, but with a cutoff value $v_2 \leq$ **P*>** v_h (where v_2 is the second-highest computer value), in which *h* goes for it, winning both units with positive expected profit; otherwise *h* drops out on both units at the cutoff point **P*.** At the other middle value, v_h = \$4.40, *h* "goes for it" ($b_1 = b_2 \geq$ \$7.50) in the SB auctions, regardless of the number of computer rivals. In the clock auction *h* continues to employ a cutoff strategy but with a higher cutoff value.

Bidding is substantially closer to optimal play in the clock auctions (see Table 5), consistent with the evidence from virtually all other auction environments. Further, in most cases bidders behave sensibly, though not optimally: The highest valuation, where optimal play is relatively transparent, generates the highest level of optimal play, comparable to the levels reported in any experimental auction environment. Estimated demand functions for the SB auctions are monotonically increasing in bidders' valuations. And in the clock auctions, there is a higher frequency of "going for it" at the two middle valuations when the optimal play requires it than at the lowest valuation, where demand reduction should occur.

[Insert Table 5 here]

[76] Since single-unit bidders have a dominant strategy independent of *h*'s valuation, KL could employ a limited number of values for *h* without distorting equilibrium predictions.

Nevertheless, there is much out-of-equilibrium play in both the SB and clock auctions, with the most interesting and dramatic differences for the two middle valuations with its exposure problem. In the clock auctions the primary deviation from optimal play consists of demand reduction as opposed to “going for it” as the theory predicts. In contrast, in the SB auctions bidders consistently bid above value on both units (often well above what they should bid and with different bids on each item). This suggests that the clock auction makes it much more transparent to bidders that they are liable to lose money as a consequence of bidding above value. While this clearly helps to generate close to equilibrium play in single unit demand auctions, in the present case it may hold bidders back from achieving maximum profit, generating deviations from the equilibrium outcome.

Absent the possibility of package bids, multi-unit demand bidders with synergies face an exposure problem. For single-unit demand bidders to win against a multi-unit demand bidder, the sum of what they are willing to pay must beat the larger player’s bid, so that smaller bidders must *coordinate* their bids to reach the *threshold* needed to beat the multi-unit demand bidder. However, each small bidder has an incentive to let the other one bid more aggressively in order to the item at the lowest possible costs. This is referred to as the threshold problem. There is no threshold problem in UP auctions for single-unit demand bidders since under the UP rule no small bidder can obtain a unit at a lower price than the other small bidder. However small bidders face a threshold problem in discriminatory (pay what you bid) auctions. All of this extends to cases where “regional” bidders with synergies, but more limited (non-overlapping) market areas (e.g., the North and the South), compete against a larger global bidder who has positive demand and synergies over the entire market area.

Chernomaz and Levin (2012; CL) investigate bidding in a highly stylized version of just such an environment. They look at a FPSB auction with and without package bidding. Despite the general preference for iterative auctions, FPSB auctions have been used in a number of cases (Cantillon and Pesendorfer 2007, Epstein et al. 2002), having several attractive features such as their resistance to collusive behavior. They consider two regional bidders each demanding a single item competing against a global bidder with flat demand for two items. They employ a two-by-two experimental design, varying the auction rules (with and without package bidding) and the synergy level (0% and 50%). The two local bidders are restricted to having the same value for their respective items (based on a single random draw), which under the symmetric RNNE should result in the same bids. The global bidders value for winning a single unit is s_g, drawn from the same distribution, with the value for winning both units $v_g = 2\beta s_g$, where β represents the synergy value. This highly structured environment permits solving analytically for equilibrium outcomes.[77] Among other things, with single-item bidders having the same valuations, under the RNNE there is no exposure problem for the global bidder as he either wins both items or loses both. But local bidders still faces a threshold problem with package bidding which, somewhat surprisingly, is present even with no synergies, as absent the ability to coordinate their bids, the marginal benefit to single-unit bidders for raising their bids is lower than without package bids. This, in turn induces the global bidder to bid less, which in turn adversely impacts revenue and efficiency. The threshold problem is so strong in this model that sellers using package auction are predicted to raise substantially less revenue than selling the items separately under the two synergy levels studied.

Changes in revenue are qualitatively consistent with the model as less aggressive bidding with package bidding has a substantial negative effect on revenue. This is primarily driven by the strong response of single item bidders to the threshold problem, which is much more severe in FPSB auctions given their limited ability to coordinate bids (compared to an ascending price auction), which induces the global bidder to bid less as well. This, in conjunction with the negligible positive effect of package bids on efficiency when synergies are present, lead CL to sound a cautionary note regarding the efficacy of FPSB auctions in environments such as this.

Katok and Roth (2004) also look at auctions with synergies comparing a descending price (Dutch) auction with an ascending, UP auction. Each auction has three bidders with supply of two homogenous units; one “big” bidder who has a high value for both items and two small bidders who each want one unit. The Dutch auction is, in effect, a package auction since the winner gets to choose how many units to purchase, thereby mitigating the exposure problem (which is very much present in their UP

[77] CL require the global bidder to place the same bid on both items in the absence of package bids.

auctions). As already noted, the UP auction mitigates the threshold problem since under the UP rule no small bidder can obtain a unit at a lower price than the other small bidder. *Summary:* To date there have been very limited small-scale experimental studies focusing on multi-unit demand auctions with synergies. The results of the experiments reported here confirm the existence of an exposure problem in the presences of synergies which results in less aggressive bidding, with smaller than predicted synergies realized. The introduction of package bidding in CLs SB auctions introduces significant threshold problems for local bidders. Results from the few VCG package auction experiments reported at the end of the previous section suggest that this is not a viable alternative to dealing with multi-unit demand auctions with synergies, as the frequency of sincere bidding is relatively low and subjects only bid on a small percentage of the packages available (even in auctions with very few items), both of which can severely compromise the promised efficiency gains. Further, the VCG mechanism can result in very low revenues as well, which are politically unacceptable.

Kagel, Lien and Milgrom (2010, 2014; KLM) report results comparing a combinatorial clock auction (CCA) mechanism which permits package bidding with a simultaneous ascending clock auction (SAA) mechanism. They have two regional bidders (demanding multiple units with synergies) competing against a global bidder with demand for all items (with synergies over all items). What is relevant here is: (1) KLM identify a clear threshold problem in some of the CCA auctions. However, the magnitude of the effect was relatively small, and in some cases was mitigated by local bidders bidding on packages including items which had zero own value (but positive value to the other local bidder). While rarely getting caught holding any zero value items, this forces other local bidders to increase their bid if they hope to win any items (KLM, 2014). (2) Similar to the results reported in CT for the VGM mechanism with package bidding, subjects bid on only a tiny fraction of the packages available to them even though they were explicitly encouraged to do so and had a computer interface that made placing bids very easy. This package selection problem also underlies inefficiencies in package auctions as bidders tend to bid on their most profitable packages as well as their "named" packages (i.e., for regional bidders all the items they have positive value for and for the global bidder all items), as the named packages are typically quite profitable. This generates high revenue and efficiency as long as the "named" packages constitute the efficient outcome (i.e., either of the two regional bidders getting all their named items or the global bidder getting all items). However, in cases where the efficient outcome requires that all bidders obtain one or more items, or the items be split between a regional bidder and the global bidder, there are marked reductions in efficiency under the CCA (and relative to the SAA). What drives this last result is that when the named package is no longer the most profitable package, the amount bid on the named package must be greater than the bid on the most profitable package (since the latter contains fewer items). This, in conjunction with the CCA auction assigning packages to maximize seller revenue means that, other things equal, the CCA algorithm would pick a bidder's named package over the bidder's most profitable package, which reduces efficiency when the named package no longer coincide with the bidders most profitable package. Similar package selection problems can be found other multi-unit demand auctions with strong synergies (Brunner et al., 2010, Goeree and Holt, 2010, and Scheffel et al. (2012)).

3.4 Sequential Auctions

Robert and Montmarquette (1999; RM) study sequential auctions in which each of eight bidders have positive demand for m^i units, where m^i is iid from a *Poisson* distribution with a maximum m^i of 15, and with a total supply of 15 units in each auction. Once m^i is determined, the value for each of the m^i units is iid from a *uniform* distribution on [0, 100], and ranked in decreasing order for a downward sloping demand curve for each bidder. RM compare bidding in three types of sequential auctions: Dutch (descending-price), English (ascending-price) and mixed Dutch and English. A round of Dutch auctions was conducted as follows. The first unit was offered at the highest possible price of 100 with the price lowered by one ECU every two seconds until a unit was purchased. The second unit was then offered at an initial selling price of 5 ECUs above the winning price for the first item, with this process repeated until all 15 units were sold. Bidders knew when a unit was purchased and the price at which it was purchased. English auctions followed similar rules with starting prices 5 ECUs below the winning price for the previous unit. In the Dutch-English auctions the first unit was sold following Dutch auction rules, with the second unit sold using English auction rules, with this process repeated until all units were sold.

RM characterize the properties of a symmetric RNNE yielding an efficient allocation for each of the three auctions as a reference point against which to evaluate bids. Unfortunately, there is no assurance that the equilibrium identified is unique. However, their model does demonstrate that there are sufficiently rich strategies to induce an efficient allocation in these complicated, multi-unit sequential auctions, with the equilibrium outcomes generating the same expected revenue (assuming risk-neutral bidders) across the three auction formats. In addition, the model offers sharp predictions about bidding: In each auction, the winner is the individual with the highest (re-indexed) valuation for the unit supplied in that stage, with the price paid for each unit higher (relative to its value) as fewer items remain to be sold. Finally, the theoretical model predicts *increasing* prices.

Efficiency is measured in the usual way as the sum of the valuations of the 15 units allocated divided by the sum of the 15 highest valuations. Losses, relative to full efficiency, averaged 0.84%, 0.94% and 0.45% for the Dutch, English and mixed auctions respectively. This compares to average efficiency losses of 14.3% in each auction under completely random bidding and 2.3% for budget constrained random bidders (whose bids are restricted to be between 0 and their valuation), suggesting that bidders were at least in part following the equilibrium bidding strategy. All three auction types had decreasing average prices in contrast to the increasing average prices the model predicts. Using simulations based on structurally estimated bid functions, RM note that at the start of each auction the standard deviation associated with the distribution of winning bids is quite large, which initiates a bias pushing winning bids higher than predicted at the beginning of an auction sequence, forcing adjustments later on that are responsible for the declining prices. They suggest that this is the result of the complexity associated with bidding on early units with so many units available to bid on. Their auction is, no doubt, quite complex.

Brosig and Reiß (2007; BR) look at the effects of capacity constraints on bidding in sequential auctions.[78] They argue that although many real life auctions run independently of each other, from the point of view of bidders, they form sequences of

[78] Pitchik and Schotter (1988) have an earlier paper on budget-constrained bidders in sequential auctions. Their subjects have full information about each others values and budget constraints as their experiment focuses on testing between different equilibrium refinements.

auctions once capacity considerations are taken into account in procurement auctions, or credit constraints are accounted for in ascending price auctions.[79] BR's experimental work focuses on isolating the role of opportunity costs on bids in this sort of environment.

They study an IPV auction with two bidders and two consecutive FPSB procurement auctions, where it is common knowledge that bidders only have the capacity to undertake a single project. Bidders learn their own project completion costs for projects A and B (where A is the first project bid on), with both their costs and their competitor's costs randomly drawn from the same uniform distribution with support [20, 100]. Bids greater than 100 were not accepted. BR employ a 2 × 2 design, varying the nature of the opponent (human or computer rival) and information feedback (no feedback or feedback regarding winners and prices). In all cases potential bidders on project B know if anyone entered and won on project A.

Equilibrium outcomes are reasonably complicated in this setup, but most of the key implications are reasonably clear. First, consider a bidder with a cost advantage (lower cost) for project B. They would prefer that the other bidder win project A, since in this event they would be the only bidder on project B, earning $100 – C^B$ (where C^B) is their cost for completing project B. As such, if they bid on A they should bid the maximum amount, 100. However, a bidder with a cost advantage for project B might decide to skip bidding on A if their cost advantage is large enough. In contrast, bidders with a cost advantage for project A always participate in the first auction as they can, potentially earn more than their largest possible payoff in B. Bids in this case are always higher than in a standard single item procurement auction since one's competitor does not always bid on A, and submits higher bids than in the single item case if he does participate. Further, conditional on meeting competition when bidding on project B, bids are lower than in the single item case since it implies that competitor's completion costs are skewed to the low side given that he skipped bidding on project A.

[79] BR refer to two empirical studies as providing support for their design: Jofre-Bonet and Pesendorfer (2000, 2003) found that firms that did not win a highway paving contract earlier in a sequence of auctions were more likely to enter a subsequent auction than firms that had already won a contract. De Silva et al. (2002) found that in auctions held by the Oklahoma Department of Transportation firms that lost in morning auctions bid more aggressively in the afternoon auctions compared to firms that had won in the morning. Also see DK who report that the overhead rate attached to bids by general contractors are positively related to the number of jobs already won.

BR's data shows minimal differences in results when competing against human or computerized rivals, and with and without information feedback, so the data analysis is pooled over these treatments. The pooled results show that more than 70% of the entry decisions on project A are correct, which is significantly better than an "always enter A rule." Further, the higher a subject's expected cost of an incorrect entry, the higher the average frequency of correct entry. As predicted, bids on A are higher than in single item (control) auctions. Conditional on $C^A > C^B$, close to 77.9% of all bids are exactly at the predicted level of 100, with an additional 12.6% in the interval [99,100). However, subjects do not appear to correctly update their beliefs about their competitor's costs according to Bayes rule when meeting competition for project B since, if anything, bids tend to be higher than in the single item case.

Leufkens, Peeters, and Vorsatz (2006; LPV) consider the impact of positive synergies between items when bidding in a sequential private value auction. There are two stochastically equivalent objects for sale using a SPSB auction with values iid from a uniform distribution on [0,100], with the same four bidders participating in both auctions. Valuations for the second auction were unknown when bidding in the first auction, but winning the first auction increased the winner's value in the second auction by a factor $s > 1$. LPV investigate three treatments: a baseline with no synergies ($s = 1$), one with mild synergies ($s = 1.5$) and one with strong synergies ($s = 2.0$). Subjects participated in 50 rounds of two auctions each.

Their model predicts that with $s > 1$ all bids in round 1 will be above bidders' valuations. However, if bidding is symmetric (as assumed), round-one efficiency will not be affected. Their results show that positive synergies reduce round-one efficiency, with the percentage of auctions won by the high value holder decreasing from 92.4% to 84.4%, to 77.8% for $s = 1$, 1.5 and 2, respectively. These efficiency reductions are not very surprising given the presence of the exposure problem, in conjunction with heterogeneity in bidder risk preferences. As predicted the larger the synergy factor, the higher bids are above value in round one, with average and median overbids of 4.23/8.12/12.16 and 0.00/4.30/7.0 with $s = 1$, 1.5 and 2 respectively. They found no statistical support for the prediction that prices would decrease between rounds one and two in the presence of positive synergies.

LPV's experiment is notable for the introduction of synergies into a sequential auction framework where predicted outcomes could be solved analytically. The main weakness in their design is that there is huge uncertainty as bidders have no idea what their round two values are when bidding in round one, which creates an unrealistically severe exposure problem for bidders in round one. This, in turn, may have a strong impact on actual behavior that is not captured by the assumption of risk neutral bidders.

The papers reported on in this section have only begun to scratch the surface with respect to more complicated issues in sequential auctions. This leaves a number of unexplored questions to be investigated.

IV Additional Topics

4. 1. Collusion in Auctions

An issue of enduring concern in auctions is the possibility of collusion. This is not just an intellectual/theoretical exercise as collusion has been identified in a number of cases: Krishna (2002) reports that in the 1980s 75% of the cartel cases in the United States involving collusion were related to auctions. Klemperer (2002) argues that the issues of primary importance in practical auction design have to do with discouraging collusion, entry deterrence and predatory behavior. Collusion is a difficult topic to study in the laboratory since it is almost impossible to effectively introduce side payments, and experimental sessions have a natural end point which is likely to induce some unraveling. Research reviewed in the 1995 survey involved providing subjects with explicit opportunities (even encouragement) to discuss and coordinate bidding strategies. We take up work since then, much of which still focuses on opportunities for bidders to discuss collusive strategies with impunity, and nearly all of which involve auctions with multiple units for sale.[80]

Sherstyuk (2002) looks at tacit collusion in ascending-price auctions. She gives tacit collusion its "best chance" by incorporating a number of facilitating factors: small numbers of bidders (three with supply of two units) and repeated play between the same set of bidders. She compares a weak bid improvement rule (rivals need only match a bid in order to have standing as the high bidder with tied bids settled randomly) versus a

[80] See Hu, Offerman, and Onderstal (2009) for the sole single-unit auction study we have identified since the 1995 survey.

strict bid improvement rule, under either a narrow or wider support for bidders private valuations (the *increase* in bidder profits resulting from collusion is greater with the narrow support). Discussions were prohibited.

Her results show that with a weak improvement rule and the narrower support, prices are quite low, although it takes some time to converge to the reserve price (see Figure 12a).[81] Collusion largely results from bid matching. In contrast, with the narrow support and a strict bid improvement rule, prices are substantially higher (compare prices between the 90-100 cases in Figures 12a and b). With strict bid improvements, collusion tends to take the form of a bid rotation rule.

[Insert Figure 12 here]

In contrast, with the wider support, prices are close to the CE throughout regardless of the bid improvement rule, which she concludes results from the smaller increase in profits available with collusion with the wider support. However, this conclusion is premature since in a companion treatment with California Institute of Technology students with the weak bid improvement rule, there are high levels of collusion regardless of which of the two supports employed (University of Melbourne students were used earlier). There are at least two important differences between these two subject populations (i) the Cal Tech students were veteran experimental subjects, the Melbourne students were all inexperienced subjects and (ii) Cal Tech students are among the brightest subjects one can enroll in experiments. In this respect it is particularly unfortunate that she did not run strict improvement sessions with the Cal Tech subject population and did not run experienced subject sessions with the Melbourne students.

Goswami, Noe and Rebello (1996) (GNR) look at collusion in multi-unit share auctions designed to resemble Treasury bill auctions. They compare the effect of nonbinding pre-play communication between bidders in UP versus discriminatory auctions. In each auction there were 100 units for sale, with a value of 20 for all bidders. There were 11 bidders in each auction, with bidders specifying the number of units they were willing to purchase at each of three possible prices: 10, 15 and 20, with each bidder able to bid for up to 100 units. In the class of symmetric, pure strategy, Nash equilibria

[81] For similar results but almost immediate convergence to the reserve price see Sherstyuk (1999). In these auctions bidders' values were common knowledge.

for the UP auction, there exists both a CE and a collusive equilibrium in which bidders extract full surplus from the auction. (There are also a variety of other collusive equilibria without full surplus extraction.) The collusive equilibria do, however, require a great deal of delicate bid coordination. For example, in the most collusive equilibrium each of the 11 bidders demands 9 units at a price of 20, with all other bids at 10. This strategy profile results in each bidder getting 9 units at the lowest possible price of 10 (with one additional unit assigned randomly). It is easy to see that any unilateral deviation to get a larger share results in raising the price to 20, significantly lowering profits. In the discriminatory auction there is a unique symmetric Nash equilibrium in undominated strategies with all bids at 15.[82]

All sessions had at least 12 auctions, with a single set of bidders in each session. In the communication treatments bidders were allowed to speak to each other in between every other round. Following each auction bidders were told the actual market clearing price, their own allocation and their own payoff.

There were essentially no differences in clearing prices between the discriminatory auctions with and without communication: none cleared at the lowest price of 10, with 65% clearing at 15 without communication versus 69% with communication (with the remainder clearing at the price of 20). In contrast, in the UP auctions with communication 36% cleared at 10 versus 0% without, and another 30% clearing at 15 with communication versus 16% without. As such average prices were substantially lower in the UP auctions with communication than without, with no difference with and without communication for the discriminatory auctions. Naïve collusive outcomes predominated; e.g., all bidders agreeing to place all bids at 10, as opposed to the rather elaborate self enforcing collusive Nash equilibrium.[83] The results suggest that UP share auctions are more susceptible to collusion than discriminatory share auctions.

Sade, Schnitzlein, and Zender (2006) (SSZ) conduct an experiment similar to GNRs but with different results, as average revenue is quite similar between the

[82] There is also a Nash equilibrium with all bids at 20, but since bidders earn zero profits with discriminatory pricing, bidding 20 is dominated.
[83] Unfortunately there is no direct accounting for the number of auctions that actually achieved the self enforcing collusive equilibria. But the impression one gets is that none of them did.

discriminatory and UP formats. One key difference between SSZ and GNR is that in SSZ there were four possible prices of 17, 18, 19, and 20 versus three possible prices of 10, 15, and 20 in GNR. Thus, there were fewer alternatives to coordinate on in GNR and the potential profits from collusion were substantially higher in GNR, both of which would tend to promote collusion.

One interesting sidelight of the SSZ experiment is their use of both students and finance industry professionals, with the professionals generating higher average revenue (under both mechanisms) than the students, even though they had the same opportunities to collude. Regulations precluded cash payments to the professionals, so they were rewarded with prizes bearing the logos of the sponsoring universities. As such "winning" might have been more salient for the professionals.

Phillips, Menkhaus, and Coatney (2003) (PMC) study collusion in a series of sequential English auctions designed to mimic livestock auctions.[84] Several facilitating practices were employed: the same set of bidders over a series of seven auctions, knowledge about the number of units for sale, and communication via an online chat program. They investigate auctions with six and two bidders and between 19 and 30 (homogenous) units for sale in any given auction. Bidders had identical negatively sloped demand curves, with a reservation price set 20 points below the average price had all units been sold to the highest value bidders at their induced values. Collusion increased with bidder experience so we focus on bidding in the last auction in each session.

The six bidder control treatment yields average prices at 77% of a norm in which each unit is sold at its valuation going from the highest to lowest value. Communication, with or without bidder identification, reduced average prices to between 50% and 52% of this norm. These lower prices were accomplished primarily through bid rotation rules that communication facilitated. Further, while there was some cheating over the last several units in each set of auctions, it did not destroy effective rotation in subsequent auctions and/or lead to substantial unraveling in the last auction (see Figure 13). Information about quantity for sale had no impact compared to the control treatment.

[84] In auctions with two buyers, individual bidder demands were augmented in order to keep aggregate demand constant compared to the six bidder treatment. See Menkhaus, Phillips, and Coatney (2003) for a related experiment.

[Insert Figure 13 here]

The baseline treatment with two bidders had average prices at 75% of the norm in which each unit is sold at its valuation going from the highest to lowest value. Communication reduced average prices to 58% of this norm. Unlike the six bidder auctions, information about quantity for sale without any opportunity for communication had almost the same effect as communication with average prices at 61% of the norm. PMC, using the chat records for support, suggest that the somewhat smaller effect of communication in the two buyer auctions resulted from disputes as bidders compared their relative gains, whereas it was too difficult to go beyond a simple bid rotation rule in the six buyer case. Note that collusion might have been even more effective in this study had there been no reserve price in place. Further, as a subsequent paper shows, in seller active auctions (where live sellers replace the experimenter), who decide in advance how many units to offer for sale, the number varies (sometimes quite widely) between auction periods, which significantly disrupts the collusive effect of a constant supply with small numbers of buyers (Phillips and Menkhaus (2009). It remains to be seen if this would have a similar effect when small numbers of buyers are allowed to communicate.

Kwasnica and Sherstyuk (2007) (KS) look at collusion in simultaneous ascending multi-unit demand (SAA) auctions. The experiment is inspired by Brusco and Lopomo (2002) (BL) who show that there exist collusive Nash equilibria in SAA auctions whereby bidders start bidding on their highest valued item and, if there are no competing bids, stop bidding. This equilibrium is supported by the threat of competition and higher prices if rivals do not cooperate.[85] Although this equilibrium does not require repeated interactions with the same set of bidders, KS look for it in a repeated play setting as (i) this adds collusive opportunities via bid rotation to the strategy set and is more relevant to many auction settings outside the lab and (ii) it is no doubt substantially more difficult to achieve BL style collusion in one-shot games.[86] Their experimental design involved two

[85] See BL for a full characterization of the Nash equilibrium, which also holds for strong synergies between items and when two or more bidders have higher values for the same unit. Cramton and Schwartz (2002) provide evidence for BL type collusion in the FCC's auctions for spectrum licenses. EG (section 3.1) report attempts at collusion in their SAA auctions with repeated matching.

[86] On this last point KLM report two clear instances of such a collusive outcome in CCA auctions with random rematching in each auction. Bidding stopped after only a couple of rounds with all (experienced) bidders earning reasonable profits. The facilitating practices in KLM consisted of announcing provisional

objects for sale, with complementarities between items in some sessions, along with an uncertain end point and no opportunity for discussions between bidders. In the no complements case they define collusion as occurring with prices below 50% of the CE; in the case of complements, when both items are awarded to the bidder with the highest value for the package at a price equal to the second highest valuation. (The standard for complements is more problematic since bidders face an exposure problem which in and of itself may prevent an efficient allocation.)

KS's strongest results are in auctions with two bidders: Absent complements 10% of the auctions with inexperienced bidders, and 55% with experienced bidders, are classified as collusive, with a number of auctions reasonably closely following the BL mechanism for tacit collusion. Collusion was reasonably frequent in markets with two bidders and modest complements, averaging 31% of all auctions with inexperienced subjects. But was much less common with larger complementarities: 0 out of 16 auctions with inexperienced subjects and 2 out of 11 auctions with experienced subjects. In the case of complements, collusion was achieved through bid rotation rules.[87] In contrast, none of their five bidder auctions were collusive, regardless of bidder experience and the presence or absence of complements.

Li and Plott (2009) (LP) study collusion in multi-unit demand SAA auctions with eight bidders and eight items. Their strategy is to induce collusion by using an 'incubator' technology and then study factors capable of mitigating the collusion. Their incubator technology involves: (i) Bidders valuations being "aligned" and "folded" so that each pair of bidders has a unique item they value the most, with bidder i's second highest valued item very close to bidder j's highest valued item and vice versa (in this way it's easy for a bidder to retaliate should her closest rival compete for her highest valued item), (ii) There is complete information about *all* bidders' valuations, and (iii) The same set of bidders compete over several auctions with an unknown end point and there are no opportunities for discussion between rivals. Under these conditions there

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winners and determining provisional allocations randomly (as opposed to maximizing the number of players with no items) in case of multiple (tied) allocations that maximize seller revenue.

[87] Interestingly, BL style tacit collusion can be achieved in the case of large complements but not with moderate complements.

exists a collusive Nash equilibrium of the sort specified in BL, as well as a Nash equilibrium with competitive prices.

Once collusion is established, LP explore several remedies including (i) dropping bidder identification, (ii) removing information about rivals values, (iii) using a fixed end point for the auction as opposed to a soft ending (bidding continues until no new bids are entered for 30 seconds), (iv) removing several items for sale (thus increasing competitive pressure) and (v) changing bidders expectations by having some pairs of bidders with the highest value for the *same* item. Remedies (i) – (iii) alone had minimal impact. Adding treatment (v) to remedies (i) – (iii) reliably broke up collusion, with competitive outcomes continuing after the aligned and folded preference structure was reinstated (but not announced).[88]

Offerman and Potters (2006) (OP) look at whether auctioning of entry licenses induces collusion in the product market. Standard economic arguments hold that entry fees constitute a sunk cost so that they will not affect pricing in the product market. However, many companies claim that they will have to charge higher prices in the product market in order to recoup entry fees. In addition, OP note that if entry rights are auctioned off, this will result in selecting bidders with the highest profit expectations in the product market, which might foster tacit collusion as this is one way of achieving these higher profits.

OP employ a product market with price-setting duopolists with differentiated products, with a unique stage-game Nash equilibrium in which each duopolist charges a price of 60 ECUs and earns a profit of 5000 in each period. This compares with the joint profit maximizing collusive outcome with both firms charging 150 and earning profits of 9000.[89] Subjects received feedback following each period about their own and their opponent's price, quantity, revenue, cost and profit but were not allowed to discuss strategies. There were three treatments: (1) an auction treatment in which four subjects bid for entry rights, with the two highest bidders paying their bids, (2) a fixed cost treatment where the entry rights were randomly assigned at an exogenously determined

[88] Brown, Sullivan, and Plott (2009) show both theoretically, and in an experiment, that switching to a simultaneous *descending* price auction in which all bids are final, serves to break up the collusive Nash equilibrium within the incubator structure.
[89] Demand was simulated in the product market with price taking consumers.

entry fee comparable to the average fees in the auction treatment, and (3) a baseline treatment in which the entry rights were assigned randomly with no entry fees. In all three treatments, subjects first played the duopoly game for 10 periods against the same opponent. After that each subject was randomly assigned to a group of four which included their rival from the first 10 periods. These groups remained fixed until the end of the experiment (20 more periods) with entry licenses, valid for five periods, auctioned off at the start of each block of five periods. The two remaining subjects received a fixed payment of 1000 per period, compared to expected earnings of 5000 in the (competitive) stage game Nash equilibrium.

[Insert Figure 14 here]

Figure 14 shows average prices in periods 1-10, which were approximately the same, before the three different entry treatments were introduced. In the first of the two five period blocks with entry (periods 11-20) average prices were significantly higher in both the auction and fixed cost treatments compared to the baseline treatment ($p < .10$), but not significantly different from each other. These differences from the baseline treatment were much less pronounced in the last ten entry periods, and were no longer statistically significant ($p > .10$). Average winning bids were close to 20,000, the net expected profit from the stage game Nash equilibrium, so that auction winners earned excess profits. The role of entry fees in fostering collusion is supported by Spearman rank order correlations between entry fees and average prices, which were positive and statistically significant at the 10% level in periods 11-20 for the auction treatment ($p = .14$ for the fixed cost treatment) and significant at the 5% level or better for both treatments in periods 21-30. Finally, the data show that collusion is “clustered” so that some groups had prices close to the stage game Nash equilibrium while others set prices at higher levels. As such it would be more accurate to say that entry fees increased the *probability* of collusion than that they increased the *degree* of collusion.[90] Further, the similarity in outcomes between the auction treatment and the fixed cost treatment would support industry arguments that entry fees by themselves will lead to higher prices (via tacit collusion) in concentrated industries.

[90] There is considerably more to this rich experiment than reported on here including a monopoly treatment in which monopoly rights are bid for or simply awarded.

Summary: All of the auctions considered here involved the same set of subjects competing in a series of auctions, usually with an unannounced end point. Repetition with the same cohort appears to be a key facilitating factor, a factor likely to be at play in field settings as well. Communication between bidders reliably facilitates collusion, which seems hardly surprising. However, Whinston (2006) notes there is little in formal economic theory about the way in which prohibitions on (nonbinding) price agreements prevent anticompetitive prices, with the published empirical work offering surprisingly little evidence that preventing oligopolists from talking has a substantial effect on the prices they charge. In contrast to this, the experimental data show quite strong effects when certain facilitating practices are in place. SB, pay what you bid type, auctions are more collusion proof than ascending price auctions which provide easier opportunities to detect and punish non-cooperators. Competitive pressures seem to play a role as well as suggested by the role played in breaking up collusion in LP and the role played (in the form of the support from which values were drawn) in Sherstyuk (2002).

4.2. Bidder's Choice Auctions: Creating Competition Out of Thin Air

The National Association of Realtors defines a bidders' choice auction as:[91]

> "A method of sale whereby the successful high bidder wins the right to choose a property (or properties) 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 and so on, until all properties are sold."

This type of bidding is very popular when selling time-shares, condominiums, and building lots. Goree, Plott and Wooders (2004; GPW) were the first to study this type of auction experimentally, noting that it can create competition between bidders who are interested in *different* items. They illustrate this with the following example: Consider the case of two bidders and two items, with each bidder interested in a different item. In a standard SAA revenue is zero when bidders prefer different items, which occurs with probability one half. In contrast, in the first stage of an ascending price right to choose

[91] See http://www.aaauctionservice.com/glossery_files/glossery.htm

(ARTC) auction there is always competition since bidders, not knowing their rival's preferences, run the risk that the stage-one winner will take their preferred item. GPW show that if bidders are risk neutral, the ARTC will raise the same average revenue as the SAA, but if they are risk averse, the ARTC will raise more revenue, which may account for its popularity.

In GPW there are four bidders in each auction, with two items for sale, A and B. Each bidder had a 50% chance that either item A or B (but not both) will be their "preferred item," drawn iid from a uniform distribution with support [20, 920].[92] The value for their non-preferred item was effectively set to zero, so that each bidder had positive value for only one of the two items in any given auction (zero substitution possibilities between items). In the ARTC, after the first item was sold, bidders observed the item chosen, with the remaining item sold in an ascending price auction. In the SAA, items were sold simultaneously through two ascending price auctions, with bidders restricted to bidding in only one of the two auctions at any given time. Revenues were 19.3% higher in the ARTC than in the SAA, with 100% efficiency in the SAA versus 98.4% efficiency in the ARTC. The estimated coefficient of relative risk aversion, 1-r, is 0.39, consistent with the higher revenues in ARTC.

Eliaz, Offerman, and Schotter (2008; EOS) studied an RTC auction with four different items for sale, with two buyers for each type of good who only value that good (zero substitution possibilities between goods for all buyers). In the RTC auction, all eight buyers participate in a SPSB auction in which the winner has the right to pick which item she wants, paying the second-highest bid price from among the eight bids submitted. The item selected is announced so that the other buyer interested in that particular item exits the auction. This process repeats itself with the remaining bidders until all four items are sold. The control treatment involves four separate good-by-good (GBG) auctions, in which the two bidders interested in each item compete in four separate SPSB auctions. Two GBG treatments were employed, one with no minimum bid requirement and one with a revenue maximizing minimum bid requirement. With risk neutral

[92] There were no restrictions on the probabilities so that it was possible to have less than two bidders whose preferred item was A or B.

bidders, expected revenue is the same between the RTC and GBG (with no minimum bid requirement), with risk aversion generating higher expected revenue in the RTC auction.

The RTC auctions raised significantly more revenue than either the unrestricted or optimal GBG formats (40.4% and 13.9% higher revenue respectively). Average efficiency was comparable between the RTC and unrestricted GBG auctions (98.2% versus 98.3%) and higher than in the optimal GBG* auctions (87.9%). To test whether risk aversion was the source of the higher revenue in the RTC auctions, EOS employed a no information RTC (NIRTC) auction where, after each phase, bidders were not informed as to which item was sold and losing bidders were not eliminated from the auction. Winning bidders whose good was taken in the previous phase are randomly assigned one of the goods (with zero value for that bidder). As a result, following the first item sold, buyers are essentially bidding in a SP auction in which the high bidder wins a lottery that awards her most preferred good with positive probability and a zero value item with the complementary probability. Risk neutral buyers will bid the expected value, but risk averse bidders will bid strictly less than the expected value of the item. Assuming homogeneous risk averse bidders, the RTC auction with risk aversion provides a better fit to the data than with risk neutrality. However, the NIRTC auction with risk aversion provides a worse fit to the data. Thus, EOS reject risk aversion as the key factor behind higher revenue in RTC versus GBG auctions. Rather, their preferred explanation rests on probability (mis-) weighting with subjects acting as if they face fiercer competition than they actually do.

Salmon and Iachini (2007; SI) examine a "pooled" RTC auction, with a number of similarities to the NIRTC auctions in EOS. They conduct a discriminatory SB auction with multiple units for sale with all bidders submitting a *single* bid at the same time. Bidders' values are perfectly correlated across items, so that each bidder has the exact same ordinal ranking across items. (Think of selling several condominiums in a given building, each of which is ranked from highest to lowest based on its scenic view. But because of the location of the building relative to where bidders work, bidder *i* ranks each apartment uniformly higher than bidder *j*.) Thus, unlike the other RTC auctions reported on, there are some substitution possibilities between items, albeit with common ordinal preferences over the goods.

Bids are ranked from highest to lowest with the high bidder getting first choice, the second highest bidder second choice, and so on, with all winners paying what they bid. Following Menezes and Monteiro (1998), assuming symmetric bidding strategies, SI solve for bid functions numerically for both risk neutral and loss averse bidders.[93] Loss aversion is relevant here since bidders can lose money when bidding according to the RNNE, as a bid designed to get a higher valued unit may end up securing a unit with a lower value, with bidders paying what they bid. They compare outcomes in the pooled RTC auctions to an SAA in which subjects are restricted to holding the high bid on one item at a time.[94]

Their results show that revenue is uniformly, and substantially, higher in the pooled RTC auctions than in the SAA (41.8% higher), well above the revenue predicted under the RNNE for the RTC auctions. In fact, bidders suffer persistent losses, with bidder profits well below those in the SAA. Revenue and prices in the SAA are very close to those predicted under the efficient allocation. Efficiency is essentially the same between the two auction formats, averaging around 95% in both cases. Looking at individual bids in the RTC auction, the shape is essentially the same as the theory predicts, but bid functions are displaced upward relative to where they would be under risk neutrality. SI explore a number of alternative explanations for this upward displacement of the bid function, with their preferred explanation consisting of a probability (mis-) weighting model: In this case "attentional" bias whereby bidders focus most of their attention on winning their most preferred 2 or 3 units in the auction, largely ignoring the possibility of being "stuck" with lower valued units. Finally, SI note that assuming their results translate outside the laboratory, the kind of pooled auction format they employ would have trouble sustaining itself, as persistent losses would reduce incentives to bid in these auctions, as well as generating defaults on bids.

Summary: The three RTC experiments reported on provide strong evidence for their revenue raising ability compared to either an SAA or a GBG format. The results reported

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[93] The loss averse specification uses the utility function and parameter values reported in Tversky and Kahneman (1992). SI note that there is little difference between risk neutral and risk averse bidding given their parameter values.

[94] Their SAA follows the format employed in the FTC spectrum auctions, with a countdown clock that resets every time a new bid is submitted. The auction ends when no new bids are submitted for any items, with winning bidders paying what they bid.

in EOS and SI lie totally outside what theory predicts. The losses associated with the pooled RTC auctions in SI would seem to limit their use in field settings. The total lack of substitutability between commodities in the GPW and EOS experiments seems unrealistic for the situations these auctions are intended to represent. Thus, there is scope to explore either an ascending, or sequential, RTC auction in which bidders demand a single unit but the items have some degree of substitutable, comparing outcomes to either an SAA or GBG auction. Nevertheless, the results of these three experiments are an exciting new application of experimental methodology designed to better understand the basis for RTC auctions found in field settings. On a theoretical level both EOS and SI attribute the higher than predicted revenue to bidders systematically misweighting probabilities of one sort or another, which ties back to results reported elsewhere in this survey (see, especially Section 1.1) on bidding above the RNNE in FPSB auctions.

4.3 Internet Auction[95]

Internet auctions provide new opportunities to conduct experiments, with considerable potential for applications. Lucking-Reiley (1999; LR) used the Internet to sell collectable trading cards under the four standard auction formats (Dutch, English, FPSB and SPSB auctions), investigating the RET. He finds that Dutch auctions produce 30% higher revenue than FP auctions, a reversal of previous laboratory results, and that English and SP auctions produce roughly the same revenue. These results are interesting but lack the controls present in more standard laboratory experiments; i.e, there may well be a common value element to the trading cards, and Dutch auctions provide an opportunity to use the game cards immediately, which cannot be done until the fixed closing time in the FP auctions.

eBay auctions have a fixed closing time with many bidders submitting bids just seconds before the closing time (sniping), while others increase their bids over time in response to higher bids. In contrast, Amazon auctions automatically extend the closing time in response to late bids (as "soft" closing), with much less last minute bidding than in comparable eBay auctions. These differences raise two questions addressed by Roth and Ockenfels (2002; RO): (1) Why the sharp differences in last minute bidding between the

[95] Bajari and Hortacsu (2004) and Ockenfels, Reiley, and Sadrich (2006) provide surveys of theoretical, empirical, and experimental work on Internet auctions.

two auction designs and (2) since eBay has a number of characteristics similar to a standard SP auction, why the increased bidding by the same bidder over time?

RO suggest several (rational) reasons for sniping in (essentially) private value eBay auctions with their fixed deadline: (i) implicit collusion on the part of snipers in an effort to get the item at rock bottom prices since congestion will result in some of the last minute bids not being recorded at the web site and/or (ii) a best response to incremental bidding on the part of less sophisticated bidders in an effort to avert a bidding war. They also note that motivation for sniping for items with a significant CV component could result from (i) better informed bidders' efforts to conceal their superior information on high valued collectables and/or (ii) bidders updating their valuation of items as bids come in. Because there are a number of other differences between eBay and Amazon than their ending rules, as well as the difficulty of clearly distinguishing between private value and CV auctions in field settings, Ariely, Ockenfels, and Roth (2005; AOR) conduct a laboratory experiment in which the only difference between auction institutions is the ending rule for private value goods – a dynamic eBay auction with either a .8 or 1.0 probability that a late bid will be accepted and an Amazon style auction with a .8 probability that a late bid will be accepted, in which case the auction is automatically extended. Their results show quite clearly that there is more late bidding in both eBay auctions compared to the Amazon auction. Further, there is significantly more late bidding in the eBay treatment where last minute bids would be recorded with probability 1 than with probability .8, which rules out tacit collusion as the *only* basis for sniping, and more than likely represents, at least in part, best responding to incremental bidding on the part of less sophisticated bidders.

Ely and Hossain (2009) compare sniping with "squatting" (a single early bid) in a series of eBay auctions (actual bids they made for recently released movie DVDs). Their experiment represents an attempt to look at more general equilibrium effects of sniping versus the alternative of squatting. They corroborate that sniping is a best response to naïve bidding of the sort studied in AOR. But sniping does not lead to large increases in surplus in their experiment because of multiple eBay auctions for the same item, with early bids (squatting) deterring entry into that particular auction. At the same time they recognize that sniping would be more effective if instead of done randomly, as in their experiment, it was directed at eBay auctions with the lowest standing bid.

Salmon and Wilson (2008) investigate the practice of second-chance offers to non-winning bidders in Internet auctions when selling multiple (identical) items. They compare a two-stage game with a SP auction followed by an ultimatum game between the seller and the second-highest bidder versus selling the two items in a sequential English auction. As predicted the auction-ultimatum game mechanism generates more revenue than the sequential English auction, providing a potential explanation for the practice of second-chance offers to losing bidders.

Shahriar and Wooders (2011; SW) study "buy-it-now" (BIN) options popular in eBay and Yahoo and other Internet auctions.[96] They employ an English clock auction (with a soft close) and a BIN price that must be exercised prior to the start of the auction. For a private value auction when bidders are risk averse a suitably chosen BIN will raise revenue as it extracts a risk premium from bidders wishing to avoid uncertainty over whether they will win and the price paid (Reynolds and Wooders, 2009). In contrast, for CV auctions, if bidders are sophisticated and do not suffer from a WC, there is no BIN that raises revenue for risk neutral or risk averse bidders.

SW's results support the risk aversion predictions for the private values case as auctions with a BIN option raised average revenue by 6.8% compared to the control treatment, and by 11.9% conditional on the BIN being accepted ($p < .01$ in both cases). The BIN was accepted in 45% of the auctions. Introducing a BIN that is a little above the (unconditional) expected value of the item in an ascending-price CV auction raises revenue by 4.2% ($p > .10$), but consistent with a WC is accepted in 78.9% of the auctions. Further, bidders tend to drop out earlier when the BIN was not accepted compared to controls, even though rejection of the BIN is completely uninformative. SW explain these anomalous results through an extension of the naïve bidding model developed in KL (1986) in which bidders make no adjustment to the adverse selection effect conditional on winning the item and fall prey to the WC.

Ivanova-Stenzel and Kroger (2008; ISK) investigate BIN auctions in which a seller (played by one of the participants) offers a BIN to one of the two potential buyers. If the buyer rejects the BIN, a SPSB auction with no reserve price results with both bidders

[96] Different Internet auction platforms adopt different BIN options. In eBay bidders have a chance to get the item at a fixed price before any bids are placed. In Yahoo the BIN can be exercised after bidding starts.

active. With two risk neutral buyers and a risk neutral seller, it is optimal for the seller to offer a BIN price greater than or equal to the mid-point of the uniform support underlying buyers' valuations, which will not be accepted. However, with risk averse (or impatient) buyers, the BIN may be accepted when it offers the buyer a higher probability of getting the item, albeit at a higher price (Matthews, 2003). Further, if sellers are risk averse they may offer a BIN as it reduces the variance in revenue.

ISK report a substantial number of BIN prices below the mid-point of the support of buyers' valuations, as well as a substantial number of BIN prices that were above a risk neutral bidder's threshold for acceptance. Allowing for (heterogeneous) risk averse buyers, with risk aversion estimates in line with those reported in the literature, rationalizes many of these acceptances. However, accounting for risk aversion does not achieve nearly the same level of success for sellers: Simulations show that 29% of all BINs are below reasonable estimates of buyers risk preferences (even accounting for risk loving buyers), with one-third of all sellers offering a BIN below this threshold more than half the time. Alternative explanations in terms of "noise" in the data are rejected on the grounds that the observed distribution of BIN prices is far from uniform, as one would expect based on random selection, and do not decline over time as subjects gain experience. Rather, ISK liken the persistence of the low BINs to a "seller's curse," resulting from a failure to account for the adverse selection effect of low BINs selecting low value buyers to exercise the option.[97]

4.4 Entry into Auctions[98]

Most of the theoretical literature on auctions treat the number of bidders, N, as fixed. The fixed N paradigm simplifies the analysis and allows for easy comparisons of revenue and efficiency between different auctions mechanisms, and is an essential assumption underlying the RET. The key motivation for looking at endogenous entry is that it's both costly and time consuming to prepare bids so that it is part and parcel of the auction process. As such it should not be swept under the rug by assuming an exogenously determined number of entrants. Further, casual observation shows that the

[97] Grebe et al (2009) repeat the ISK experiment with two buyers and one seller using true eBay rules (an English auction with proxy bidding possible and a hard close), subjects with eBay experience, and induced valuations.
[98] Most of the research on this topic is in the context of a private value auction environment.

number of bidders in similar situations can vary a lot, leaving the impression that it is governed by a stochastic, rather than a deterministic, process. A natural question, both theoretically and experimentally, is how sensitive are the typical auction results to dropping the fixed N assumption, as opposed to allowing for endogenous entry.[99]

There have been two main approaches to modeling auctions with entry. Both start by assuming N potential entrants and an entry cost, c, (e.g. bid preparation costs) since otherwise all potential bidders enter and we are back in the fixed N setup. The first approach assumes that *ex-ante* bidders are symmetrically informed so that any information bidders' have before they enter the auction is public information, learning their private information signals only after incurring the entry cost. In this case the theory has focused on two types of equilibria: A *deterministic, asymmetric equilibrium* in which bidders use pure entry strategies with exactly n* bidders, the number of bidders that can enter profitably, entering the auction. The remaining (N– n*) bidders remain out and have no further impact on the auction (see Smith, 1982, 1984, Engelbrecht-Wiggans, 1987, 1993, and McAfee and McMillan, 1987). The second model Levin and Smith (1994; LS) has a unique *symmetric mixed strategy equilibrium* that determines a probability of entry, q*, which leaves all bidders just indifferent between entering and staying out.[100] This results in entry being a random variable that is governed by a binomial distribution with N and q* as the two parameters, with q* depending on the expected rewards from entry relative to its cost, q* = Q*(c, N).[101] We refer to the first equilibrium as ‘‘deterministic” and to the second as ‘‘stochastic.” A second modeling approach is to assume that the N potential bidders obtain information about their type *before* they decide to enter. This approach generates a unique pure strategy equilibrium characterized by a cutoff value, which is a function of a bidders' type, which determines who enters and who stays out (see, for example, Palfrey and Pevnitskaya, 2008). Here, the realized number of entrants is a random variable governed by a binomial distribution

[99] Endoginizing entry decisions also forces one to take account of bidders' preferences over auction institutions (Mathews, 1987, McAfee and McMillan, 1987).
[100] There are an enormous number of asymmetric equilibria involving subsets of bidders that enter, or stay out, deterministically while the rest enter with the same probability.
[101] This approach also allows for symmetric risk-averse bidders. For example if $u(x) = x^{\rho}$ where ρ being the CRRA parameter than in equilibrium q* = Q*(c, N| ρ).

with N and q*, where q* in this case represents the probability of a player's type exceeding the cutoff level.

Smith and Levin (2001; SL) conduct an experiment to examine whether their stochastic bidding model predicts better than the deterministic model. The experiment focuses on entry so that payoffs match a bidder's expected gain in the symmetric RNNE after entering. That is, there is no bidding phase after entry. Their model provides a rich set of comparative static predictions to use in discriminating between the stochastic and deterministic models.[102] Each experimental session consisted of a series of market periods with subjects electing to enter the ''market'' or stay out, with the latter paid a fixed sum of money representing the opportunity cost of entry. Before each period, the number of potential entrants, N, the cost of entering, c, and the schedule of payoffs conditional on entering (which were deceasing with the number of entrants, *n*) were publicly announced. Subjects received feedback regarding the total number of entrants after each round of play. There were two main treatments, one with a small number of potential entrants (N = 4) and one with a larger number of potential entrants (N = 8), with four different costs of entry within each treatment.[103] Payoffs were such that at each cost level there was room for "profitable" entry by at least one bidder but not more than three bidders.

The aggregate data strongly support the stochastic model. First, the deterministic model predicts that the number of bidders actually entering the auction is, other things equal, independent of the potential number of entrants (N) as opposed to the stochastic model's prediction that average entry will increase with larger N.[104] This prediction is satisfied for all cost levels, with the increases significantly different from zero for three of the four cost levels. Further, although the average increase in entry rates was somewhat

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[102] There is a large, closely related, earlier experimental literature on coordination games (see Ochs, 1995, and Rapoport et al, 1998, and references therein). The key difference between SL's experiment and these earlier ones is linking the payoff structure to what would have been earned in the RNNE of a well defined auction market. These predictions are sensitive to bidders' risk preferences. However, the apparent risk premium demanded by subjects was close to zero, so that predictions for the risk-neutral case are used throughout.

[103] Entry costs of {$0.50, $1.00, $1.50, $4.00}.

[104] There are two competing forces at work here: larger N decreases the probability of any given bidder entering, but there are more potential entrants. The net effect is an increase in *n* under their treatment conditions. LS were not able to prove this holds in general, but conjecture that it increases asymptotically monotonically to a fixed *n* as N increases.

greater than predicted in the stochastic model, none were significantly greater than predicted. Both models predict that the average number of entrants will fall as entry costs increase, but by varying degrees. At each of the cost levels with sufficient numbers of observations to perform exact tests, the observed reduction in entrants is significantly smaller than the deterministic prediction. In contrast, although there is a tendency for entry rates to decrease more than predicted in the stochastic model, in no case were the differences large enough to reject the stochastic model's prediction. The stochastic model predicts that subjects will enter with sufficient frequency to reduce expected profits to zero, since in equilibrium bidders are indifferent between entering and staying out. Profits for entrants averaged -\$0.02 per subject, per period, over all auctions, very close to the zero-profit prediction and substantially below the \$0.34 profit level of the deterministic model.[105] Finally, the stochastic model predicts that the total surplus generated in the auction will *increase* when the number of potential entrants *decreases*, whereas the deterministic model predicts no change. Simulating seller revenue and adding it to bidders' actual profits to compute total surplus, for all cost levels reductions in N caused social surplus to increase. This provides strong empirical support for one of the most intriguing policy implications of the stochastic model: Other things equal thicker markets are less efficient due to increased costs of entry, so that society may benefit from measures designed to limit somewhat the number of potential bidders.

While the preceding shows that the stochastic model organizes the aggregate data rather well, substantially better than the deterministic model, there were also some significant deviations from the stochastic model at the individual subject level. The stochastic model assumes that bidders are symmetric, which implies that for each treatment they all employ the same (symmetric) entry probability. The data soundly reject this. Among inexperienced subjects this hypothesis is rejected (at the 5% level) 26% of the time, and is rejected 33% of the time for experienced subjects, far greater than the 5% expected rejection rate. Thus, it does not appear that all subjects rely on the common entry probability, q*, underlying the stochastic model. The failure to find a

[105] These are "pure economic profits" above and beyond the return for staying out.

uniform probability of entry across all subjects invites further research to identify a more accurate, stochastic *asymmetric* entry model.[106]

The main weakness of the LS model is that its symmetric equilibrium uses a mixed strategy. When the N potential bidders are risk-neutral, or symmetrically risk averse, a mixed strategy equilibrium is unavoidable. Palfrey and Pevnitskaya (2008; PP) purify the mixed strategy equilibrium by assuming that the number of potential entrants, N, are drawn from a population with heterogeneous (homegrown) risk preferences. As such there is a critical level of risk-aversion (the cut off level) for which bidders who are more risk-averse select to stay out in order to avoid entry costs, while the less risk averse enter.

PP explore an environment with either 4 or 6 potential bidders in an IPV FPSB auction. Sessions with no entry costs and fixed numbers of bidders served as the control treatment. Entry costs, ω, were represented by a fixed payoff for staying out. Varying N, the upper bound of the support from which valuations were drawn, $\bar{u}$, and the value of the outside option, they employed treatments where the RNNE entry probability, q*, was either .5 or .35, representing "high" and "low" anticipated entry rates. Bidders' types, needed to purify the mixed strategy equilibrium, are determined by their risk preferences, with bidders who are more risk tolerant entering the auction, after which they learn their value for the item.

Comparing auctions with endogenous versus exogenous entry, as predicted the estimated slopes of the bid functions are smaller with endogenous entry in 11 out of 12 cases, consistent with the prediction that with endogenous entry the more risk averse subjects choose to stay out of the auction. Further, comparing estimated slopes of bid functions for different realized values of n, slopes are larger with $q^* = .5$ than .35 in all cases, again consistent with the prediction that with higher entry rates more risk averse bidders enter the auctions, resulting in more aggressive bidding. PP conclude that subjects who enter the auction are, on average, less risk averse than those who stay out.

However, entry rates were consistently higher than RNNE rate, indicating excess entry, and resulting in average profits for entrants that were substantially and consistently lower than the outside option (approximately 50% less). One potential source of this

[106] On this score also see Ochs (1995).

excess entry is that not entering is boring, with entering providing some entertainment value. To test this, PP employ a treatment in which non-entrants have the opportunity to play a simple computer game. While the average entry rate declined significantly from .61 to .54 (with $q^* = .50$), it was still significantly above the predicted upper bound for entry. One important difference between this experiment and SL who got close to risk neutral entry rates is that potential entrants were better informed about the expected value of entering versus staying out in SL (due to the fact that entrants shared the expected payoff for entry without actually bidding). The importance of clear information concerning expected profits will be shown in the next experiment reported on here.

Finally, the most direct test of the cut-off entry model would be to examine individual subject behavior: Do the same, least risk-averse, subjects almost always enter under the same treatment conditions? Unfortunately, the authors do not provide this data.

Ivanova-Stenzel and Salmon (2008; ISS) compare bidding in a FPSB auction with an English clock auction when bidders have a choice as to which auction to enter. That is, they take endogenous entry to its logical conclusion by having bidders choose which of two different auction formats to bid in. In this case the cost of entry is the opportunity cost of participating in the other auction. The key question posed in this experiment is whether revenue equivalence can be restored through competition between auction formats.

Bidders first participated in a "learning phase," where they bid in both the clock auction and the FPSB auction with exogenously determined numbers of bidders, in order to provide subjects with experience with both auction formats. Further, to insure that bidders knew the likely payoffs from the two formats, at the end of the learning phase they received feedback regarding the session-wide average profit for each format for all values of n. In the second phase subjects split into two groups of six bidders each and proceeded to bid in 30 rounds of auctions, choosing which auction to participate in.[107] Their main result is that the clock auctions attracted more bidders than the SB auctions, so that average revenue was essentially the same in both formats, as was average

[107] To assure competitiveness one bidder was assigned to each format without any choice so that each of the remaining four bidders could not enter and find herself the only bidder in that market. See ISS for a number of other important details regarding the innovative procedures employed.

efficiency. However, winning bidders earned slightly more money on average in the clock auctions.

ISS conclude that the key result in their study is not the approximate revenue equivalence, but rather that revenue in the English auctions increases sufficiently with endogenous entry to call into question the assumed revenue superiority of the FPSB auction, as bidders' arbitrage between mechanisms. This may well be true in a laboratory study where subjects are well informed regarding expected profits between the two mechanisms, as well as in field settings where bidders have extensive experience with both mechanisms. However, LR's field experiment investigating the same issue showed that FPSB auctions consistently raised more revenue than e-Bay "English" auctions, consistent with inexperienced bidders' lack of information regarding expected cost of participating in the two auction institutions. Alternatively, LR's English auctions took considerably more time to complete than the FPSB auctions, so that bidders anxious to get their playing cards sooner rather than later, would prefer the FPSB auction. This alternative explanation is consistent with the fact that in slow moving English auctions, bidders commonly resort to jump bids to speed things up (Isaac, Salmon, and Zillante, 2005), while LR's eBay auctions had a fixed ending time.

Several other entry related studies are worth mentioning. Goeree, Offerman and Sloof (2013) study multi-unit demand auctions when two incumbent firms face a potential negative externality in the form of a new entrant who, if winning items, will compete in the resulting product market.[108] Their paper compares entry rate in a UP clock auction with that of a SB discriminatory auction. Their results show that both auction formats induced similar high levels of entry. However, the mechanism behind the entry rates differed between the two auctions: In the ascending price auctions entry levels are between those predicted by the preemptive equilibrium in which incumbents completely block entry and the demand reduction equilibrium in which at least one of the incumbents always permits. In the discriminatory auctions there is more entry than predicted because of incumbents' failure to coordinate their bids to deter entry. As a result potential

[108] The experiment was inspired by developments in spectrum auctions in both the US and Germany.

entrants' prospects for successfully entering the market were similar between the two formats.[109]

Kagel, Pevnitskaya, and Ye (KPY, 2008) look at entry in markets with indicative bidding. Indicative bidding is a two-stage process sometimes used in the sale of business assets with very high values. In the first stage the auctioneer solicits a large group of interested buyers to submit non-binding bids, with the highest of these non-binding bids used to establish a short list of final (second-stage) bidders. These short-listed bidders then engage in extensive studies to acquire more information about the asset for sale, after which they submit firm and final bids (typically in a FPSB auction). Ye (2004) shows that there does not exist a symmetric increasing equilibrium with indicative bidding. As a result the most qualified bidders may not be selected to be on the short-list, which may result in substantial efficiency losses. In contrast, there are a number of alternative two-stage bidding procedures that, in theory at least, guarantee that the short-list consists of those bidders with the highest preliminary (first-stage) valuations, while preserving the best properties of indicative bidding; namely, avoidance of the costly asset valuation process for all but the short-listed bidders. Most prominent among these is a binding UP first-stage auction in which the highest rejected first-stage bid establishes an entry fee (Ye, 2004) for stage-two bidders. This is the type of situation tailor made for an experiment since there is no guarantee that the alternatives to indicative bidding will produce fully efficient outcomes, nor any other way to evaluate the efficiency losses associated with indicative bidding.

KPY's results show that indicative bidding performs as well as the UP auction in terms of those bidders with the highest first-stage valuations bidding in stage-two. This is a result of (1) sufficient heterogeneity in first-stage bids so that entry is not 100% efficient under the UP auction and (2) first-stage bids under indicative bidding highly correlated with first-stage values, resulting highly efficiency entry. The latter is reflective of the fact that bidders with low first-stage values lost money, on average, as a result of entry, while those with higher valuations consistently earned positive profits. Further,

[109] Hu et al. (2013) report results from a single-item experiment in which a potential entrant, if she wins the auction, imposes a negative externality on two incumbents. Entry rates are significantly higher in the FPSB auction compared to the clock auction, consistent with the model's prediction. Although actual entry rates are a bit higher under each auction format compared to predicted levels, they are not materially different from the predicted entry rate differential under the two auction formats.

indicative bidding does better on other dimensions as it yields higher average profits and fewer bankruptcies in the initial auction periods due to systematic overbidding in the UP auctions. Although these higher revenues are good for sellers in the short-run, they would more than likely destroy its long run viability. KPY report similar problems with a discriminatory first-stage auction. These results suggest a trade-off between types of mechanisms: One with clear equilibrium predictions insuring efficiency in theory, but involving relatively complex rules and calculations for bidders, the other with no clear equilibrium prediction but with relatively simple rules. The results are similar to those reported in KL (2010) for multi-unit demand Vickrey type auctions where a mechanism with a weaker solution concept achieves higher efficiency than one with a stronger solution concept due to its relative transparency (see section 3.2 above).

Goeree, Offerman, and Schram (2006; GOS) compare revenue between FPSB auctions versus simultaneous ascending auctions (SAA) for selling heterogeneous licenses under a market structure mimicking the 2002 Dutch sale of air wave rights auctions, a market with strong incumbents and relatively weak potential entrants. The key question addressed in this relatively uncompetitive situation is whether a FPSB auction would be more attractive to potential entrants than an ascending price auction, thereby generating more revenue and a more competitive aftermarket. Klemperer (2002) predicts this outcome on the grounds that the uncertainty inherent in the SB format encourages incumbent (strong) bidders to shave their bids less, while the ascending auction format discourages entrants as strong bidders simply "trail" weaker ones, overbidding them by the minimum amount required until they drop out. GOS confirm Klemperer's concerns, as in auctions with endogenous entry of weak bidders, their probability of winning was higher, and their rate of entry was higher in the FPSB auctions.[110] However, revenue was essentially the same between the two auction formats as was efficiency.

V Summary and Conclusions

Experimental research in auctions has continued apace along with the extensive theoretical work on auctions since the appearance of Kagel's survey in *The Handbook of*

[110] Three different FP formats were employed – all licenses sold at the same time, sequential sale of licenses and a simultaneous descending (Dutch auction) format. Entry rates were lower, with the probability of winning essentially the same, under the sequential FP format compared to the SAA.

Experimental Economics in 1995. Results reported in the original, 1995 survey focused on the Revenue Equivalence Theorem and initial investigations of the winner's curse, so they could be easily summarized. In contrast, it is impossible to summarize the work reported on here in a few sentences given the much broader scope of the issues covered since 1995. We anticipate a continued flow of auction experiments given the many applications of auctions: privatization of government assets, the continued growth of online and business-to-business auctions, and theorists' attempts to better understand the many variations in auction design in practice, and to design better auction institutions.

References

Andreoni, J., Y. K. Che, and J. Kim. 2007. Asymmetric information about rivals' types in standard auctions: An experiment. *Games and Economic Behavior* 59:240-259.

Ariely, D., A. Ockenfels, and A. E. Roth. 2005. An experimental analysis of ending rules in internet auctions. *RAND Journal of Economics* 36:890-907.

Armantier, O. 2002. Deciding between the common and private values paradigm: An application to experimental data. *International Economic Review* 43:783-801.

Armantier, O. and N. Treich.. 2009 Subjective probabilities in games: An application to the overbidding puzzle. *International Economic Review* 50:1079-1102.

Ashenfelter, O. 1989. How auctions work for wine and art. *Journal of Economic Perspectives* 3:33-36.

Ashenfelter, O. and D. Genesove. 1992. Testing for price anomalies in real estate auctions. *American Economic Review: Papers and Proceedings* 82:501-505.

Ausubel, L. M. 2004. An efficient ascending-bid auction for multiple objects. *The American Economic Review* 94:1452-1475.

Ausubel, L. M. and P. C. Cramton. 1996. Demand reduction and inefficiency in multi-unit auctions. Mimeograph. University of Maryland.

Ausubel, L and Milgrom, P. 2006. The lovely but lonely Vickrey auction. In *Combinatorial Auctions,* P. Cramton, Y. Shohani and R. Steinberg (eds). MIT Press.

Avery, C. and J. H. Kagel. 1997. Second-price auctions with asymmetric payoffs: An experimental investigation. *Journal of Economics and Management Strategy* 46:573-604.

Ayers, I and Cramton, P. 1996 "Deficit reduction through diversity: How affirmative action at the FCC increased auction competition" *Stanford Law Revue* , 48 (April): 761- 813.

Bajari, P. and A. Hortacsu. 2005. Are structural estimates of auction models reasonable? Evidence from experimental data. *Journal of Political Economy* 113:703-741.

Bajari, P. and A. Hortacsu. 2004. Economic insights from internet auctions. *Journal of Economic Literature* 42:457-486.

Bazerman, M. H. and W. F. Samuelson. 1983. I won the auction but don't want the prize. *Journal of Conflict Resolution* 27:618-634.

Bell, D. E. 1982. Regret in decision making under uncertainty. *Operations Research* 30:961-981.

Bikchandani, S. 1988. Reputation in repeated second-price auctions. *Journal of Economic Theory* 46:97-119.

Blecherman, B. and C. F. Camerer. 1998. Is there a winner's curse in the market for Baseball Players? Mimeograph. Brooklyn Polytechnic University**.**

Bolton, Gary E. and Axel Ockenfels. 2000. ERC: A theory of equity, reciprocity and competition. *American Economic Review*, 90, 166-193.

Brosig, J. and J. P. Reiss. 2007. Entry decisions and bidding behavior in sequential first-price procurement auctions: An experimental study. *Games and Economic Behavior* 58:50-74.

Brown, A. L., H. Sullivan, and C. R. Plott. 2009. The nature of collusion facilitating and collusion breaking power of simultaneous ascending price and simultaneous descending price auctions. *Economic Inquiry*. 47 (3), 395-424

Brusco, S. and G. Lopomo. 2002. Collusion via signaling in simultaneous ascending bid auctions with heterogeneous objects, with and without and complementarities. *Review of Economic Studies* 69:407-436.

Brunner, C., J. K. Goeree, C. A. Holt, and J. O. Ledyard. 2010 An experimental test of flexible combinatorial spectrum auction formats. American Economic Journal: Microeconomics,2(1), 39-57

Bulow, J. M. Huang and P. Klemperer. 1999. Toeholds and takeovers. *Journal of Political Economy* 107:427-454.

Burns, P. 1985. Experience and decision making: A comparison of students and businessmen in a simulated progressive auction. In *Research in Experimental Economics*, V. L. Smith (ed.) Jai Press, Greenwich, CT.

Camerer, C. 1995. Individual decision making, in *The Handbook of Experimental Economics*, . J. H. Kagel and A. E. Roth (eds) Princeton University Press.

Campbell, C. and D. Levin. 2006. When and why not to auction. *Economic Theory* 27:583-596.

Cantillon, E. and M. Pesendorfer. 2007. Combination bidding in multi-unit auctions. CEPR discussion paper No. 6083.

Capen, E. C., R. V. Clapp, and W. M. Campbell. 1971. Competitive bidding in high-risk situations. *Journal of Petroleum Technology* 23: 641-653.

Casari, M., J. C. Ham, and J. H. Kagel. 2007. Selection bias, demographic effects and ability effects in common value auction experiments. *American Economic Review* 97:1278-1304.

Cassing, J. and R.W. Douglas. 1980. Implications of the auction mechanism in baseball's free agent draft. *Southern Economic Journal* 47:110-121.

Cason, T. N. 1995. An experimental investigation of the seller incentives in the EPA's emission trading auction. *American Economic Review* 85: 905-922.

Cason, T. N. and D. Friedman. 1997. Price formation in single call markets. *Econometrica* 65: 311-345.

Cason, T. N. and D. Friedman. 1999. Learning in a laboratory market with random supply and Demand. *Experimental Economics* 2: 77-98.

Charness, G. and D. Levin. 2009. The origin of the winner's curse: A laboratory study. *American Economic Journal: Microeconomics*, 1: 207-236.

Chen, Y. and K. Takeuchi. 2010. Multi-object auctions with package bidding: An experimental comparison of *i*BEA and Vickrey. *Games and Economic Behavior* 68:557-579.

Chen-Ritzo, C. H., T. P. Harrison, A. M. Kwasnica, and D. J. Thomas. 2005. Better, faster, cheaper: An experimental analysis of a multi-attribute reverse auction mechanism with restricted information feedback. *Management Science* 51: 419-434.

Chen-Ritzo, Ching-Hua, Terry P. Harrison, Anthony M. Kwasnica, and Douglas J. Thomas, 2005. Better, faster, cheaper: An experimental analysis of a multi-attribute reverse auction mechanism with restricted information feedback, *Management Science*, 52: 1753-1762.

Chernomaz, K. 2012. On the effects of joint bidding in independent private value auctions: An experimental study.. *Games and Economic Behavior*, 76:690–710

Chernomaz, K. and D. Levin. 2012. Efficiency and synergy in a multi-unit auction with and without package bidding: An experimental study. . *Games and Economic Behavior*, 76: 611–635

Clarke, E. 1971. Multi-part pricing of public goods. *Public Choice* 11:19-33.

Cooper, D. J. and H. Fang. 2008. Understanding overbidding in second price auctions: An experimental study. *Economic Journal*, 118: 1572-1595.

Cooper, D. J. and J. H. Kagel. 2008. Other regarding preferences: a selective survey. Working paper.

Cooper, R. W., D. DeJong, R. Forsythe, and T. Ross. 1993. Forward induction in the battle of the sexes games. *American Economic Review* 83:1303-1316.

Coppinger, V. M., V. L. Smith, and J. A. Titus. 1980. Incentives and behavior in English, Dutch and sealed-bid auctions. *Economic Inquiry* 43:1-22.

Corns, A. and A. Schotter. 1999. Can affirmative action be cost effective? An experimental examination of price-preference auctions. *American Economic Review*, 89, 291-305.

Cox, J. C. and V. Sadiraj. 2006. Small- and large-stakes risk aversion: implications of concavity calibration fro decision theory. *Games and Economic* Behavior 56: 45-60.

Cramton, P. C. 1997. The FCC spectrum auctions: An early assessment. *Journal of Economics and Management Strategy 6:431-495.*

Cramton, P. and J. A. Schwartz. 2002. Collusive bidding in the FCC spectrum auctions. *Contributions to Economic Analysis and Policy* 1:1-20.

Crawford, V. and N. Iriberri. 2007. Level-k auctions: Can boundedly rational strategic thinking explain the winner's curse? *Econometrica* 75:1721-70.

De Silva, D. G., T. Dunne, and G. Kosmopoulou. 2002. Sequential bidding in auctions of construction contracts. *Economic Letters* 76:239-244.

Dessauer, J. P. 1981. *Book publishing*. New York: Bowker.

Dorsey, R. and L. Razzolini. 2003. Explaining overbidding in first price auctions using controlled lotteries. *Experimental Economics* 6:123-140.

Duffy, J. and Ochs, J. 2009. Cooperative behavior and the frequency of social interactions. . *Games and Economic Behavior*. 66: 785-812

Dyer, D., J. H. Kagel, and D. Levin. 1989. A comparison of naive and experienced bidders in common value offer auctions: A laboratory analysis. *Economic Journal* 99:108-115.

Dyer, D. and J. H. Kagel. 1996. Bidding in common value auctions: How the commercial construction industry corrects for the winner's curse. *Management Science* 42:1463-1475.

Elbittar, A. A.. 2009 Impact of valuation ranking information on bidding in first-price auctions: a laboratory study. *Journal of Economic Behavior and Organization* 69 (1), 75-85

Eliaz, K., T. Offerman, and A. Schotter. 2008. Creating competition out of thin air: An experimental study of right-to-choose auctions. *Games and Economic Behavior* 62:383-416.

Elmaghraby, Wedad, Elena Katok and Natalia Santamaŕia. 2010. A laboratory investigation of rank feedback in procurement auctions. *Manufacturing & Services Operations Management* 14:128-144.

Ely, J. C. and T. Hossain 2009. Sniping and squatting in auction markets. *AEJ Microeconomics*, 1: 68-96.

Engelbrecht-Wiggans, R. 1987. On optimal reservation prices in auctions. *Management Science* 33:763-770.

Engelbrecht-Wiggans, R. 1989. The effect of regret on optimal bidding in auctions. *Management Science* 35:685-692

Engelbrecht-Wiggans, R. 1993. Optimal auctions revisited. *Games and Economic Behavior* 5:227-239.

Engelbrecht-Wiggans, R. and C. M. Kahn. 1998. Multi-unit auctions with uniform prices. *Economic Theory* 12:227-258.

Engelbrecht-Wiggans, R., J. A. List, and D. H. Reiley. 2005. Demand reduction in Multi-unit auctions: Evidence from a sportscard field experiment: Reply. *American Economic Review* 95:472-476.

Engelbrecht-Wiggans, R., J. A. List, and D. H. Reiley. 2006. Demand reduction in multi-unit auctions with varying numbers of bidders: Theory and evidence from a field experiment. *International Economic Review,* 47:203-231.

Engelbrecht-Wiggans, R. and E. Katok. 2008. Regret and feedback information in first-price sealed-bid auctions. *Management Science*, 54 : 808-819.

Engelbrecht-Wiggans, R. and E. Katok. 2009 A direct test of risk aversion and regret in first price sealed-bid auction. *Decision Analysis,* 6 : 75-86.

Engelbrecht-Wiggans, R., E. Haruvy, and E. Katok. 2007 A comparison of buyer-determined and price-based multi-attribute mechanisms. *Management Science*, 26: 629-641..

Engelmann, D. and Grimm, V. 2009. Bidding behaviour in multi-unit auctions – An experimental investigation and some theoretical insights. *Economic Journal*, 119: 855-882.

Engel, R. 2009. First price auctions, lotteries, and risk preferences across institutions. Unpublished paper.

Epstein, R., L. Henríquez, J. Catalán, G. Y. Weintraub, and C. Martínez. 2002. A combinational auction improves school meals in Chile. *Interfaces* 32:1-14.

Eyster, E. and M. Rabin. 2005. Cursed equilibrium. *Econometrica* 73:1623-1672.

Fehr, Ernst and Klaus M. Schmidt. 1999. A theory of fairness, competition and cooperation. *Quarterly Journal of Economics*, 114: 817-68.

Feynman, R. P. 2005. *Classic Feynman: All the Adventures of a Curious Character*. New York: W. W. Norton.

Filiz, E. and E. Y. Ozbay. 2007. Auctions with anticipated regret. *American Economic Review* 97:1407-1418.

Fisher R. A. 1935. *The Design of Experiments* Edinburgh: Oliver and Boyd.

Fréchette, G. 2012. Session effects in the laboratory. *Experimental Economics*, 15: 485-498

Fréchette, Guillaume R. (2010) "Laboratory Experiments: Professionals versus Students" in *The Methods of Modern Experimental Economics*, Guillaume Fréchette and Andrew Schotter (editors), Oxford University Press, forthcoming.

Garratt, R., M. Walker, and J. Wooders.. 2012 Behavior in second-price auctions by highly experienced eBay buyers and sellers. Experimental Economics, 15: 44-57

Garratt, R. and T. Troeger. 2006. Speculation in Standard Auctions with Resale. *Econometrica*, 74: 753-769.

Georganas, S. and J. H. Kagel.. 2011 Asymmetric Auctions with Resale: An Experimental Study. *Journal of Economic Theory*.146: 359-371

Georganas, S., D. Levin and P. McGee. 2010. Do irrelevant payoffs affect behavior when a dominant strategy is available: experimental evidence from second-price auctions. Ohio State University working paper.

Georganas, S. and R. Nagel. 2011. Auctions with Toeholds: An experimental study. *International Journal of Industrial Organization.* .29: 34-45

Goeree, J. K., C. A. Holt, and T. R. Palfrey. 2002. Quantal response equilibrium and overbidding in private-value auctions. *Journal of Economic Theory* 104:247-272.

Goeree, J. K. and T. Offerman. 2002. Efficiency in auctions with private and common values: An experimental study. *American Economic Review* 92:625-643.

Goeree, J. K. and T. Offerman. 2003. Competition bidding in auctions with private and common values. *Economic Journal* 113:598-614.

Goeree, Jacob K. and Theo Offerman. 2004. The Amsterdam auction. *Econometrica*, 72, 281-294.

Goeree, J. K., C. Plott, and J. Wooders. 2004. Bidders' choice auctions: Raising revenues through the right to choose. *Journal of the European Economics Association* 2:504-515.

Goeree, Jacob K., Theo Offerman, and Arthur Schram. 2006. Using first-price auctions to sell heterogeneous licenses. *International Journal of Industrial Organization*, 24: 555-581.

Goeree, Jacob K. and Holt, Charles A. 2010. "Hierarchical Package Bidding: A Paper & Pencil Combinatorial Auction." *Games and Economic Behavior*, 70 (1):146-169.

Goeree, J. K., T. Offerman, and R. Sloof. 2013. Demand reduction and preemptive bidding in multi-unit license auctions. *Experimental Economics*, 16: 52-87

Goswami, G., T. H. Noe, and M. J. Rebello. 1996. Collusion in uniform-price auction: Experimental evidence and implications for treasury auctions. *The Review of Financial Studies* 9:757-785.

Grebe, Tim, Radosveta Ivanova-Stenzel, Sabine Kröger. 2009. Buy-it-now prices in eBay auctions – The field in the lab. SFB/TR 15 Discussion Paper No. 294

Grimm, V. and D. Engelmann 2005. Overbidding in first-price private value auctions revisited: Implications of a multi-unit auctions experiment, in *Advances in Public Economics: Utility, Choice and Welfare*, U. Schmidt and S. Traub (eds). Dordrecht: Springer, pp 235-54.

Groves, T. 1973. Incentives in teams. *Econometrica* 41:617-631.

Güth, W., R. Ivanova-Stenzel, and E. Wolfstetter. 2005. Bidding behavior in asymmetric auctions: An experimental study. *European Economic Review* 49:1891-1913.

Hafalir, I. E. and V. Krishna. 2008. Asymmetric Auctions with Resale. *American Economic Review*, 98: 87-112.

Haile, P. A. 2003. Auctions with Private Uncertainty and Resale Opportunities. *Journal of Economic Theory*, 108: 72-110.

Ham, J. C., J. H. Kagel, and S. F. Lehrer. 2005. Randomization, endogeneity and laboratory experiments: The role of cash balances in private value auctions. *Journal of Econometrics* 125:175-205.

Hansen, R. G. and J. R. Lott, Jr. 1991. The winner's curse and public information in common value auctions: Comment. *American Economic Review* 81:347-61.

Haruvy, Ernan and Elena Katok. 2013 Increasing revenue by decreasing information in procurement auctions. *Production and Operations Management*, 22: 19-35

Harrison, G. W. and J. A. List. 2008. Naturally occurring markets and exogenous laboratory experiments: A case study of the winner's curse," *Economic Journal*, 118: 822-843.

Hausch, D. B. 1987. An asymmetric common value auction model. *RAND Journal of Economics* 18:611-621.

Hendricks, K., R. H. Porter, and C. A. Wilson. 1994. Auctions for oil and gas leases with an informed bidder and a random reservation price. *Econometrica*. 62:1415-1444.

Holt, C. and S. Laury. 2002. Risk aversion and incentive effects. *American Economic Review* 92, 1644-1655.

Holt, C. A. Jr. and R. Sherman. 1994. The loser's curse and bidder's bias. *American Economic Review* 84:642-652.

Hu, Y, Kagel, J. H., Xu, X., and Ye, L. 2013. Theoretical and Experimental Analysis of Auctions with Negative Externalities. *Games and Economic Behavior* 82: 269-91.

Isaac, R. M. and D. James. 2000a. Just who are you calling risk averse? *Journal of Risk and Uncertainty*. 20:177-187.

Isaac, R. M. and D. James. 2000b. Robustness of the incentive compatible combinatorial auction. *Experimental Economics* 3:31-53.

Isaac, R. M. and J. M. Walker. 1985. Information and conspiracy in sealed bid auctions. *Journal of Economic Behavior and Organization* 6: 139-159.

Isaac, R. Mark, Timothy C. Salmon and Arthur Zillante. 2005. An experimental test of Alternative models of bidding in ascending auctions. *International Journal of Game Theory*, 33, 287-313.

Ivanov, A., D. Levin, and M. Niederle. 2010. Can relaxation of beliefs rationalize the winner's curse?: an experimental study. *Econometrica* 78: 1435-1452.

Ivanova-Stenzel, Radosveta and Sabine Kröger. 2008. Price formation in a sequential selling mechanism. *Journal of Economic Behavior & Organization*, 67, 832-843.

Ivanova-Stenzal, R., and T. C. Salmon. 2008. Revenue equivalence revisited. . *Games and Economic Behavior*, 64: 171-192

James, D. 2007. Stability of risk preference parameter estimates within the Becker-DeGroot-Marschak procedure. *Experimental Economics*, 10, 123-142.

Jap, S. D. 2002. Online reverse auctions: issues, themes and prospects for the future. *Journal of Academic Marketing Science* 30: 506-525.

Jofre-Bonet, M. and M. Pesendorfer, 2000. Bidding behavior in a repeated procurement auction. *Euorpean Economic Review* Revised 44:1006-1020.

Jofre-Bonet, M. and M. Pesendorfer, 2003. Estimation of a dynamic auction game. *Econometrica* 71:1443-1489.

Johnson-Laird, P. N. 1999. Deductive reasoning. *Annual Review of Psychology* 50:109-135.

Kagel, J. H. and D. Levin. 1986. The winner's curse and public information in common value auctions. *American Economic Review* 76:894-920.

Kagel, J. H., R. M. Harstad, and D. Levin. 1987. Information impact and allocation rules in auctions with affiliated private values: A laboratory study. *Econometrica* 55:1275-1304.

Kagel, J. H. and D. Levin. 1991. The winner's curse and public information in common value auctions: Reply. *American Economic Review* 81:362-369.

Kagel, J. H. and D. Levin. 1993. Independent private value auctions: Bidder behavior in first-, second- and third-price auctions with varying numbers of bidders. *Economic Journal* 103:868-879.

Kagel, J. H. and D. Levin. 1999. Common value auctions with insider information. *Econometrica* 67:1219-1238.

Kagel, J. H., S. Kinross, and D. Levin. 2001. Comparing efficient multi-object auction institutions. Working paper, Ohio State University.

Kagel, J. H. and D. Levin. 2001. Behavior in multi-unit demand auctions: Experiments with uniform price and dynamic Vickery auctions. *Econometrica* 69:413-454.

Kagel, J. H. and J. F. Richard. 2001. Super-experienced bidders in first-price common value auctions: Rules of thumb, Nash equilibrium bidding and the winner's curse. *Review of Economics and Statistics* 83:408-419.

Kagel, J. H. and D. Levin. 2002. Bidding in common value auctions: A survey of experimental research. In *Common Value Auctions and the Winner's Curse.* Princeton University Press.

Kagel, J. H. and D. Levin. 2005. Multi-unit demand auctions with synergies: Behavior in sealed-bid versus ascending-bid uniform-price auctions. *Games and Economic Behavior* 53:170-207.

Kagel, J. H., S. Pevnitskaya, and L. Ye. 2008. Indicative bidding: An experimental analysis. *Games and Economic Behavior* 62:697-721.

Kagel, J. H., Y. Lien, and P. Milgrom. 2010. Ascending prices and package bidding: An experimental analysis. *American Economic Journal: Microeconomics* 2: 160-85.

Kagel, J. H., Y. Lien, and P. Milgrom. 2014. Ascending Prices and Package Bidding: Further Experimental Analysis. *Games and Economic Behavior* 85: 210-231.

Kagel, J. H., S. Pevnitskaya, and L. Ye. 2007. Survival auctions. *Economic Theory* 33:103-119.

Kagel, J. H. and D. Levin. 2009. Implementing efficient multi-object auction institutions: An experimental study of the performance of boundedly rational agents. *Games and Economic Behavior* 66:221-237.

Kagel, J. H. 1995. Auctions: a survey of experimental research. In *The Handbook of Experimental Economics*, Alvin E. Roth and John H. Kagel, Editors, Princeton University Press.

Katok, E. and A. E. Roth. 2004. Auctions of homogeneous goods with increasing returns: Experimental comparison of alternative "Dutch" auctions. *Management Science* 50:1044-1063.

Keser, C. and M. Olson. 1996. Experimental examination of the declining-price anomaly. In *Economics of the Arts: Selected Essays.* V. Ginsburg and P-M Menger (eds). Amsterdam: Elsevier.

Klemperer, P. 1998. Auctions with almost common values: The 'Wallet Game' and its applications. *European Economic Review* 42:757-769.

Klemperer, P. 2002. How (not) to run auctions: The European 3G Telecom auctions. *European Economic Review* 46:829-845.

Krishna, V. 2002. *Auction Theory*. Academic Press.

Kwasnica, A. M. and K. Sherstyuk. 2007. Collusion and equilibrium selection in auctions. *Economic Journal*, 117: 120-145.

Lange, A., J. A. List, and M. K. Price.. 2011 Auctions with Resale When Private Values Are Uncertain: Theory and Empirical Evidence. International Journal of Industrial Organization, 29: 54-64.

Leufkens, K., R. Peeters, and M. Vorsatz. 2006. Sequential auctions with synergies: An experimental study. METEOR Research Memorandum 06/040, Maastricht University.

Levin, D. 1990. Horizontal mergers: The 50 percent benchmark. *American Economic Review* 80:1238-1245.

Levin, D. 2005. Demand reduction in Multi-unit auctions: Evidence from a sportscard field experiment: A comment. *American Economic Review* 95:467-471.

Levin, D. and J. Smith. 1994. Equilibrium in auctions with entry. *American Economic Review* 84:585-599.

Levin, D., J. H. Kagel, and J. F. Richard. 1996. Revenue effects and information processing in English common value auctions. *American Economic Review* 86:442-460.

Levin, D. and J. H. Kagel. 2005. Almost common-value auctions revisited. *European Economic Review* 49:1125-1136.

Li, J. and C. R. Plott.. 2009. Tacit collusion in auctions and conditions for its facilitation and prevention: Equilibrium selection in laboratory experimental markets. *Economic Inquiry*, 47 (3), 425-448

Lind, B. and C. R. Plott. 1991. The winner's curse: Experiments with buyers and with sellers. *American Economic Review* 81:335-346.

List, J. A. and D. Lucking-Reiley. 2000. Demand reduction in multi-unit auctions: Evidence from a sportscard field experiment. *American Economic Review* 90:961-972.

Loomes, G. and R. Sugden. 1982. Regret theory: An alternative theory of rational choice under uncertainty. *Economic Journal* 92:805-824.

Lucking-Reiley, D. 1999. Using field experiments to test equivalence between auction formats: Magic on the Internet. *American Economic Review* 89:1063-1080.

Manelli, A. M., M. Sefton, and B. S. Wilner. 2006. Multi-unit auctions: A comparison of static and dynamic mechanisms. *Journal of Economic Behavior and Organization* 61: 304-23.

Maskin, E. and J. Riley. 2000. Asymmetric auctions. *Review of Economic Studies* 67:413-438.

Mathews, T. 2003. The impact of discounting on an auction with a buy-out option: A theoretical analysis motivated by eBay's Buy-It-Now feature. *Journal of Economics (Zietschrift für Nationalökonomie*) 81:25-52.

McAfee, R. P. and J. McMillan. 1987. Auctions with entry. *Economic Letters* 23:343-347.

McAfee, R. P. and D. Vincent. 1993. The declining price anomaly. *Journal Economic Theory* 60:191-212.

Mellers, B. A. and A. D. J. Cooke. 1996. The role of task and context in preference measurement. *Psychological Science* 7:76-82.

Menezes, F. M. and P. K. Monteiro. 1998. Simultaneous pooled auctions. *Journal of Real Estate Finance and Economics* 17:219-232.

Menkhaus, D. J., O. R. Phillips and K.T. Coatney. 2003. Shared agents and competition in laboratory English auctions. *American Journal of Agricultural Economics* 85:829-839.

Morgan, J. 2002. Combinatorial auctions in the information age: an experimental study. *Advances in Applied Microeconomics* 11:191-207.

Myerson, E. 1981. Optimal auction design. *Mathematics of Operations Research*. 6:58-73.

Neugebauer, T. and R. Selten. 2006. Individual behavior and first-price auctions: The importance of information feedback in computerized experimental markets. *Games and Economic Behavior* 54:183-204.

Neugebauer, T. and P. Pezanis-Christou. 2007. Bidding behavior at sequential first-price auctions with(out) supply uncertainty: A laboratory analysis. *Journal of Economic Behavior & Organization* 63: 55-72.

Niederle, M. and L. Vesterlund. 2007. Do women shy away from competition? *Quarterly Journal of Economics* 122:1067-1101.

Ochs, J. 1995. Coordination problems. In J. H. Kagel and A. E. Roth (ed) *Handbook of Experimental Economics*. Princeton University Press, Princeton. 195-251.

Ockenfels, A. and R. Selten. 2005. Impulse balance equilibrium and feedback in first price Auctions. *Games and Economic Behavior* 51: 155-170.

Ockenfels, A., D. H. Reiley and A. Sadrich. 2006. Online auctions. In *Handbook of Information Systems.* T. Hendershott (ed). Elsevier, xxxx. 571-628.

Offerman, T. and J. Potters. 2006. Does auctioning of entry licenses induce collusion? An experimental study. *Review of Economic Studies* 73:769-791.

Pagnozzi, M, and K. J. Saral. 2014 "Multi-object auctions with resale: an experimental analysis." Working paper, Università di Napoli Frederico II.

Palfrey, T. and S. Pevnitskaya. 2008. Endogenous entry and self-selection in private value auctions: An experimental study. *Journal of Economic Behavior and Organization* 66:731-747.

Pezanis-Christou, P. 2002. On the impact of low-balling: Experimental results in asymmetric auctions. *International Journal of Game Theory* 31:69-89.

Phillips, O. R., D. J. Menkhaus, and K. T. Coatney. 2003. Collusive practices in repeated English auctions: Experimental evidence on bidding rings. *American Economic Review* 93:965-979.

Phillips, O. R. and D. J. Menkhaus. 2009. Maintaining tacit collusion in repeated ascending auctions. *Journal of law and Economics* 52: 91-110.

Pitchik C. and A. Schotter. 1988. Perfect equilibria in budget-constrained sequential auctions: An experimental study. *Rand Journal of Economics* 19**:**363-388.

Porter, D. and R. Vragov. 2006. An experimental examination of demand reduction in multi-unit versions of the uniform-price, Vickery, and English auctions. *Managerial and Decision Economics* 27:445-458.

Rabin, M. 2000. Risk aversion and expected utility theory. *Econometrica* 68:1281-1292.

Rapoport, A., D. Seale, I. Erev, and J. Sundali. 1998. Equilibrium play in large group market entry games. *Management Science* 44:119-141.

Reynolds, S. S. and J. Wooders. 2009. Auctions with a buy price. *Economic Theory* 38: 9-39.

Riley, J. G. and W. F. Samuelson. 1981. Optimal auctions. *American Economic Review* 71:381-392.

Robert, J. and C. Montmarquette. 1999. Sequential auctions with multi-unit demand: Theory, experiments and simulations. CIRANO working paper, 99s-46.

Roll R. 1986. The hubris hypothesis of corporate takeovers. *Journal of Business* 59:197-216.

Rose, S. L. and J. H. Kagel. 2008. Bidding in almost common value auctions: An experiment. *Journal of Economic Management Strategy*17: 1041-1058.

Rose, S. L. and D. Levin. 2008. An experimental investigation of the explosive effect in almost common value auctions. *Journal of Economic Behavior and Organization*, 67: 927-946.

Roth, A. E. and A. Ockenfels. 2002. Last-minute bidding and the rules for ending second-price auctions: Evidence from eBay and Amazon auctions on the internet. *American Economic Review* 92:1093-1103.

Sade, O., C. Schnitzlein, and J. F. Zender. 2006. Competition and cooperation in divisible good auctions: An experimental examination. *Review of Financial Studies* 19:195-235.

Salmon, T. C. and B. J. Wilson. 2008. Second chance offers versus sequential auctions: Theory and behavior. *Economic Theory* 34:47-67.

Salmon, T. C. and M. Iachini. 2007. Continuous ascending vs. pooled multiple unit auctions. *Games and Economic Behavior* 61:67-85.

Salomon, G. and D. N. Perkins. 1989. Rocky roads to transfer: Rethinking mechanisms of a neglected phenomenon. *Education Psychologist 24:113-142.*

Samuelson, W.F. and M.H. Bazerman. 1985. The winner's curse in bilateral negotiations, in V.L. Smith (ed.), *Research in Experimental Economics,* 3. Greenwich, CT.: JAI Press.

Scheffel, Tobias, Ziegler, Georg, and Martin Bichler. 2012. "On the impact of package selection in combinatorial auctions: an experimental study in the context of spectrum design." *Experimental Economics*, 15: 4, pp. 667-692.

Shahriar, Q. and J. Wooders.. 2011 An experimental study of auctions with a buy price under private and common values.. *Games and Economic Behavior*. 72 (2), 558-573

Shachat, Jason and J. Todd Swarthout. 2010. Procurement auctions for differential goods. *Decision Analysis*, 7: 6-22.

Shogren, J. F., G. M. Parkhurst, and C. McIntosh. 2006. Second-price auction tournament. *Economics Letters* 92:99-107.

Smith, J. 1982. Equilibrium patterns of bidding in OCS lease sales. *Economic Inquiry* 20:180-190.

Smith, J. L. 1984. Further results on equilibrium patterns of bidding in OCS lease sales. *Economic Inquiry* 22:142-146.

Smith, J. and D. Levin. 2001. Entry coordination in auctions and social welfare: An experimental investigation. *International Journal of Game Theory* 30:321-350.

Tor, A and M. H. Bazerman. 2003. Focusing failures in competitive environments: Explaining decision errors in the Monty Hall game, the acquiring a company game, and multiparty ultimatums. *Journal of Behavioral Decision Making* 16:353-374.

Turocy, T. L. and E. Watson.. 2012. Reservation values and regret in laboratory first-price auctions:Context and bidding behavior. Southern Economic Journal 78(4): 1163-1180. .

Turocy, T. L., E. Watson and R. C. Battalio. 2007. Framing the first-price auction. *Experimental Economics* 10:37-52.

Tversky, A. and D. Kahneman. 1992. Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Unvertainty* 5:297-323.

Walker, J. M., V. L. Smith, and J. C. Cox. 1987. Bidding behavior in first-price sealed-bid auctions: Use of computerized Nash competitors. *Economic Letters* 23:239-244.

Whinston, M. D. 2006. *Lectures on Antitrust Economics*. MIT Press.

Wilson, B. R. 1967. Insider competitive bidding with asymmetric information. *Management Science* 13:816-820.

Vickrey, W. 1961. Counterspeculation, auctions, and competitive sealed tenders. *Journal of Finance* 16:8-37.

Wan, Zhixi, Damian R. Beil, and Elena Katok.2012. When does it pay to delay supplier qualification? Theory and experiments. Management Science 58 (11), pp. 2057-2075

Weber, R. J. 1983. Multiple-object auctions, in *Auctions, Bidding and Contracting: Uses and Theory*, R. E. Engelbrecht-Wiggans, M. Shubik, and R. Stark (eds). New York University Press.

Ye, L. 2004. Optimal auctions with endogenous entry. *Contributions to Theoretical Economics* 4:1-27.

Table 1

Realized and Predicted Prices: First Price Sequential Auctions

	Unit 1	Unit 2	Unit 2	Unit 4
Predicted[a] Average (std)	444 (41)	446 (80)	449 (100)	426 (133)
Realized				
Mean (std)	500 (104)	474 (76)	463 (70)	454 (121)
Median	492	470	461	456

a Based on bidders' realized valuations

std = standard deviations

From Keser and Olson (1996).

Table 2

Inexperienced Bidders: Actual versus Theoretical Revenue Changes and Profit Levels[a] in English versus First-Price Auctions

	n=4						n=7					
	Average Change in Revenue: English Less First-Price (standard error)		Average Profit (standard error)				Average Change in Revenue: English Less First-Price (standard error)		Average Profit (standard error)			
			First-Price		English				First-Price		English	
ε	Actual	Theoretical	Actual	Theoretical	Actual	Theoretical	Actual	Theoretical	Actual	Theoretical	Actual	Theoretical
$6	-1.54*	1.54**	-2.13	2.76	0.58	1.23	-1.98*	0.10	-3.85	0.99	-1.87	0.89
	(0.72)	(0.49)	(0.52)	(0.38)	(0.50)	(0.30)	(0.87)	(0.34)	(0.71)	(0.19)	(0.51)	(0.29)
			[29]		[28]				[18]		[18]	
$12	0.54	2.76**	-1.32	5.01	-0.78	2.25	-1.95	1.08	-3.75	2.76	-1.80	1.68
	(1.25)	(0.92)	(0.79)	(0.60)	(0.95)	(0.69)	(1.19)	(0.65)	(0.89)	(0.53)	(0.77)	(0.40)
			[41]		[45]				[30]		[43]	
$24	1.09	8.10**	1.20	9.83	0.11	1.73	ND	ND	ND		ND	
	(3.29)	(2.32)	(1.93)	(1.25)	(2.64)	(2.14)						
			[25]		[13]							

[a] All values reported in dollars.

+ The null hypothesis that the value is greater than or equal to zero can be rejected at the 10% significance level.

* The null hypothesis that the value is greater than or equal to zero can be rejected at the 5% significance level.

** The null hypothesis that the value is greater than or equal to zero can be rejected at the 1% significance level.

ND No data

From Levin, Kagel and Richard (1996)

Table 3

Super-Experienced Bidders: Actual versus Theoretical Revenue Changes and Profit Levels[a] in English versus First-Price Auctions

	n=4						n=7					
	Average Change in Revenue: English Less First-Price (standard error)		Average Profit (standard error)				Average Change in Revenue: English Less First-Price (standard error)		Average Profit (standard error)			
			First-Price		English				First-Price		English	
ε	Actual	Theoretical	Actual	Theoretical	Actual	Theoretical	Actual	Theoretical	Actual	Theoretical	Actual	Theoretical
$18	2.21*	3.96**	3.37	6.77	1.16	2.82	-0.25	2.85**	0.76	3.86	1.01	1.01
	(0.95)	(0.73)	(0.50)	(0.48)	(0.88)	(0.53)	(0.86)	(0.61)	(0.65)	(0.50)	(0.56)	(0.37)
			[163]		[107]				[75]		[96]	
	1.20	2.98	8.45	11.27	7.25	8.29						
$30	(3.10)	(2.30)	(1.28)	(1.34)	(2.76)	(1.93)	ND		ND		ND	
			[31]		[33]							

[a] All values reported in dollars. Super-experienced bidders had participated in at least two previous first-price common value auction sessions.
* The null hypothesis that the value is greater than or equal to zero can be rejected at the 5% significance level.
** The null hypothesis that the value is greater than or equal to zero can be rejected at the 1% significance level.
ND No data

From Levin, Kagel and Richard (1996)

Table 4

Change in Seller's Revenue: Auction with Insider versus No Insider
(Super-Experienced Bidders)

	n=4			n=7		
	Change in Revenue: Insider *less* No Insider[a] (t-stat)[b]	Mean Profits (σ^2)		Change in Revenue: Insider *less* No Insider[a] (t-stat)[b]	Mean Profits (σ^2)	
		Insiders	No Insiders		Insiders	No Insiders
$\varepsilon = \$18$	1.759 (2.057)*	2.063 (8.561)	3.822 (49.972)	0.739 (1.573)+	1.492 (6.770)	2.231 (19.221)
$\varepsilon = \$30$	2.734 (1.097)	6.148 (24.334)	8.876 (59.731)	0.919 (0.425)	4.517 (17.978)	5.436 (15.839)

* Significantly different from 0 at $p < .05$, one-tailed test.
\+ Significantly different from 0 at $p < .10$, one-tailed test.
From Kagel and Levin (1999)

Table 5
Comparing Frequency of Equilibrium Play Under Different Auction Institutions

v_h (Predicted outcome)	No. Computers	Clock	Sealed Bid*
$3.00 (Full demand reduction)	3	46.3%	2.6%
$4.00 (Bid above value)[a]	3	23.7%	1.6%
	5	22.3%	3.1%
$4.40 (Bid above value)[b]	3	38.8%	27.7%
	5	35.8%	27.1%
$5.10 (Go for it)[c]	5	79.2%	40.6%

V_h is value for human bidder.

[a] SB auction: Bid $4.34 with 3 computers; $4.16 with 5 computers.
Clock auction: if $v_2 \leq \mathbf{P}^* =$ \$4.50 go for it winning both units; otherwise drop out (v_2 is second highest computer value).

[b] SB auction: Go for it bidding at or above maximum computer value.
Clock auction: if $v_2 \leq \mathbf{P}^* =$ \$5.70 go for it winning both units; otherwise drop out (v_2 is second highest computer value).

[c] Bidding at or above maximum computer value.

From Kagel and Levin (2005)

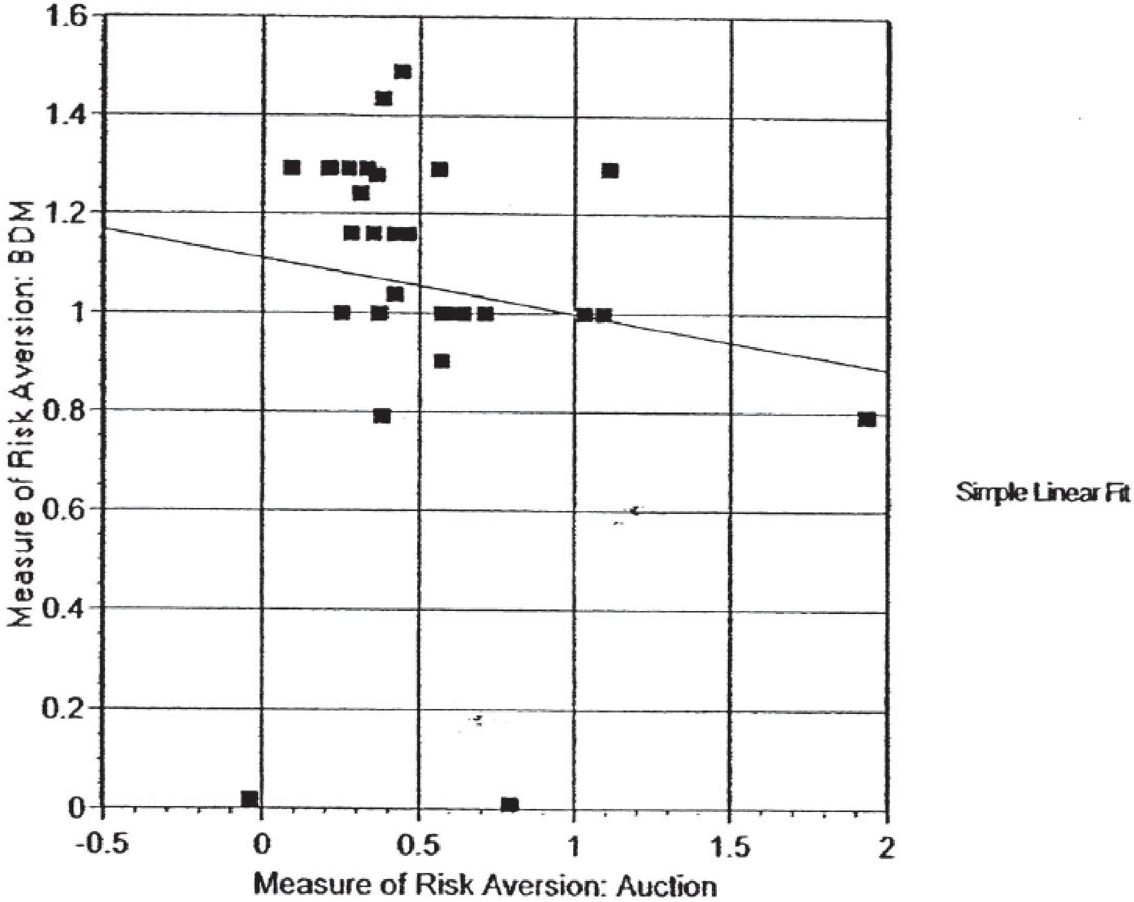
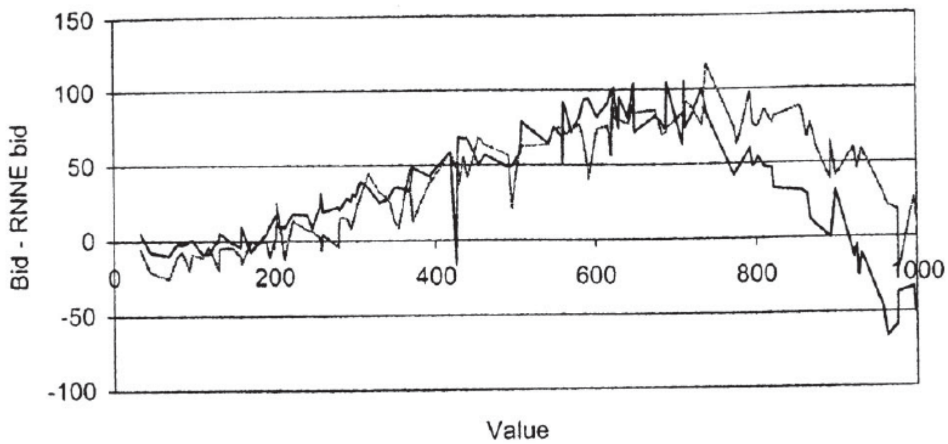


Figure 1: From Isaac and James (2000)



Deviations of mean auction bids (gray) and mean lottery-equivalent bids (black) from RNNE bid.

Figure 2: From Dorsey and Razzolini (2003)

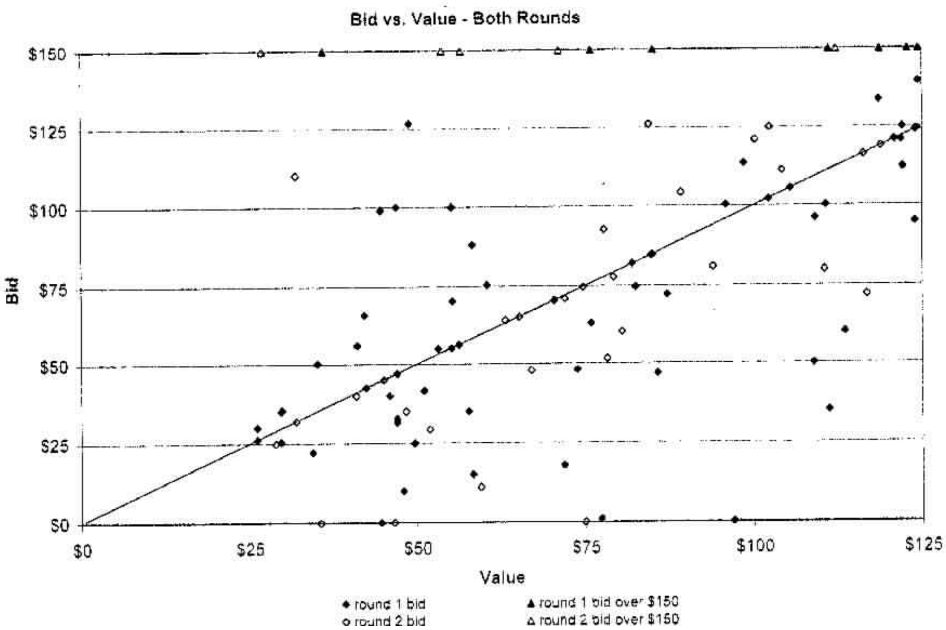
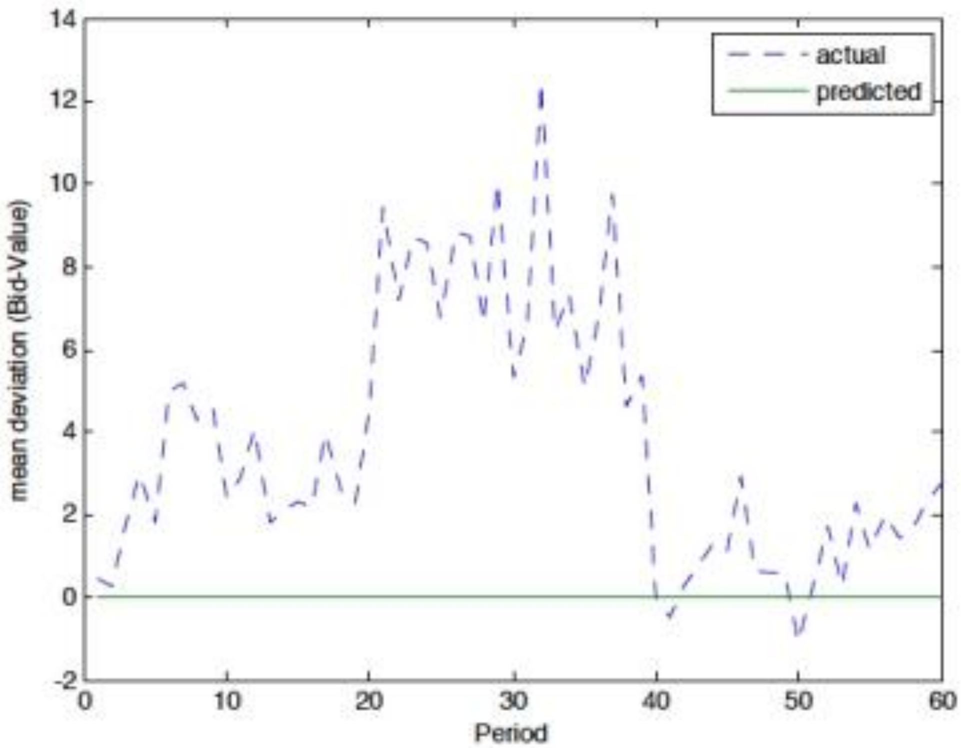


Figure 3: Bids and values in second-price internet auctions.

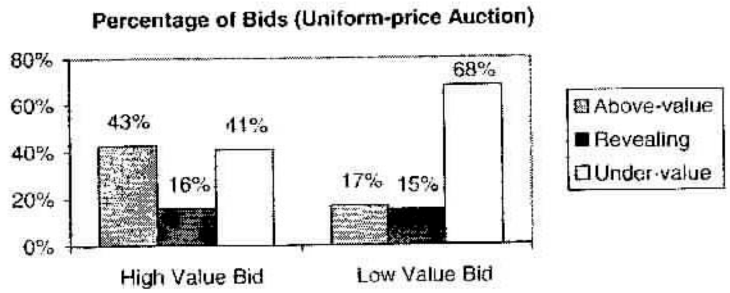
From Garrat, Walker and Wooders (2012)



Per 1-20 $\beta = 1$
Per 21-40 $\beta = 0.1$
Per 41-60 $\beta = 20$

Figure 4: Effect of multiplying any realized losses in SPSB auctions by a factor β.

From: Georganeous, Levin, and McGee (2010)



Classification of bids in the Uniform-price treatment. Bids within 5% of value are categorized as revealing.

Figure 10: From Porter and Vragov (2006)

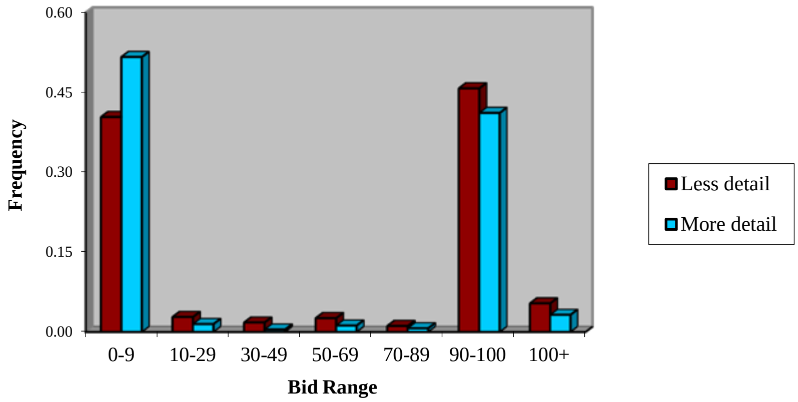


Figure 5: Bid frequencies in two value treatment in Charness and Levin (2009).

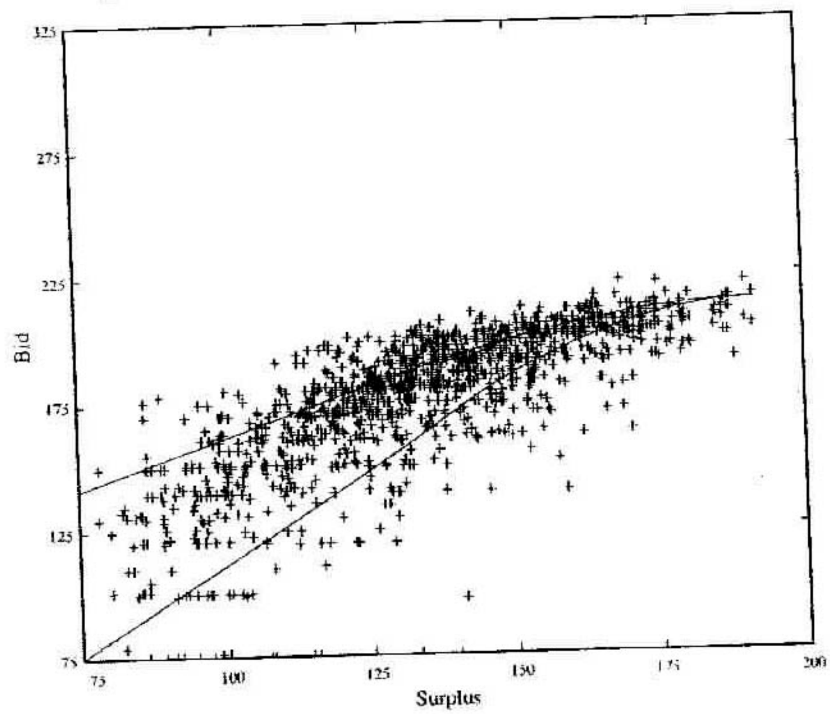
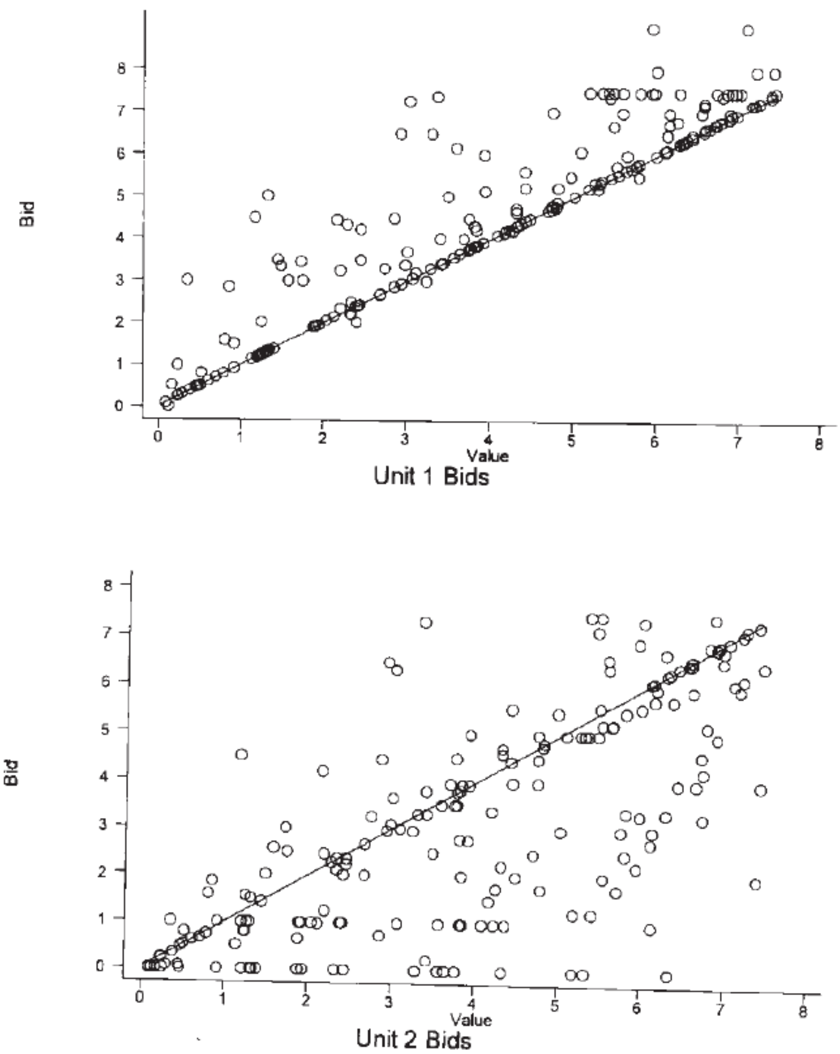


Figure 6: Bids (+) together with Nash Bids (lower line) and Naïve Bids (top line). Amount of overbidding (relative to Nash) tends to be higher when surplus is smaller as winning the auction is more informative about the common value in this case.

From Goeree and Offerman (2002).

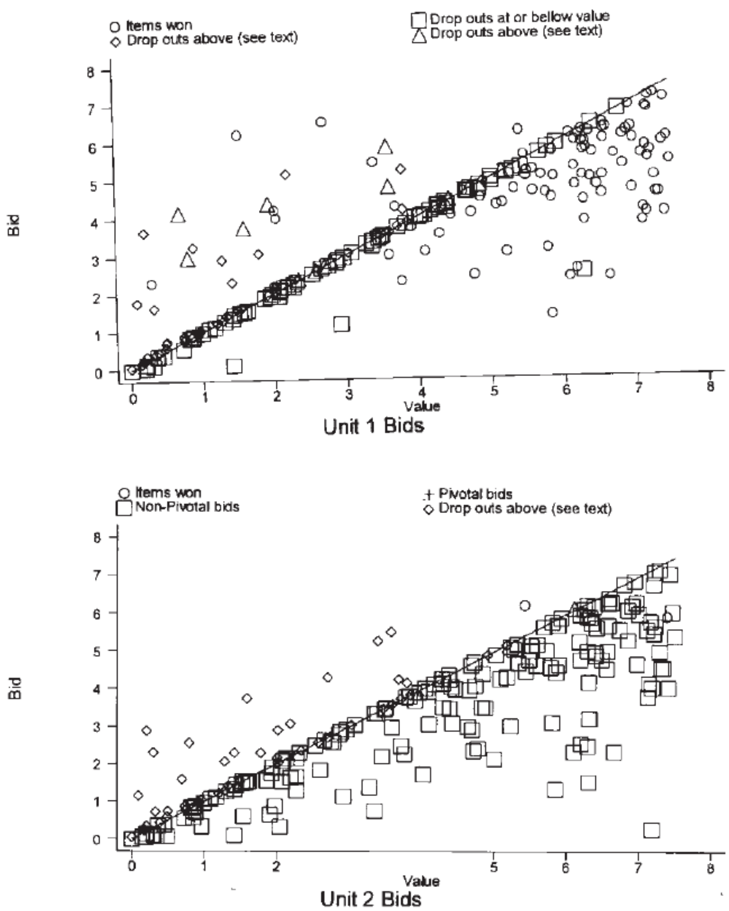
Figure 7



Bids relative to value for last 12 auctions. Solid line bids equal to value.

From Kagel and Levin (2001).

Figure 8

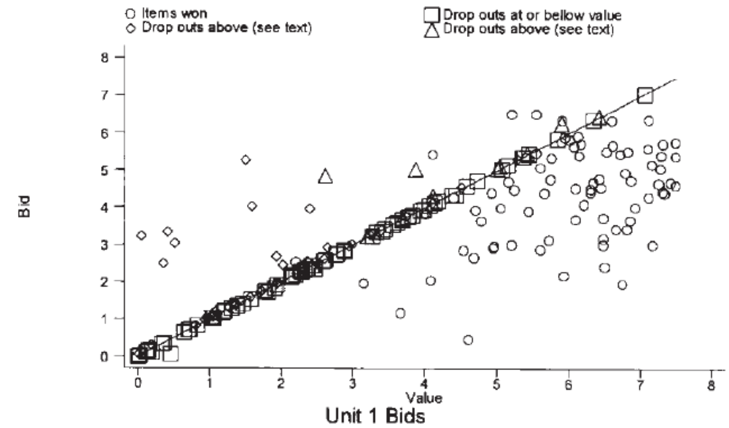


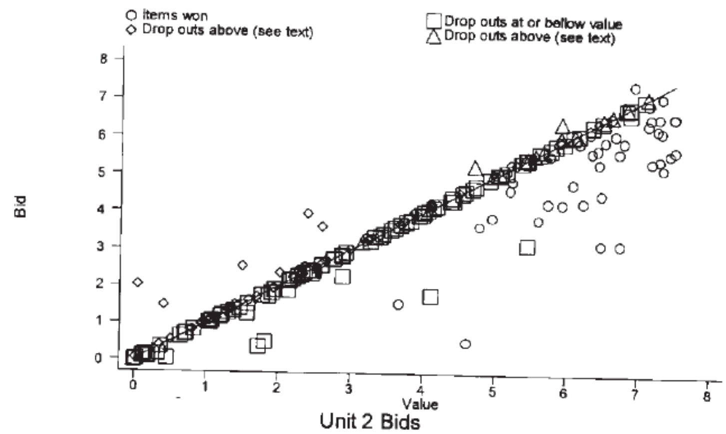
Top panel: Unit 1 bids. Bids relative to value in last 12 auctions. Circles are winning (censored) bids. Squares are dropouts at or below resale value. Triangles are bids above value that could have resulted in losses (dropping out after the third highest computerized bidder had dropped). Diamonds are harmless bids above value as dropout occurred while the third highest computerized bidder was active. Solid line: Bid equal to value.

Bottom panel: Unit 2 bids. Bids relative to value in last 12 auctions. Circles are winning (censored) bids. Squares are dropouts at or below second highest computer value (optimal bids having no effect on the market price). Pivotal dropout (that set the market price and are suboptimal) are +'s. Diamonds are harmless bids above value as dropout occurred while the third highest computerized bidder was still active. Solid line: Bid equal to value.

From Kagel and Levin (2001).

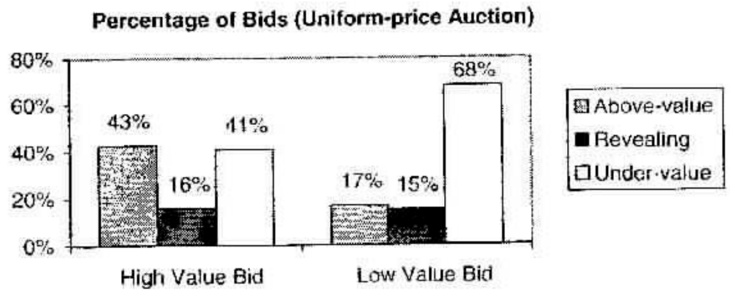
Figure 9





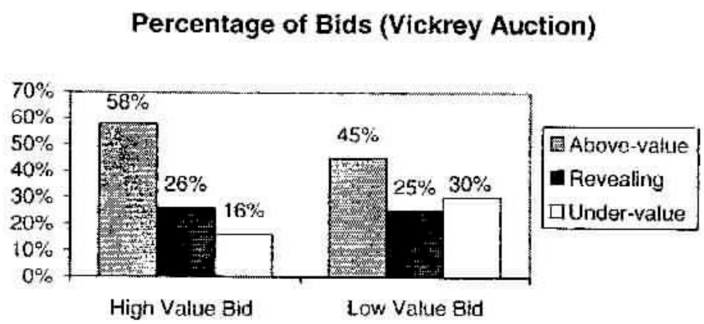
Bids relative to value in last 12 auctions. Circles are winning (censored) bids. Squares are dropouts at or below resale value (dropouts below value are dominated). Triangles are bids above value that could have resulted in losses (bidding above value when the next computer dropout guarantees clinching an item). Diamonds are harmless bids above value (two or more computerized bidders were still active). Solid line: Bid equal to value.

From Kagel and Levin (2001).



Classification of bids in the Uniform-price treatment. Bids within 5% of value are categorized as revealing.

Figure 10: From Porter and Vragov (2006)



Classification of bids in the Vickery treatment. Bids within 5% of value are categorized as revealing.

Figure 11: From Porter and Vragov (2006)

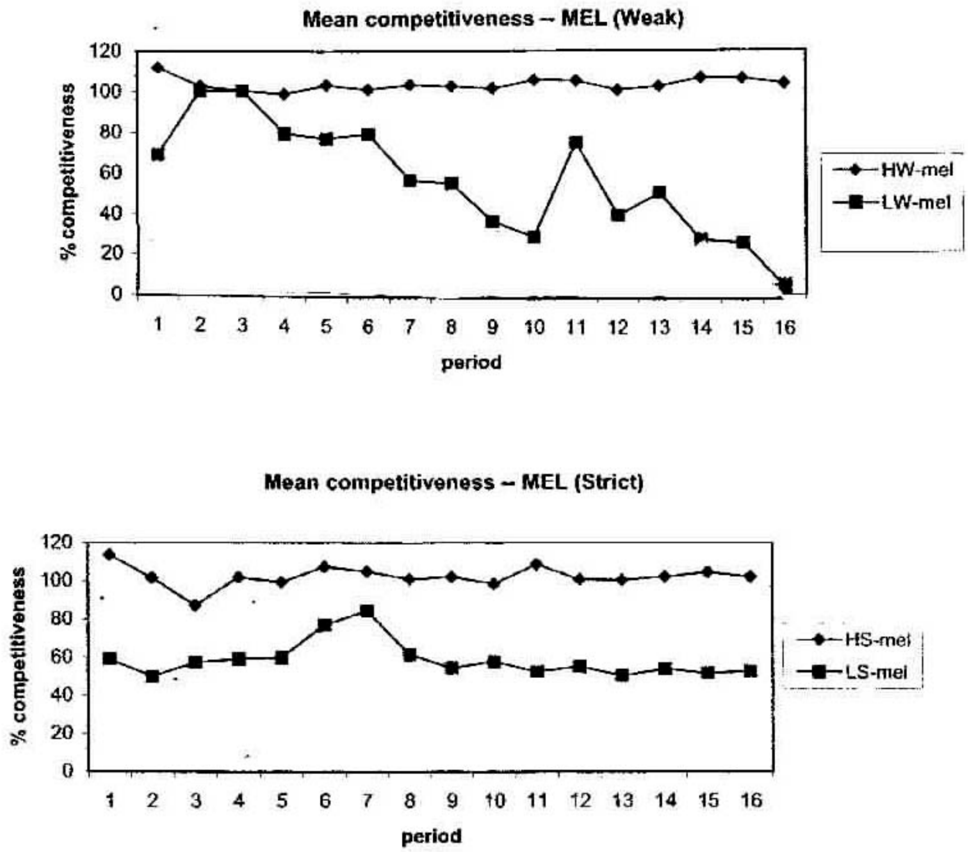
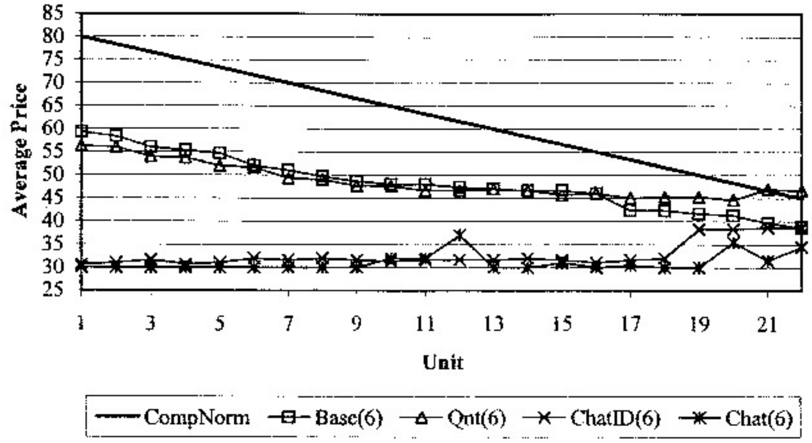
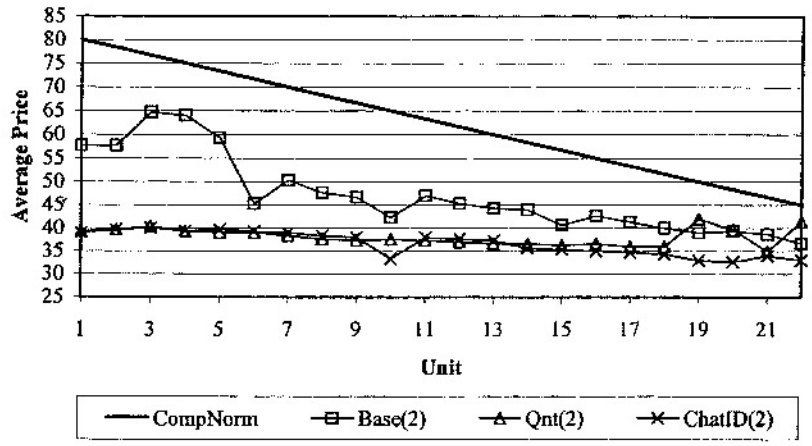


Figure 12: Bids under weak improvement rule (top panel) with support [50, 90] (♦) and support [90, 100] (■). Bids under strict improvement rule (bottom panel) with support [50, 90] (♦)and support [90, 100] (■).

From Sherstyuk (2002).



AVERAGE PRICES BY TREATMENT, AUCTION SESSION 7, SIX BUYERS



AVERAGE PRICES BY TREATMENT, AUCTION SESSION 7, TWO BUYERS

Figure 13: Average prices under different treatments in sequential auctions six and two buyer cases respectively. Qnt - bidders know the number of units for sale. Chat - bidders are allowed to chat and collude. ChatID - Chat with bidder IDs revealed in sales.

Source: Phillips, Menkhaus, and Coatney (2003)

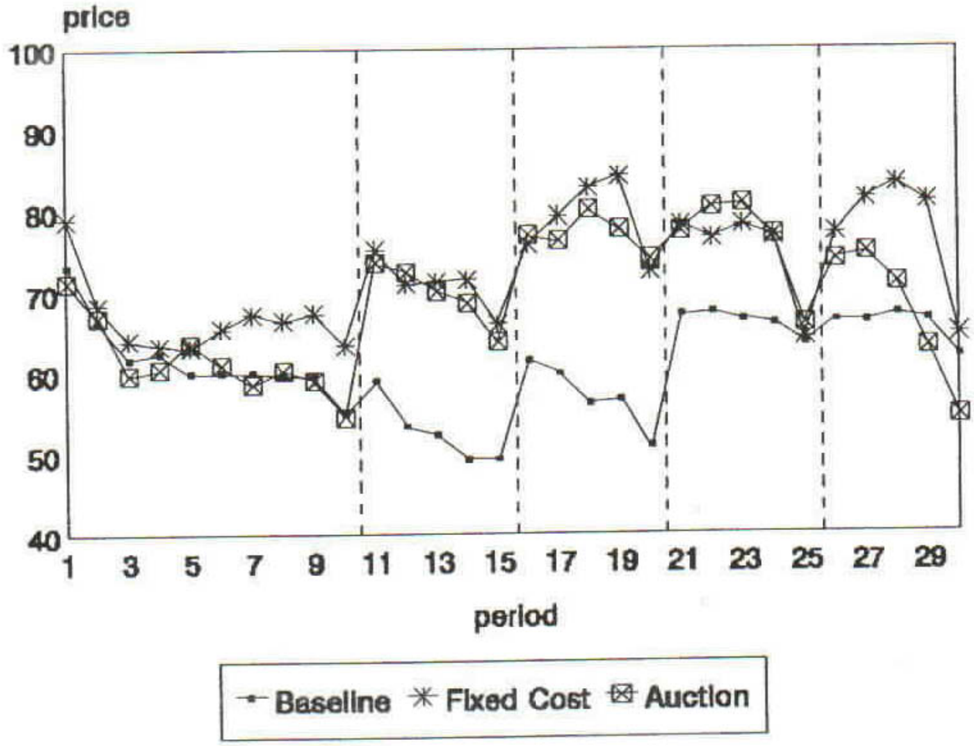


Figure 14: Effects on market prices of entry fees. Periods 1-10 no entry fees; Periods 11-30 entry fees. In Baseline right to produce for market randomly assigned. In Fixed Cost treatment entry right randomly assigned, with entrants paying exogenously determined fees. In Auction treatment potential entrants bid for the right to enter the market.

From Offerman and Potters (2006).