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ABSTRACT

Auction theory is one of the richest areas of research in economics over the past three decades. Yet whether and to what extent the introduction of secondary resale markets influences bidding behavior in sealed bid first-price auctions remains under researched. This study begins by developing theory to explore auctions with resale when private values are uncertain. We put our theory to the test by examining both field data and experimental data from the lab. Our field data are from a unique data set that includes nearly 3,000 auctions (over 10,000 individual bids) for cutting rights of standing timber in British Columbia from 1996-2000. In comparing bidding patterns across agents who are likely to have resale opportunities with those who likely do not, we find evidence that is consistent with our theoretical predictions. Critical evaluation of the reduced-form bidding model, however, reveals that sharp tests of the theoretical predictions are not possible because several other differences may exist across these bidder types. We therefore use a laboratory experiment to examine if the resale opportunity by itself can have the predicted effect. We find that while it does have the predicted effect, a theoretical model based on risk-averse bidders explains the overall data patterns more accurately than a model based on risk-neutral bidders. More generally, the paper highlights the inferential power of combining naturally occurring data with laboratory data.

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I. Introduction

Auctions have a long and storied past. From the human slave auctions carried out in ancient Egypt to the marriage auctions for brides in Asia Minor to the Praetorian Guard auctioning off the Roman Empire in A.D. 193, auctions have been used to allocate goods and services. While auctions have certainly served an important purpose throughout history and are now used to sell almost anything one can imagine – vintage wines, Treasury bills, pollution permits, baseball cards, etc. – economists have only recently begun to explore rigorously the theoretical underpinnings of various auction formats. The seminal work is due to Vickrey, who made several contributions – deriving the Nash equilibrium bidding strategy for first-price auctions, demonstrating revenue equivalence, and proposing the second-price auction as strategically equivalent to the English auction – in his 1961 study.[1]

An extensive literature examining the optimal design and application of auctions has since developed. Our point of departure in this study is to relax the maintained assumption that individual valuations are known with certainty at the time of the first-price sealed bid auction.[2] By relaxing the assumption of known use values and allowing secondary (resale) markets, we find ourselves in an environment that is quite common in practice. U.S. Forest Service timber auctions, the procurement of governmental contracts, estate auctions, art auctions, FCC auctions and the like all fit in this general

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[1] This third contribution has recently been called into question by Lucking-Reiley (2000), who argues that stamp auctioneers were using second price auctions some 65 years before Vickrey's seminal work.

[2] It is well established in the literature that when bidders receive multi-dimensional or uncertain signals, auctions may generate inefficient allocations (Pesendorfer and Swinkels (2000), Jehiel and Moldovanu (2001), Goeree and Offerman (2003)). Efficiency and bidding strategies in such an environment are dependent upon the weight individual bidders assign to both the private and common value components of a signal and upon the number of participants in a given market. However, this literature has not considered the effects of secondary markets.

class of allocation mechanisms.[3] Unlike the traditional auction literature that assumes independent private values (IPV) that are known with certainty, when bidders have *ex ante* uncertainty about independent private values and anticipate resale opportunities, equilibrium bidding strategies are dependent upon option values conveyed from the secondary market. Intuitively, bidder behavior in this case is fundamentally linked to the existence and structure of potential resale markets.

Our study attempts to make both theoretical and empirical advances in this area. Theoretically, we advance Haile (2001, 2003) by relaxing the maintained assumption of risk-neutral preferences. With known valuations in an IPV first price auction, it is well documented that risk-averse agents will submit bids that first-order stochastically dominate those of risk-neutral counterparts. In the context of a symmetric, common-value auction, it is well documented that risk-averse agents submit bids that are first-order stochastically dominated by a risk-neutral counterpart. Since the auction markets considered herein contain features of both common and independent private values, we are a priori unable to predict the effects of risk aversion on bidder behavior without first developing an extension of extant theory. By allowing symmetric agents with CARA preferences, we derive several testable implications.

Our main empirical objectives are to (i) evaluate the validity of our theoretical model of auctions with resale, and (ii) provide empirical evidence of behavior in such markets that can aid in the design and implementation of efficient mechanisms for the allocation of goods and services. To achieve these objectives, we combine insights from

[3] There is a growing theoretical literature that examines the impacts of such resale opportunities on bidder behavior and a seller's optimal choice of auction format (see, for example, Bikhchandani and Huang (1989), Gupta and Lebrun (1999), Haile (2000, 2001, 2003), Troger (2003), and Garratt and Troger (2003)).

naturally occurring data with insights gained from a controlled laboratory experiment. One benefit of our approach is that it enables a comparison of behavior across two different environments with varying levels of control and realism.

Our naturally occurring data are drawn from nearly 3,000 timber auctions (over 10,000 individual bids) from the Small Business Forest Enterprise Program (SBFEP) for the interior region of British Columbia (BC) for the period 1996-2000. These data can be viewed as extending the empirical findings in Haile (2001), who used U.S. timber auction data to explore bidding behavior before and after a federal regulation that allowed resale. Unlike his temporal identification strategy, our identification rests on static comparisons between bidding patterns of three very different bidder groups: loggers on the coast and interior of BC and mills located in the BC interior. While we find evidence consonant with our theoretical predictions and in line with Haile's (2001) findings, we are cautious to make strong inference because exact comparisons cannot be unequivocally made. As in Haile's (2001) study, where several identification assumptions are necessarily imposed, in our case variations in the underlying valuations, risk posture, and structure (nature) of secondary markets are largely unobserved and therefore may frustrate appropriate inference. This fact highlights the difficulty of evaluating the impacts of resale on bidder behavior using uncontrolled field data.

One way to approach this quandary is to make use of a laboratory experiment. By studying artificial markets that differ only in whether a secondary market is available, we are permitted a unique insight into whether the resale market by itself can lead to such predicted consequences. Experimental methods thus allow us to study the effects of resale possibilities that would be difficult to identify in naturally occurring data. Keeping an eye toward designing a laboratory setting that resembles naturally occurring markets while maintaining a strong theoretical link, we designed an experiment using the first-price auction with both a second stage optimal auction (OA) as well as an English auction (EA) continuation game of complete information. This particular design choice allows a controlled test of existing theory and a useful benchmark for making inference from field data, since the secondary market in BC most likely lies within these two market extremes.

The lab results are broadly in line with theoretical expectations. We find that experimental subjects submit bids that are significantly higher in markets with resale organized by an optimal auction than in those without such opportunity (or with secondary markets organized by an EA). An interesting data pattern not anticipated by extant theory is that over lower ranges of the signal space, realized bids are less than the risk-neutral theoretical predictions, while over higher ranges of the signal space, realized bids are greater than the risk-neutral theoretical predictions. Yet these tendencies are consonant with our theory of bidding by agents with CARA preferences.

The remainder of the paper is crafted as follows. Section II provides an overview of the SBFEP auction market and our strategy for identifying resale differences using reduced-form bid functions. Section III develops a theory of bidding by agents with CARA preferences in auction markets that parallel our laboratory setting. Section IV discusses the laboratory experiment and results. Section V concludes.

II. The SBFEP Auction Market

The SBFEP Auction – Background and Predictions

Our naturally occurring data are drawn from nearly 3,000 timber auctions (over 12,000 individual bids) from the British Columbia SBFEP for the period 1996-2000 – the identical data set that BC is using to begin its new pricing approach under the changed circumstance agreement for the U.S.-Canadian softwood lumber dispute.[4] To examine the effects of ex post resale opportunities on bidder behavior, we compare reduced-form bid functions across distinct subsets of bidders that face different market conditions. Our general approach is in the spirit of, for example, Porter and Zona (1999), in that we employ reduced-form methods to infer the nature of resale effects from differences in bidding patterns across subsets of bidders.

SBFEP auctions in BC allocate standing timber of less than 50,000 metric board feet cubed (mb^3) to small logging companies and contractors. SBFEP timber sales account for approximately 13 percent of the harvested timber in the province. About half of this timber is allocated via sealed bid tenders to the highest bidder under section 20 of the province's Forest Act. These auctions are subdivided into two types: Category 1 and Category 2, where Category 1 auctions include only market loggers. Category 2 auctions are open to both registered market loggers and registered owners of processing facilities.

Category 1 bidders purchase timber cutting rights and sell harvested timber to end users. In the interior of BC almost all harvested timber is sold to either major forest license holders or local sawmills. Ex ante, bidders contract with a prospective buyer to arrange an agreement in principle to sell/buy if they win the auction. The bidders then submit bids and the winner consummates the agreement in principle and chooses to lock in the stumpage price he bid. In the coastal region of BC, Category 1 bidders ex ante contract with prospective buyers to deliver a portion of harvested timber and sell the

[4] See Price and List (2004) for a discussion of the solution to the trade dispute.

remaining harvested timber on the Vancouver log market.[5] Category 2 bidders purchase timber cutting rights to obtain raw materials for their processing operations. Bidders either process harvested timber or trade it to obtain needed materials. Since both loggers along the coast and processing facilities are actively engaged in the ex post buying and selling of harvested logs whereas loggers in the interior contract ex ante to deliver all harvest to a given buyer, we believe that resale might enter into the bidding strategies of the former but not the latter. Intuitively, since the former set of bidders have an outside option to sell logs on a spot market whereas the latter do not have such an option, one would expect that loggers from the coast and processing facilities would provide an upper envelope on the observed bids of loggers from the interior. It is thus hypothesized that bids should differ across these groups in the direction that theory predicts. To identify whether this effect holds, we rely upon cross sectional variation.[6]

Identifying Resale Effects from Reduced-Form Bid Functions

A bidding strategy $B_i(\cdot): X \to R_+$ maps characteristics to a bid function. Assuming that firms are risk neutral and "invert" the bid function $B_i(\cdot)$ by defining the set of all firm characteristics that lead to a bid lower than b_i as $\varphi_i(b_i) = \{x_i \in X \mid B_i(x_i) \leq b_i\}$, then the probability of a firm submitting a bid of b_i winning an auction is

$$Q_i(b_i) = \Pr(x_j \in \varphi_i(b_i) \text{ for all } j \neq i) = \prod_{j \neq i} F_j(\varphi_j(b_i)). \tag{1II}$$

[5] Along the interior region of BC, no spot market for logs has developed due to differences in infrastructure and associated transportation costs that limit the profitability of spot market exchange.

[6] In this sense, our identification strategy is much different from Haile (2001), who analyzes individual bids from the U.S. timber auctions and makes use of the temporal variation in the imposition of federal regulations by examining bids prior to the onset of the regulations that effectively prohibited resale and comparing them to bids after the regulations took effect.

Without resale, firm i's expected profits depend on its own (expected) value of the good given its characteristics, $t(x_i)$, and are thus given by

$$\pi_i\left(b_i, x_i; B_{-i}\right) = \left(t_i(x_i) - b_i\right) Q_i(b_i). \tag{2II}$$

A competitive bidder derives an optimal bid strategy conditional upon his likely valuation and some probability distribution over the valuations (and hence bids) of all possible competitors. In equilibrium, this imposes a structure on the relationship between a given firm's bid and the probability of that bid winning the auction. However, when bidders have resale opportunities, equation (2) must be adjusted to reflect expected profits from resale trade. For example, when the second-stage continuation game is an optimal auction with complete information, the winning bidder obtains in equilibrium a payoff equal to the highest use value among all players, minus the price paid to the initial seller. In such an environment, firm i's expected profits are thus given by

$$\pi_i\left(b_i, x_i; B_{-i}\right) = \left(t_1 - b_i\right) Q_i\left(b_i\right), \tag{2II'}$$

where t_1 is the highest use value among all bidders in the auction and $Q_i(b_i)$ is again the probability that bidder i wins the auction. Haile (2003) examines bidder behavior in such situations and shows that optimal bid strategies in first-price auctions with resale represented by an OA continuation game differ from those of an equivalent first-price auction without resale. Across all signal (valuation) ranges, bids in the former environment weakly dominate those in the latter.

To identify resale effects, we employ a general approach that is in the spirit of, for example, Porter and Zona (1993, 1999). We employ reduced-form methods to infer the nature of resale effects by differences in bidding patterns across subsets of firms facing different outside options. Our identification strategy characterizes equilibrium bidding behavior as a function of both observed and unobserved auction-specific and firm effects assumed to affect firm *i*'s valuation and/or probability of winning a given auction. Once an equilibrium bid function has been specified, a pooled regression model for the set of coastal Category 1, interior Category 1, and Category 2 bids is estimated using interaction effects for these distinct subsets of bidders. Theoretically, if resale effects are present in the Category 2 and coastal bids, then parameter estimates from the interaction of these groupings with observed auction covariates should differ from those of the model covariates for interior loggers. In particular, we should observe that the estimated comparative static effect of competition on observed bids is smaller for interior Category 1 auctions than it is for otherwise equivalent Category 2 or coastal Category 1 auctions.

Specifically, assume that equilibrium bidding behavior for symmetric, risk-neutral agents in a first-price sealed bid auction follows the linear specification

$$P_{ij} = \beta X_{ij} + \varepsilon_{ij}, \tag{3II}$$

where P_{ij} is the *i*th bidder's bonus bid in auction *j*. X_{ij} is a set of regressors underlying the i^{th} firm's valuation for tract *j* plus a set of interaction terms between these regressors and dummy variables for coastal loggers and mills; $\varepsilon_{ij} = \alpha_i + u_{ij}$; $E[\alpha_i] = 0$, $E[\alpha_i^2] = \sigma_\alpha^2$, $E[\alpha_i\alpha_k] = 0$ for $i \neq k$; α_i and u_{ij} are orthogonal for all *i* and *j*. α_i is a random effect assumed to capture heterogeneity that would be left uncontrolled in a standard cross-sectional model.

The SBFEP Auction Data - Empirical Results

We observe 2,671 (247) SBFEP sealed-bid tender first-price auctions conducted in the interior (coast) of British Columbia for the period January 1996 through December 2002. These auctions provide more than 11,500 individual bids, from which we eliminate any bids submitted in auctions with only a single bidder, any bids submitted by a suspected cartel firm, any bids submitted in an auction with an estimated net cruise volume of less than 1,000 mb^3, and any bids submitted in an auction employing a format other than a first-price sealed tender. This results in a sample of nearly 1,300 firms that submit nearly 5,700 bids for the interior and a sample of nearly 475 firms that submit nearly 1500 bids on the coast.[7]

To generate the data for the empirical model, we combine information from a number of sources. First, a list of all bidders currently registered to participate in SBFEP timber auctions was provided by the Ministry of Forests (MOF) in BC. This listing was used to generate unique identification codes for each bidder in the data set. Second, the MOF provided bid sheets for each of the 2,918 auctions. The bid sheets provide information on (i) the regional office holding and date of the auction, (ii) the estimated net cruise volume of timber on the plot, (iii) the announced upset rate for the auction, and (iv) the identity and bonus bid per metric board feet cubed for each participant in the auction. Finally, the MOF provided a database that contains detailed information on the characteristics of each plot.[8]

To condition behavior on observed auction characteristics in tests for resale effects, we estimate a series of reduced-form bid functions. Specifically, we assume that equilibrium bidding behavior follows the linear specification in equation (3), and therefore estimate

$$P_{ij} = \beta X_{ij} + \varepsilon_{ij} , \tag{4II}$$

[7] Collusion was evident among a subset of firms (Price and List 2004), thus we exclude these observations.
[8] Due to differences in how data is reported across the coastal and interior regions, the information on plot characteristics was used largely to fill in any missing information from the bid sheets.

where all variables are as defined above. Auction covariates included in the vector of regressors include:

- Mills – dummy variable that equals 1 if the bidder is a mill
- Coast – dummy variable that equals 1 if the bidder is from the coast
- Upset – the announced upset rate per mb^3
- $Upset^2$ – the square of the upset rate
- Bidders – the number of bidders in auction j
- $Bidders^2$ – the square of the number of bidders
- NCV – the announced net cruise volume in mb^3
- NCV^2 – the square of the announced net cruise volume
- Coast_upset – an interaction of the coastal dummy and the upset rate
- $Coast\_upset^2$ – an interaction of the coastal dummy and $upset^2$
- Coast_bidders – an interaction of the coastal dummy and bidders
- $Coast\_bidders^2$ – an interaction of the coastal dummy and $bidders^2$
- Coast_ncv – an interaction of the coastal dummy and NCV
- $Coast\_ncv^2$ – an interaction of the coastal dummy and NCV^2

Table 1 provides parameter estimates for equation (4) estimated for the set of 7,185 observations across a number of specifications.

Empirical results for the pooled model in Table 1 are consistent with economic intuition. First, since we consider SBFEP auctions as first-price IPV sealed bid tenders, economic theory predicts that bids should increase in the number of bidders over the relevant range (n=15 (n=18) is the boundary for the number of auction participants in the interior (on the coast).[9] The positive and significant coefficient on the number of bidders across all model specifications is consistent with this prediction. Second, bidders respond positively to the announced upset rate. Since the announced upset rate is correlated with the value a bidder assigns to a given tract, this finding is consistent with economic theory.

[9] We follow Haile (2001) and Athey and Levin (2001) in assuming these are IPV auctions. This is intuitively appealing for these data considering that bidders face different capacity constraints (and possibly possess different technologies), suggesting that idiosyncratic, firm-specific cost factors are more important than plot-specific, uncertain costs.

Finally, there are temporal effects in bidder behavior. Across all model specifications, the inclusion of fixed year effects improves the overall predictive power of our model.

Empirical results presented in Table 1 suggest an important difference in the behavior of mills and loggers along the coast relative to loggers in the interior that are suggestive of resale for the former set of bidders: measured at the sample means, the estimated marginal effect of adding an additional bidder in an auction for our fully interactive model specification (F) with year fixed effects is approximately 47.16 percent ($2.259 to $1.535) greater for Category 2 auctions than it is for Category 1 auctions. For Category 1 bidders along the coast, this estimated difference is 30.29 percent ($2.00 to $1.535). These estimates are consistent with resale opportunities for the former set of bidders and not for the latter. Equilibrium bidding strategies in auctions with resale are conditioned upon information related to other bidders in the market that is absent in the strategy of a firm bidding in a market without resale. Hence, we would expect greater competition in the former case when the secondary market institution is an OA continuation game of complete information (or a similar analog), as we assume for the Category 2 mills and Category 1 loggers along the coast. This finding is consonant with the predictions and analysis employed by Haile (2001) to identify resale effects for U.S. timber auctions. Combined with other parameter estimates in Table 1 (e.g., the estimated parametric shifter terms in the model), we take the empirical results to suggest that resale opportunities influence bidding in the direction that theory would predict.

III. Risk, Resale, and Bidder Behavior – First-Price Auctions

Although we are able to extend the empirical findings of Haile (2001) and identify empirical differences across bidders indicative of the predicted comparative static effects of resale opportunities on bids, the field data on SBFEP auctions do not allow us to control properly for many underlying determinants like the (expected) value from using the good, the division of surplus on the resale market, or the risk-posture of the firms.[10] The effects of resale are inferred from differences in reduced-form parameters across the subsets of bidders. Such analysis is sensitive to issues of model specification and the interpretation of estimated parameters. In practice, both the "true" underlying model specification and its associated interpretation are unknown and/or unobserved in naturally occurring data. While one may report empirical evidence consistent with the predicted comparative static effects of resale, to make more powerful inference of whether such differences are in fact generated by the existence and nature of secondary markets, one can examine behavior in a controlled environment. We follow this line of reasoning and complement the field results with lab experiments. To derive testable predictions, we first develop a model that allows risk aversion.[11]

Consider a first-price auction with resale opportunities with *n* symmetric, risk-averse players. We assume that players are risk averse with constant absolute risk aversion (CARA). That is, the von-Neumann-Morgenstern utility is given by

[10] For example, there is a possibility that loggers are able to mitigate risk in the field by entering into contractual relationships with processors and/or logging companies that Category 2 bidders are unable to mitigate. If so, then one could argue that loggers are less risk averse than are mills. Hence, it is possible that estimated differences in behavior across these two groups are generated by differences in unobserved risk posture rather than differences in *ex post* resale opportunities.

[11] As noted by Haile (2003), auction markets with resale have components of both common and private value auctions. It is well documented in the experimental literature that in a private value setting risk-averse agents submit bids that first-order stochastically dominate those of risk-neutral agents. In common value settings, however, this tendency is reversed. Risk-averse agents in a common value auction submit bids that are stochastically dominated by risk-neutral counterparts. Given the persistence of risk-averse behavior on the part of student subjects in the lab, and lacking an *a priori* theoretical prediction/conjecture about the effects of risk aversion on behavior in our setting, it is important to develop such theory to enable us to filter out the effects of risk aversion from those of resale opportunity. Without such theory, empirical tests are potentially confounded and do not permit a direct test of our desired treatment effect.

$\rho(z) = -\frac{1}{\sigma}\exp(-\sigma z)$. Prior to bidding, each player i receives a signal X_i on her use value U_i. The signals $X_i \in [x_l, x_u]$ are independently and identically distributed according to a differentiable and strictly increasing distribution $F(\cdot)$. Use values $U_i \in [u_l, u_u]$ are assumed to follow the conditional distribution $G(\cdot \mid X_i)$, which is differentiable with $G_u > 0$ on the support $[u_{\min}(X_i), u_{\max}(X_i)]$. Furthermore, we assume that $G(u \mid x)$ is continuous and decreasing in x, i.e., $G(u \mid x)$ stochastically dominates $G(u \mid y)$ if $x > y$.[12] This implies that both $u_{\min}(x), u_{\max}(x)$ are increasing in x.

We make the following assumption on the probability distributions:

Assumption (A1): We assume that $\frac{d}{du}\log G(u \mid x)$ is increasing in x.

Note that Assumption A1 is satisfied in particular for all uniform distributions: $G(u \mid x) = \frac{u - u_{\min}(x)}{u_{\max}(x) - u_{\min}(x)}$. Here, $\frac{d}{du}\log G(u \mid x) = \frac{1}{u - u_{\min}(x)}$, which increases in x as $u_{\min}(x)$ is increasing in x.

Bidder Behavior in Markets without Resale

In order to provide a reference case, we first reconsider the case in which there is no secondary resale market. In this case, the distribution of the use value is given by $G(\cdot \mid X_i)$. A player with signal x who wins the auction with a bid of b has expected utility given by

[12] G(u | x) is assumed strictly decreasing on the interior of the support.

$$\int_{u_l}^{u_u} \rho(u-b)dG(u \mid x) = \frac{\rho(0)}{\rho(b)}\int_{u_l}^{u_u} \rho(u)dG(u \mid x) \\ = \frac{\rho(0)}{\rho(b)} K_N(x) \tag{1}$$

where $K_N(x)$ refers to the expected utility from consuming the good given a signal x. Given an increasing equilibrium bid function $b_N(\cdot)$, the expected utility of a player with signal x who bids $b_N(\tilde{x})$ is given by

$$\left[\frac{1}{\rho(b_N(\tilde{x}))}\int_{x_l}^{\tilde{x}} K_N(x)dF(z)^{n-1} + (1-F(\tilde{x})^{n-1})\right]\rho(0) \\ = \left[\frac{1}{\rho(b_N(\tilde{x}))} K_N(x)F(\tilde{x})^{n-1} + (1-F(\tilde{x})^{n-1})\right]\rho(0) \quad . \tag{2}$$

Shading by a bidder of type x leads to a tradeoff between earnings and the probability of winning the auction.

Maximizing the expected utility with respect to $\tilde{x}$ and setting $\tilde{x} = x$ leads to the following differential equation defining an optimal bidding function $b_N(x)$:

$$\left(\frac{1}{\rho(b_N(x))} F(x)^{n-1}\right)' = \frac{\left(F(x)^{n-1}\right)'}{K_N(x)} . \tag{3}$$

From this expression, we obtain the following implicit definition of the optimal bidding function without resale opportunity:

$$\frac{1}{\rho(b_N(x))} = -\sigma \exp(\sigma b_N(x)) = \frac{1}{F(x)^{n-1}} \int_{x_l}^{x} \frac{1}{K_N(z)} dF(z)^{n-1} . \tag{3'}$$

Proposition 1 [corresponds to Theorem 14 of Milgrom and Weber (1982)]**:** *If no resale is possible,* $b_N(x)$ *is the unique differentiable symmetric separating equilibrium bid function.*
Proof: (see Appendix A)

Using l'Hospital's rule we obtain the following results. Under risk neutrality, an optimal bidding function is defined by

$$b_N(x) = \frac{1}{F(x)^{n-1}} \int_{x_l}^{x} \int_{u_l}^{u_u} u dG(u \mid z) dF(z)^{n-1} \text{ for } \sigma = 0 . \tag{4}$$

For infinitely high risk aversion, however, bids converge towards the minimal possible use value given a signal *x*, i.e., $b_N(x) \to u_{\min}(x)$ for $\sigma \to \infty$. Formal derivation of these results is provided in Appendix A.

Bidder Behavior in Auctions with Resale

Whenever a player can resell a commodity won at auction on a secondary market, the value the bidder places on the commodity in the primary auction market depends on the price at which resale can take place. As discussed in Haile (2003), such prices are dependent upon the informational structure and trading institution assumed on the secondary market.

We first study the case of complete information on a resale market characterized by an OA continuation game, i.e., we assume that use values are common knowledge among players and that the seller extracts the entire surplus by selling to the opponent with the highest use value on the resale market whenever such trade is profitable.

Let us denote the distribution of use values of a player given that her signal is less than or equal to *y* as

$$M(u \mid y) = \frac{\int_{x_l}^{y} G(u \mid z) dF(z)}{F(y)} .$$

Further define $\bar{G}_1(u \mid y)$ as the distribution of highest use value of an opponent of a player given that *y* is the maximal signal to an opponent. Thus we have

$$\overline{G}_1(u \mid y) = G(u \mid y) M(u \mid y)^{n-2}.$$

Then, the distribution of highest use value of all players given signal x to one player and y being the maximal signal to an opponent is given by

$$G_1(u \mid x, y) = G(u \mid x) \overline{G}_1(u \mid y).$$

The expected utility of a player with signal x – facing opponents with maximal signal y – who wins an auction with a bid of b is given by

$$\begin{aligned} \int_{u_l}^{u_u} \rho(u-b) dG_1(u \mid x, y) &= \frac{\rho(0)}{\rho(b)} \int_{u_l}^{u_u} \rho(u) dG_1(u \mid x, y) \\ &= \frac{\rho(0)}{\rho(b)} K_{OA}(x, y) \end{aligned}, \quad (5)$$

where $K_{OA}(x, y)$ refers to the expected utility from consuming the good given a signal x, where y is again the maximal signal of all opponents. Not winning the auction yields a payoff of zero.

If an English auction is carried out on the resale market, the second highest use value is decisive. Define $\overline{G}_2(u \mid y)$ as the distribution of second highest use value of an opponent of a player given that y is the maximal signal to an opponent. Thus we have

$$\overline{G}_2(u \mid y) = M(u \mid y)^{n-2} + (n-2) G(u \mid y) M(u \mid y)^{n-3} \left[1 - M(u \mid y)\right].$$

Further, $G_2(u \mid x, y)$ is the probability that neither the use value of a player with signal x nor the second highest use value of opponents whose highest signal is y exceeds u.

Then, the value of the good to a player with signal x – facing opponents with maximal signal y – who wins an auction with a bid of b is given by his own use value if he has the highest or second highest use value, or the second highest use value of all opponents otherwise. The expected utility from winning the auction is therefore given by

$$\int_{u_l}^{u_u} \rho(u-b)\bar{G}_2(u \mid y)dG(u \mid x) + \int_{u_l}^{u_u} \rho(z-b)G(z \mid x)d\bar{G}_2(z \mid y)$$

$$\begin{aligned} &= \int_{u_l}^{u_u} \rho(u-b)dG_2(u \mid x, y) \\ &= \frac{\rho(0)}{\rho(b)} \int_{u_l}^{u_u} \rho(u)dG_2(u \mid x, y) \\ &= \frac{\rho(0)}{\rho(b)} K_{EA}(x, y) \end{aligned} \tag{6a}$$

where $K_{EA}(x, y)$ refers to the expected utility from obtaining the good given a signal x and y being the maximal signal of all opponents.

If a player does not win the auction, she can acquire the good on the resale market if she has the highest use value. The expected value from losing the auction is therefore given by

$$\begin{aligned} &\int_{u_l}^{u_u} \left[\int_{u_l}^{u} \rho(u-z)d\bar{G}_1(z \mid y) + \int_{u}^{u_u} \rho(0)d\bar{G}_1(z \mid y) \right] dG(u \mid x) \\ &= L_{EA}(x, y)\rho(0) \end{aligned} \tag{6b}$$

Using the definitions of $K_R(x, y)$ and $L_R(x, y)$ with $R \in \{OA, EA\}$ and $L_{OA}(x, y) = 1$, we can now derive the optimal bids for both types of resale markets simultaneously.

Assuming an increasing bid function $b_R(\cdot)$, the expected utility of a player with signal x who bids $b_R(\tilde{x})$ can be written as

$$\left[\frac{1}{\rho(b_R(\tilde{x}))} \int_{x_l}^{\tilde{x}} K_R(x, z)dF(z)^{n-1} + \int_{\tilde{x}}^{x_u} L_R(x, z)dF(z)^{n-1} \right] \rho(0). \tag{7}$$

Differentiating with respect to $\tilde{x}$ and setting $\tilde{x} = x$ leads to a differential equation for the optimal bidding function $b_t(x)$:

$$(\frac{1}{\rho(b_R(x))})'\int_{x_l}^{x} K_R(x,z)dF(z)^{n-1} + \frac{1}{\rho(b_R(x))}K_R(x,x)(F(x)^{n-1})' = L_R(x,x)(F(x)^{n-1})', \quad (7')$$

which reduces to the following linear equation:

$$(\frac{1}{\rho(b_R(x))})' + \frac{1}{\rho(b_R(\tilde{x}))}H_1(x) = H_2(x) \quad , \tag{8}$$

where $H_1(x)$ is given by

$$H_1(x) = \frac{K_R(x,x)(F(x)^{n-1})'}{\int_{x_l}^{x} K_R(x,z)dF(z)^{n-1}}$$

and $H_2(x)$ is given by

$$H_2(x) = \frac{(F(x)^{n-1})' L_R(x,x)}{\int_{x_l}^{x} K_R(x,z)dF(z)^{n-1}} .$$

By a standard solution we thus obtain that an optimal bidding function $b_R(x)$ is given by

$$\frac{1}{\rho(b_R(x))} = \left[\int_{x_l}^{x} H_2(z)\exp\left(\int_{x}^{z} H_1(y)dy\right)dz\right] + c_1 \exp\left(-\int_{x_l}^{x} H_1(z)dz\right) \tag{9}$$

for some constant c_1. Noting that $\rho(u_l) \le K_R(x,y) \le \rho(u_u)$, there exists a constant c_2 such that $\int_{x_l}^{x} H_1(z)dz \le c_2 \int_{x_l}^{x} F(x)'/F(x)dz = c_2[\ln(F(x) - \ln(F(x_l)] = -\infty$. The second summand in (9) therefore vanishes and we arrive at the implicit definition for $b_R(x)$:

$$\frac{1}{\rho(b_R(x))} = \left[\int_{x_l}^{x} \frac{\exp\left(\int_{x}^{z} K_R(y,y)/\int_{x_l}^{y} K_R(y,w)dF(w)^{n-1}dF(y)^{n-1}\right)}{\int_{x_l}^{z} K_R(z,y)dF(y)^{n-1}} L_R(z,z)dF(z)^{n-1}\right]. \tag{10}$$

Proposition 2: [corresponds to Theorem 2 of Haile (2003)] *If the resale market is organized via an optimal or English auction,* $b_R(x)$ ($R \in \{OA, EA\}$) *is the unique differentiable symmetric separating equilibrium bid function.*
Proof: See Appendix A

To derive $b_R(x_l)$, we note again that $K_R(x,y)$ converges for $x, y \to x_l$ to $K_R(x_l, x_l)$. Therefore, we obtain

$$\frac{1}{\rho(b_R(x_l))} = \frac{L_R(x_l,x_l)}{K_R(x_l,x_l)} \lim_{x \to x_l} \int_{x_l}^{x} \frac{\exp\left(\int_x^z 1/F^{n-1}(y) dF(y)^{n-1}\right)}{F^{n-1}(z)} dF(z)^{n-1} = \frac{L_R(x_l,x_l)}{K_R(x_l,x_l)} \tag{11}$$

Consider the limiting case of risk neutrality, i.e., $\sigma = 0$. Applying l'Hospital's rule for $\sigma \to 0$ yields the bidding function for the optimal auction on the resale market (see Appendix A):

$$b_{OA}(x) = \frac{1}{F(x)^{n-1}} \int_{x_l}^{x} \int_{u_l}^{u_u} u dG_1(u \mid z, z) dF(z)^{n-1} \text{ for } \sigma = 0, \tag{12}$$

which mimics the optimal bid function derived by Haile (2003) for a first-price auction followed by an OA continuation game with complete information.

For the English auction continuation we obtain similarly

$$b_{EA}(x) = \frac{1}{F(x)^{n-1}} \int_{x_l}^{x} \left[\int_{u_l}^{u_u} u dG_2(u \mid z, z) - \int_{u_l}^{u_u} \int_{u_l}^{u} (u - w) d\overline{G}_1(w \mid z) dG(u \mid z) \right] dF(z)^{n-1} \text{ for } \sigma = 0, \tag{12'}$$

which is in line with Haile's result.

Furthermore, for agents with preferences characterized by infinitely high risk aversion, bids converge towards the minimal possible use value given a signal x for both continuation games, i.e., $b_R(x) \to u_{\min}(x)$ for $\sigma \to \infty$ ($R \in \{OA, EA\}$). The proof of this result is based on l'Hospital's rule and provided in Appendix A.

Implications for Optimal Bidding Strategies: Resale vs. No Resale

First, note that for infinitely high risk aversion, bids converge towards the minimal possible use value given a signal x, i.e.,

$$b_N(x) = b_R(x) = u_{\min}(x) \text{ for } \sigma = \infty .$$

Therefore, resale has no effect on bidding strategies if players are infinitely risk averse. Hence, since a large majority of agents in the population are risk averse, the differences due to the possibility of resale are generally overstated if only risk neutrality is considered.

Further, with a perfectly informative signal $u_{\min}(x) = \int_{u_l}^{u_u} u dG(u \mid x) = u_{\max}(x)$ for all x, resale also has no effect on optimal bids, independent of the level of risk aversion. To see this, note that $K_R(x, y) = \rho(x)$ for $x > y$ and $L_{EA}(x, y) = 1$. Hence

$$\left(\frac{1}{\rho(b_R(x))}\right)' F(x)^{n-1} + \frac{1}{\rho(b_R(x))}(F(x)^{n-1})' = \frac{(F(x)^{n-1})'}{\rho(x)}, \quad (3'')$$

which coincides with the bid function for markets without resale. The intuition behind this result is that with resale opportunities an agent wins the auction only if she receives the highest signal, i.e., she has the largest use value. The resale value, therefore, coincides with the use value without resale opportunity. With an imperfectly informative signal, however, resale generally increases signals since the expected resale value is not smaller than the expected use value of an agent.

Implications for Optimal Bidding Strategies: The Effect of Risk Aversion

The qualitative effects of risk aversion depend on whether the risk-neutral bids exceed or equal the minimal use value given by $u_{\min}(x)$, which depends on the specific distributions of use values and signals. However, the following cases might occur for a treatment $t \in \{N, OA, EA\}$:

1. Under risk neutrality, $b_t(x) > u_{\min}(x)$: Risk aversion decreases bids for high degrees of risk aversion.
2. Under risk neutrality, $b_t(x) < u_{\min}(x)$: Risk aversion eventually increases bids.

In our experimental markets described below, case 1 holds for small signals whereas case 2 applies to larger signals. The effects of risk aversion therefore qualitatively change over the range of signals. In our experimental markets, we would thus predict a crossing of optimal bid functions for both the resale and no-resale treatments for agents that demonstrate high levels of risk aversion.

Implications for Optimal Bidding Strategies: Minimal Observable Bids

The minimal bids in both resale and no-resale cases are given by the lowest signal type. Note that, using l'Hospital's rule again, the equilibrium bid functions lead to

$$\frac{1}{\rho(b_N(x_l))} = \frac{1}{K_N(x_l)}$$

and

$$\frac{1}{\rho(b_R(x_l))} = \frac{L_R(x_l, x_l)}{K_R(x_l, x_l)}.$$

Unless the signal is perfectly informative at $X = x_l$, we have that $K_R(x_l, x_l) > K_N(x_l)$, and further that $L_R(x_l, x_l) \leq 1$. Therefore, the smallest observable bid should be higher if resale is possible. In our experimental market, signals of $X = x_l$ are perfectly informative, and thus bids in both treatments should coincide at the lowest signal range.

IV. Experimental Design and Results

Experimental Design

A total of 90 subjects participated in our laboratory experiment, which was conducted during the Fall 2003 and Spring 2004 semesters at the University of Maryland in College Park. Each session consisted of two experimental parts: a first-price auction market with or without resale opportunity and the Holt and Laury (2002) experimental procedure to elicit the risk preference of each participant. Each part of the laboratory experiment is described below.

Part I: The Auction Market

Each subject's experience typically followed four steps: (1) consideration of an invitation to participate in an experiment, (2) learning the auction rules, (3) actual market participation, and (4) conclusion of the experiment and completion of the Holt and Laury (2002) risk-aversion experiment. In Step 1, undergraduate students from the University of Maryland were recruited using e-mail solicitations and flyers hung in academic buildings across the campus. Once the prerequisite number of subjects had responded, a second e-mail was sent to each participant inviting them to participate in an experimental session to be held at a given date/time. After subjects were seated in a room, in Step 2 a monitor thoroughly explained the experimental instructions and auction rules (included in Appendices B and C).

Before proceeding, a few key aspects of the experimental design should be highlighted. First, all bidders were informed that earnings from the auction experiment would be added to earnings from a second, unrelated experiment to determine total earnings for the session. Second, individuals were informed that they would be bidders in the experiment. In each of the 12 rounds (2 practice and 10 that count towards earnings), they would be given a bidder's card that contained a number, known only to that bidder, representing a signal of the value of one unit of the fictitious commodity. Importantly, all agents were informed that this information was strictly private and that both signals and use values would change each round. They were also informed about the number of other bidders in the market (4), that they would bid against the same four bidders for all ten rounds, and that agents may have different signals (use values).

Third, the monitor explained how signals were determined in each market period and how these signals related to the agent's final reservation (use) value. Subjects were informed that in each period, they would receive a signal from the interval [$0, $50]. These signals were determined by adding a random integer generated from a uniform distribution on the interval [-$10, $10] to the agent's final use value which was itself an integer value randomly drawn on the uniform interval [$10, $40]. Several examples illustrated the relationship between a given use value and the range of signals that the bidder could receive in the first stage, and vice versa.

Fourth, the monitor explained how earnings were determined. In the baseline, no resale treatment, the highest bidder earns the difference between their end use value and their bid. All other bidders earn zero. In the resale treatment with OA continuation game, the bidder who submits the highest bid earns the difference between the highest use value of all bidders and the winning bid. All other bidders earn zero. In the resale treatment with EA continuation game, the bidder who submits the highest bid receives the maximum of her use value and the second highest use value of all participants minus her winning bid. The bidder who does not submit the high bid but has the highest use value receives the difference between this value and the second highest use value of all other participants. All other bidders earn zero for the round. Total earnings for each treatment are computed by summing the earnings across the 10 periods.

In the resale treatment with OA continuation game, it was publicly announced that following the completion of each round, ownership of the good would be sold to the agent with the highest use value in the group at a price equal to her value. In the resale treatment with EA continuation game, it was publicly announced that following the completion of each round, ownership of the good would be sold to the agent with the highest use value in the group at a price equal to the second highest use value of all agents in the group.[13] In the baseline no-resale treatment, several examples were provided that illustrated the irrationality of bidding more than $10 above a received signal. In the resale treatments several examples were provided that illustrated the workings of the resale market and how prices for resale exchange and earnings for each bidder would be determined.[14] Fifth, individuals participated in 2 practice rounds of bidding to gain experience with the auction market and rules.

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[13] Two important features of our experimental design that we should highlight include: i) our choice to limit participation on the secondary market to bidders from the primary auction market and ii) our decision to execute trades on the secondary market at the theoretical benchmarks for both the OA and EA game of complete information. We elected to limit participation on the secondary market to maintain consistency with theory and our naturally occurring data—the interior secondary market for timber in BC is comprised of bidders registered to participate in the primary auctions. We elected to execute trade on the secondary market at the theoretical benchmarks to maintain consistency with our conceptual model. The focus of this analysis is on first-stage bidding strategies rather than secondary market exchange. Allowing the endogenous determination of prices on the secondary market would surely have an influence on bidding strategies, as it is likely that rents would not be divided on the secondary market as predicated by theory. Anticipating this, bidders would adjust first-stage bidding strategies. We hope that future work analyzes behavior in markets where prices are endogenously determined on the secondary market and new participants are allowed to enter the second-stage continuation game.

[14] An important consideration in designing our auction markets was the issue of bankruptcy and bidder behavior. Theoretically, bankruptcy was not an issue if subjects played the risk-neutral Nash equilibrium. However, equilibrium payouts in a number of the periods were low enough to raise concern if subjects determined bids with a degree of error. For reasons outlined in Hansen and Lott (1991), we decided to employ an unlimited liability rule and allow subjects to have negative earnings for Part I of the experiment.

In Step 3, subjects participated in the market. Each market consisted of 10 rounds of bidding that lasted about 3 minutes each. After each 3-minute period, a monitor privately gathered each subject's bidder card and gave the bidder a second card containing the subject's final use value that was within [-$10, $10] of the original signal. Once all bidder cards were collected, a monitor publicly announced all bids and awarded the good to the highest bidder. Final use values were publicly announced and, in the resale treatment, ownership of the commodity transferred to the agent with highest use value.

It should be noted that throughout each session careful attention was given to prohibit communications between bidders that could induce collusive outcomes. Step 4 concluded the experiment – after subjects completed the Holt and Laury (2002) experiment (described in Part II of this section), they were paid their earnings in private.

This simple procedure was followed in each of three treatments, which are summarized in Table 2. Table 2 can be read as follows: row 1, column 2 of Table 2 contains treatment NR, denoting a no-resale auction market with 5 bidders, who each have unit demand for the good. Table 3 presents buyer induced values and signals for each market period. All signals were drawn and assigned using the following procedure. We first drew 50 integer numbers on the uniform distribution between [$10, $40] using Excel's random number generator. We added an integer drawn on the uniform distribution [-$10, $10] to this number to obtain signal values. These values were then assigned so that unbeknownst to bidders, in each session (i) every bidder received the highest signal twice, (ii) each bidder received the highest use value but a lower ordered signal, and (iii) resale trade was potentially profitable in half of the periods.

Part II: The Holt-Laury Risk Experiment

Upon completion of Part 1 of the session, instructions and a decision sheet were handed out for the second part of the experiment. This second part was designed to elicit subjects' risk preferences. In this part of the session, the low-payoff treatment of Holt and Laury (2002) was used (see Appendix C for instructions).[15] The treatment is based on ten choices between paired lotteries. The paired choices are included in Appendix C. The payoff possibilities for Option A, $2.00 or $1.60, are much less variable than those for Option B, $3.85 or $0.10, which was considered the risky option. The odds of winning the higher payoff for each of the options increased with each decision, and the paired choices are designed to determine degrees of risk aversion. Holt and Laury (p. 1649) provide a table that will be used to categorize subjects' CARA risk preference levels based on their ten decision choices.

After the instructions were read and questions were answered, the subjects were asked to complete their decision sheets by choosing either A or B for each of the ten decisions. The subjects were instructed that one of the decisions would be randomly selected *ex post* and used to determine their payoffs. Part of a deck of cards was used to determine payoffs, cards 2-10 and the Ace to represent "1". After each subject completed his or her decision sheet, a monitor would approach the desk and randomly draw a card twice, once to select which of the ten decisions to use, and a second time to determine

[15] We elected to use the low-payoff treatment of the Holt and Laury (2002) experiment to measure risk preference since the domain of earnings because this treatment [$0.10 to $3.85] approximates the equilibrium domain of per period earnings for our auction markets. We also collected data for a higher-payoff treatment of the Holt and Laury (2002) experiment, where the domain of earnings [$0.40 to $15.40] approximates the equilibrium domain of earnings at the session level in our auction markets. In what follows, we report only the empirical results for risk preference based upon individual response to the low-payoff Holt and Laury (2002) design. However, all tests and results are robust to the use of response to the higher-payoff experiment.

what the payoff was for the option chosen, A or B, for the particular decision selected. After the first card was selected, it was placed back in the pile, the deck was reshuffled, and the second card was drawn. For example, if the first draw was an Ace, then the first decision choice would be used. Suppose the subject selected A in the first row. The second draw would then be made. If the Ace was drawn, the subject would win \$2.00. If a card numbered 2-10 was drawn, the subject would win \$1.60. The subjects were aware that each decision had an equal chance of being selected.

After all the subjects' payoffs were determined, they combined their payoff from Part 1 with that of Part 2 to compute their final earnings. The final payoffs were then verified against records maintained by a monitor, and subjects were paid privately in cash for their earnings. Each of the sessions lasted approximately 75 minutes and average earnings were roughly \$13.

Theoretical predictions for the laboratory auction markets

Figure 1 provides theoretical predictions for risk-neutral bidders in our experimental markets conditioned upon the signal. Across all but the lowest range of our signal space \$0.00, bidders in markets with resale opportunities represented by an OA continuation game are predicted to submit bids that are on average higher than those submitted by an equivalent bidder in a market without resale options. These differences range from mere pennies for signals less than \$5.00 to a maximum of about \$3.40 for bids submitted in the signal range around \$23.[16] For signal ranges above \$40.00 or below \$20, the predicted differences in bids between the no-resale and resale treatments are less

[16] The optimal bid functions were derived numerically. Using the theory developed in Section III, we first calculated $K_R(x,y)$ and $L_R(x,y)$ on a grid with 0.1 increments. Using interpolating functions, we then solved the respective differential equations.

than \$2.75. In resale treatments represented by an EA continuation game, risk-neutral bidders are predicted to submit bids that are on average higher than those submitted by an equivalent bidder in a market without resale at ranges of our signal space of less than \$27.00. For signals larger than \$27.00, risk-neutral bidders in our resale treatment with EA continuation game are predicted to submit bids that are on average less than those submitted by an equivalent bidder in the no-resale treatment. These differences range from a maximum of \$0.70 at a signal of approximately \$20.00 to a minimum of \$-0.56 at a signal of approximately \$46.00.

Experimental Results

Table 4 provides summary statistics for the experimental data. Entries in Table 4 are at the period level and include average bid level and its standard deviation, the average winning bid and its standard deviation, average resale price, and average earnings for the auction winner and resale buyer. Table 4 can be read as follows: on average, in period 1 of the No Resale treatment, subjects submit a bid of \$20.84 (standard deviation = 9.32) and the average winning bid is \$30.77 (standard deviation = 3.17). Perusal of the data summary in Table 4 leads to our first two results:

> *Result 1: Bids in a first-price auction followed by resale exchange in an OA continuation game are greater than those submitted in equivalent markets without resale.*

> *Result 2: Bids in a first-price auction followed by resale exchange in an OA continuation game are greater than those submitted in equivalent markets with an EA continuation game.*

These results can be seen most directly by examining both per period average and winning bids across our three laboratory treatments. Across all ten market periods, both average and winning bids in the resale treatment with OA continuation game are greater than bids in both the baseline, no-resale treatment and the resale treatment with EA continuation game. The differences in average bids range from a minimum of \$2.68 in period 4 to a maximum of \$8.29 in period 6, with an average difference of \$5.84. For the EA treatment, differences in average bids range from a minimum of \$2.84 in period 4 to a maximum of \$8.53 in period 6, with an average difference of \$5.63. For the baseline treatment, the differences in average winning bids range from a minimum of \$0.25 in period 7 to a maximum of \$4.91 in period 1, with an average difference of \$2.82. For the EA treatment, the differences in average winning bids range from a minimum of \$0.20 in period 1 to a maximum of \$5.16 in period 5, with an average difference of \$2.73.

Figure 2 provides a comparison of bids submitted in our baseline no-resale treatment and our resale treatment with OA continuation game. The figure illustrates the first part of result 1: bids in the resale treatment with OA continuation game are greater than those in the baseline no-resale treatment. Interestingly, these differences are greatest at lower and intermediate ranges of the signal domain. For signals above \$32-35, there is no discernable difference in bids across the two treatments.

Further support for these results is provided in Table 5, which presents Mann-Whitney tests for differences in bids across the various experimental treatments. Column 1 provides average differences in bids at both the individual and session levels along with differences in average winning bids between our resale treatment with OA continuation game and the baseline, no-resale treatment. As indicated in the table, average (winning) bids in the OA treatment are \$5.84 (\$2.82) greater than those submitted in the baseline treatment, and these differences are statistically significant at the $p < 0.05$ level. Column 2 provides average differences in bids at both the individual and session levels along with differences in average winning bids between our resale treatment with EA continuation game and both the baseline, no-resale treatment and the resale treatment with OA continuation game. As indicated in the table, differences in average and winning bids between the EA and OA treatments are statistically significant at the $p < 0.05$ level.

Our last piece of evidence to support Results 1 and 2 comes from a random effects bid equation:

$$B_{it} = v(Z_{it}) + \varepsilon_{it}, \tag{17}$$

where B_{it} is the bid of the ith buyer in period t. Z_{it} includes treatment dummy variables and the induced value signal the agent received; $\varepsilon_{it} = \alpha_i + u_{it}$; $E[\alpha_i] = 0$, $E[\alpha_i^2] = \sigma_\alpha^2$, $E[\alpha_i\alpha_j] = 0$ for $i \neq j$; α_i and u_{it} are orthogonal for all i and t. The random effects α_i capture important heterogeneity across agents that would be left uncontrolled in a standard cross-sectional model.

Columns A-D in Table 6 present regression results which provide support for Results 1 and 2. For example, parameter estimates in columns A-D suggest that bids in the OA treatment are 5.847 higher than bids in the baseline treatment (the omitted categorical variable), a difference that is statistically significant at the $p < .05$ level. Furthermore, using a Chow test of coefficient equality, we find that OA bids are larger than EA bids at the $p < .05$ level. As columns A-D show, these differences are robust across several different empirical specifications.

Empirical results in Tables 5 and 6 suggest that baseline bids and EA treatment bids are isomorphic. Yet, when bids are analyzed over ranges of signals less than (greater than) \$26, where our theory predicts that bids from the EA treatment are predicted to be greater than (less than) those submitted in the baseline treatment, we find evidence consonant with the theory. From Table 5, we see that over lower ranges of the signal space, bids from the EA treatment are, on average, \$2.73 larger than those from the baseline treatment, a statistically significant difference at the $p < 0.05$ level. Over higher ranges of the signal space, bids from the EA treatment average \$2.07 less than those from the baseline treatment, with these differences statistically significant at the $p < 0.05$ level. These data patterns lead to the next result:

Result 3: Over lower (higher) signal ranges, bidders in a first-price auction followed by an EA continuation game submit bids that are higher (lower) than those submitted by agents in an equivalent baseline market without resale opportunity.

Figure 3, which provides a comparison of bids submitted in the baseline no-resale treatment and bids in the resale treatment with EA continuation game, highlights this result. Over the entire signal domain, there is little discernable difference between bids, as suggested by the empirical estimates of the pooled data. At lower ranges of the signal space, however, the highest bids from the EA treatment are greater than the highest bids from our baseline auction markets. And, at a higher range of the signal space, the lowest bids from the EA treatment are less than the lowest bids from our baseline market.

Combined, these first three results lead to our fourth result:

Result 4: Theoretical predictions of Haile (2003) adequately organize differences in bidder behavior across auction markets without resale and equivalent auction markets with resale opportunities organized as both an OA and EA continuation game of complete information.

Risk Aversion and Bidder Behavior

Having found general support for the comparative static predictions of Haile (2003), we now examine more closely the point predictions of the theory by exploring the data conditioned upon underlying risk preference. Figure 4 provides an illustration of bids in our baseline no-resale market relative to the theoretical predictions for risk-neutral equilibrium bids. As can be seen from the figure, risk-neutral point predictions do not fit the data well. Over lower ranges of the signal space, realized bids are *less* than the risk-neutral theoretical predictions while over higher ranges, realized bids are *greater* than the risk-neutral theoretical benchmarks. This pattern of behavior is consistent with our theoretical model for risk-averse bidders. Similar patterns, albeit less pronounced, emerge for both the OA and EA treatments.

The theoretical model outlined in Section III indicates that there are several important differences in the equilibrium behavior of risk-averse agents relative to their risk-neutral counterparts. From our theory we create Figure 5, which provides predictions for bids in our baseline markets for various levels of CARA risk preference. The figure highlights a number of testable hypotheses regarding the behavior of risk-averse agents relative to risk-neutral agents. First, over all but the highest range of the signal space (signal > \$40), bids for risk-averse agents should be lower than bids of risk-neutral agents. For signals greater than \$40, the bids of risk-averse agents should be greater than bids of risk-neutral subjects. Second, at the lowest ranges of the signal domain (signal < \$21), the slope of the bid function is shallower for risk-averse agents, with this difference increasing in the level of risk aversion. Third, at higher ranges of the signal domain (signals > \$21), the slope of the bid function in the signal space is greater for risk-averse agents, with this difference increasing in the level of individual risk aversion. Similar patterns of predicted behavior emerge for risk-averse agents in the OA and EA treatments.[17]

[17] Of course, unlike our experimental treatments risk posture should not be regarded as something we can exogenously impose on subjects. Thus, we exercise caution when interpreting the data in that risk posture could be systematically related to person-specific unobservables that cause the data patterns discussed below.

Figure 6 presents bids for our baseline no-resale treatment grouped by revealed risk preference – either risk-neutral or risk-averse.[18] A total of 29 bidders are labeled as risk neutral and 61 are labeled as risk-averse. Figure 6 reveals two general patterns of behavior consistent with our theory of risk-averse bidding: (i) over lower ranges of the signal space, agents that are classified as risk-averse submit bids that are lower than those submitted by a risk-neutral subject, and (ii) over higher ranges of the signal space, agents that are classified as risk-averse submit bids that are higher than those submitted by a risk-neutral agent. Similar patterns emerge for risk-neutral and risk-averse agents in the OA and EA treatments.

Figures 7 and 8 reveal a number of behavioral differences between risk-averse agents in the OA (EA) treatments and agents with identical risk preference in the baseline no-resale treatments. First, over all ranges of the signal domain for the OA treatment, risk-averse agents submit bids that are greater than those of agents with identical risk preference in the baseline treatment. Second, for signals less than approximately \$20, these differences are increasing in signals. For signals greater than \$20, these differences are a decreasing function of the signal. Third, across lower ranges of the signal space (less than approximately \$21 for risk-neutral agents and up to approximately \$39 for highly risk averse agents), risk-averse agents in the EA treatment submit bids that are higher than those submitted by agents with identical risk preference in the baseline, no-

[18] We categorize the level of CARA risk preference for the agent based upon estimates provided on p. 1649 of Holt and Laury (2002). Risk-averse agents are those who select more than 4 of the "safe" choices. Slightly risk averse agents are those who select between 5 and 7 "safe" choices. Highly risk averse agents are those who select more than 7 "safe" choices in the Holt and Laury experiment. These categories correspond to a CARA value of $0.1 \leq \text{CARA} \leq 0.49$ for slightly risk averse agents and $0.5 \leq \text{CARA} \leq \infty$ for highly risk averse agents.

resale treatment. Finally, these differences are an increasing function for signals less than $20, and a decreasing function for signals above this range.

To examine these differences in a statistical model, we estimate a random effects regression model where the absolute difference: |risk neutral predicted bid – actual bid| is regressed on treatment dummy variables, individual risk preference, and an interaction of individual risk preference and signals. This estimation leads to the next result:

> *Result 5: Risk-averse bidders submit bids that differ more from the theoretical risk-neutral benchmarks than do bids of risk-neutral (loving) agents, with the difference increasing in the level of observed risk aversion.*

Support for Result 5 can be found in Table 7. For example, in column A, rows 4 and 7 of the table, we see that highly risk averse agents (denoted HRA in Table 7) submit bids that, on average, diverge from an associated risk-neutral prediction by $5.52, with this difference decreasing by $0.18 for a dollar increase in signal. Both of these differences are significant at the $p < 0.05$ level. These differences decrease to 2.88 and 0.09 when slightly risk averse agents (denoted SRA in the table) are considered. As a robustness test, we considered grouping subjects according to their CARA midpoint level. These estimates are provided in column B and provide similar insights.

Table 7 reveals that there are statistical differences in the overall levels of divergence of bids from risk-neutral predictions between risk-averse and risk-neutral agents that are consistent with our theory of risk-averse bidding. However, our theoretical model provides an additional set of testable implications for risk-averse bidding – these differences should be a decreasing function in observed signals. This implies that the slope of the bid function in the signal space should be an increasing function of risk aversion.

To evaluate this theoretical prediction, we augment equation (17) by including an interaction of the individual's risk preference with his/her induced signal and signal squared, and an interaction of these values with the treatment dummies. Empirical estimates from these models are contained in columns E and F in Table 6. We obtain the following insight from these results:

> *Result 6: Risk averse agents in both the EA and OA treatments submit bids that are conditionally more responsive to induced signals than do risk-averse agents in the baseline no-resale treatment. Furthermore, these differences decline over the range of the signal space greater than $20 for all but slightly risk averse agents in the EA treatment.*

The first part of Result 6 follows from estimated differences on the coefficients for the SRA_signal (HRA_signal) variable and the associated interaction of this variable with the treatment dummies. For example, in Column E of Table 6 the estimated marginal effect of the induced signal on realized bids of slightly risk averse agents in the baseline treatment is given by [-0.325 + 0.010*signal], which is significant at the $p < 0.05$ level. In contrast, the estimated marginal effect of the induced signal on realized bids for slightly risk averse agents in the OA resale treatment is given by [0.284 – 0.004*signal] – the difference in the parameter estimates for SRA_signal and SRA_OA_signal minus the difference in the parameter estimates for SRA_signal^2 and SRA_OA_signal^2, and for slightly risk averse agents in the EA resale treatment the difference is given by [0.042 – 0.001*signal].

The second part of Result 6 follows from Column F of Table 6, which provides parameter estimates for our bid function for all observations where the signal received by the agent was greater than $20. The estimated rate of change in the slope of the bid function in the signal space for slightly risk averse agents in the baseline treatment is

0.012. For slightly risk averse agents in the OA resale treatment this rate of change is -0.006 – the difference in the parameter estimates for SRA_signal^2 and $SRA\_OA\_signal^2$.

V. Conclusions

Auctions are ubiquitous. Yet whether and to what extent the introduction of secondary resale markets influences bidding behavior when private values are uncertain remains largely unknown. We begin by exploring a novel data set that provides insights into the importance of the resale effect. Reduced-form empirical estimates suggest that bidding patterns are consistent with theoretical predictions. Yet, akin to many empirical exercises, the strength of inference is attenuated when one considers the set of maintained assumptions needed to generate confident conclusions from these field data.

Our approach to this problem is to make use of a laboratory experiment. Such an effort gives up much of the realism associated with field data, but it permits us to investigate whether the resale market by itself can lead to such predicted consequences. We find that extant theory has considerable predictive power, but the accuracy of the theory is enhanced if we control for individual risk preferences. Besides their obvious importance normatively, these results have practical policy significance as well. For example, a necessary condition to lift the countervailing duty and anti-dumping ruling against Canadian softwood lumber exporters (who export to the U.S.) is that their auction markets be robust and not influenced unduly by collusion. Without a proper understanding of the resale opportunities of the various bidders, the modeler may very well earmark bidding disparities among certain bidder types as evidence of collusion when it is in fact due merely to secondary market considerations.

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Table 1: Random Effects Regression Estimates: SBFEP Category 1 and Category 2 Data

	Model (A)	*Model (B)*	*Model (C)*	*Model (D)*	*Model (E)*	*Model (F)*
Constant	5.830***	8.8004***	1.438**	3.938***	1.806***	4.389***
	(0.402)	(0.455)	(0.663)	(0.699)	(0.679)	(0.714)
Mills	1.117**	1.049**				
	(0.548)	(0.535)				
Coast	1.927***	1.447***				
	(0.470)	(0.475)				
Upset	0.00064	-0.174**	0.129***	0.160***	0.119***	0.147***
	(0.0085)	(0.009)	(0.025)	(0.025)	(0.028)	(0.028)
Bidders	1.159***	1.168***	2.247***	2.049***	2.108***	1.883***
	(0.043)	(0.042)	(0.174)	(0.172)	(0.178)	(0.175)
NCV	-6.70e-06	-4.25e-06	0.00002	0.00004	0.0001***	0.0002***
	(0.00001)	(0.00001)	(0.00002)	(0.00003)	(0.00005)	(0.00005)
$Upset^2$			-0.002***	-0.003***	-0.002***	-0.003***
			(0.0003)	(0.0004)	(0.0004)	(0.0004)
$Bidders^2$			-0.089***	-0.072***	-0.81***	-0.061***
			(0.012)	(0.013)	(0.013)	(0.013)
NCV^2			-1.31e-10	-4.59e-10	-3.9e-9***	-4.85e-9**
			(3.98e-10)	(3.91e-10)	(1.33e-9)	(1.37e-9)
Coast_bidder			0.168	0.249*	0.257	0.447**
			(0.143)	(0.144)	(0.225)	(0.226)
Coast_NCV					-0.0002**	-0.0002**
					(0.00006)	(0.00006)
Coast_upset					-0.103*	-0.121**
					(0.058)	(0.057)
$Coast\_bidder^2$			0.023*	0.009	0.020	0.0011
			(0.012)	(0.012)	(0.015)	(0.014)
$Coast\_ncv^2$					5.2e-9***	6.06e-9**
					(1.43e-9)	(1.04e-9)
$Coast\_upset^2$					0.005***	0.005***
					(0.001)	(0.0009)
Mills_bidder			0.592	0.650*	2.643***	2.547***
			(0.393)	(0.384)	(0.892)	(0.875)
Mills_NCV					9.89e-6	0.00002
					(0.0001)	(0.00001)
Mills_upset					-0.081	-0.0533
					(0.088)	(0.086)
$Mills\_bidder^2$			-0.060	-0.076	-0.321***	-0.320***
			(0.069)	(0.067)	(0.115)	(0.113)
$Mills\_ncv^2$					1.52e-9	1.55e-9
					(1.83e-9)	(1.80e-9)
$Mills\_upset^2$					-0.006	-0.0011
					(0.001)	(0.0012)
Time Effects	No	Yes	No	Yes	No	Yes
Likelihood Ratio	831.79	1092.19	936.55	1201.88	1043.53	1331.23
# Obs	7185	7185	7185	7185	7185	7185

Note: Cell entries indicate the marginal effect of model covariates (see text for description of covariates) on bid level.

Table 2: Experimental Design – Laboratory Markets

Resale Structure	*Market Summary*
No Resale	*NR* 5 bidders N=30
Resale – OA Continuation: Resale price = High use value	*ROA* 5 bidders N=30
Resale – EA Continuation: Resale price = Second highest use value	*REA* 5 bidders N=30

Notes: Each cell represents one unique treatment in which we gathered data in different sessions. For example, "*NR*" in row 1, column 2, denotes that the no-resale treatment had 30 subjects in groups of 5 competing in auction markets where *ex post* resale of the commodity was prohibited. No subject participated in more than one treatment.

Table 3: Bidder Signals and Use Values (in dollars)

	Pd. 1	Pd. 2	Pd. 3	Pd. 4	Pd. 5	Pd. 6	Pd. 7	Pd. 8	Pd. 9	Pd. 10
Buyer 1	36 (29)	9 (19)	25 (26)	36 (37)	14 (13)	14 (21)	44 (39)	32 (24)	40 (33)	23 (17)
Buyer 2	17 (27)	4 (12)	14 (19)	42 (32)	36 (38)	10 (14)	25 (34)	29 (22)	32 (24)	44 (40)
Buyer 3	19 (18)	41 (36)	20 (12)	32 (29)	39 (31)	32 (39)	22 (23)	25 (17)	22 (22)	26 (34)
Buyer 4	12 (10)	34 (26)	38 (37)	26 (20)	29 (28)	34 (34)	18 (22)	29 (39)	21 (17)	23 (25)
Buyer 5	37 (36)	25 (33)	33 (34)	6 (13)	25 (21)	24 (28)	23 (14)	38 (33)	35 (40)	28 (23)

Notes: Each cell entry represents the signal received by the bidder in a given period and her induced use value (in parentheses). For example, buyer #1 received a signal of $36.00 and an induced use value of $29.00 in market period 1 (column 2, row 2). Each buyer received the high signal in 2 of the market periods and the high use value in 2 of the market periods. In five of the market periods (4, 5, 6, 8, and 9) we would *ex ante* predict resale exchange, as the agent who received the high signal did not receive the high induced use value.

Table 4: Mean Performance Measures—Lab Markets

	Pd 1	Pd 2	Pd 3	Pd 4	Pd 5	Pd 6	Pd 7	Pd 8	Pd 9	Pd 10
No Resale										
Avg. Bid	$20.84	$20.07	$24.31	$26.42	$27.68	$22.35	$24.80	$29.51	$28.03	$28.31
	(9.32)	(12.74)	(7.13)	(10.02)	(8.12)	(8.89)	(9.56)	(3.40)	(6.17)	(7.36)
Win Bid	$30.77	$36.63	$33.00	$35.55	$35.47	$32.23	$37.77	$34.10	$34.15	$37.25
	(3.17)	(3.07)	(3.87)	(1.58)	(0.82)	(2.64)	(1.52)	(2.14)	(1.21)	(2.27)
Resale Price	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
OA										
Avg. Bid	$26.97	$25.86	$30.24	$29.10	$31.80	$30.64	$32.47	$35.57	$33.75	$34.39
	(7.49)	(9.38)	(5.46)	(9.97)	(6.98)	(7.25)	(5.38)	(2.86)	(7.58)	(5.41)
Win Bid	$35.68	$37.18	$36.92	$36.73	$38.68	$36.55	$38.02	$37.87	$38.15	$39.30
	(4.94)	(2.55)	(3.94)	(2.47)	(1.22)	(2.06)	(1.91)	(1.52)	(1.66)	(1.08)
Resale Price	$36	$36	$37	$37	$38	$39	$39	$39	$40	$40
EA										
Avg. Bid	$24.06	$21.55	$24.11	$26.26	$26.69	$22.11	$26.51	$29.63	$26.77	$26.96
	(9.72)	(12.47)	(10.48)	(9.31)	(7.78)	(10.99)	(7.86)	(6.53)	(7.63)	(9.27)
Win Bid	$35.48	$36.25	$35.25	$36.27	$33.52	$32.00	$34.68	$36.35	$33.17	$34.67
	(2.94)	(3.97)	(4.37)	(3.34)	(1.54)	(3.74)	(3.25)	(3.48)	(1.75)	(3.22)
Resale Price	$29	$33	$34	$32	$32	$34	$34	$33	$33	$34

Note: Entries in the table provide mean performance measures across our three experimental treatments. The data are summarized by period and can be read as follows: in period 1 of the No Resale treatment the average bid was $20.84 with a standard deviation of $9.32. The average winning bid for the round was $30.77 with a standard deviation of $3.17.

Table 5: Non-Parametric Test Results (Mean Performance Measures)

	OA	EA
	All Agents	
No-Resale Session Bids	$5.848**	$0.235
	(2.88)	(0.480)
Resale OA Session Bids		-$5.623**
		(2.882)
	All Agents	
No-Resale Individual Bids	$5.848**	$0.235
	(5.574)	(1.205)
No Resale (Signal < 26)		$2.73**
		(2.680)
No Resale (Signal > 26)		-$2.07**
		(2.090)
Resale OA Individual Bids		-$5.623**
		(4.702)
	Winning Bids Only	
No-Resale Sessions	$2.82**	$0.09
	(5.102)	(0.261)
Resale OA Sessions		-$2.73
		(4.615)
	Highly Risk Averse Agents Only	
No-Resale Individual Bids	$4.105	$3.144
	(1.155)	(1.279)

Note: Cell entries represent the difference in mean bid levels between the column and row treatments. Z-statistics for the Mann-Whitney test are in parentheses. ** Indicates statistical significance at the $p < 0.05$ level. For example, $5.848 in row 2, column 2, of the table indicates that average bids at the session level for the resale treatment followed by an OA continuation game are on average $5.85 greater than those placed in the baseline, no-resale session. This difference is significant at the $p < 0.05$ level using a Mann-Whitney test. Tests for differences in bids across highly risk averse agents in the resale and baseline treatments use the Holt and Laury (2002) measure of implied CARA risk preference.

Table 6 – Random Effects Regression Bid Levels

	Model (A)	Model (B)	Model (C)	Model (D)	Model (E)	Model (F) (Signal > 20)
Constant	25.231**	21.928**	8.359**	3.862**	4.415**	1.924
	(0.648)	(1.024)	(0.965)	(1.421)	(1.513)	(6.173)
OA	5.847**	5.847**	5.847**	5.847**	5.293**	3.488**
	(0.916)	(0.916)	(0.894)	(0.884)	(1.355)	(1.446)
EA	0.235	0.235	0.235	0.235	-0.872	-3.028**
	(0.916)	(0.916)	(0.894)	(0.884)	(1.374)	(1.448)
Signal			0.561**	0.978**	0.936**	1.244**
			(0.019)	(0.099)	(0.109)	(0.376)
$Signal^2$				-0.008**	-0.007**	-0.013**
				(0.001)	(0.002)	(0.006)
SRA_signal					-0.325**	-0.435**
					(0.120)	(0.123)
SRA_signal^2					0.010**	0.012**
					(0.002)	(0.003)
HRA_signal					-0.204	-0.322*
					(0.191)	(0.196)
HRA_signal^2					0.007	0.009**
					(0.005)	(0.005)
HRA_OA_sig					0.385	0.276
					(0.261)	(0.268)
$HRA\_OA\_sig^2$					-0.014**	-0.009
					(0.006)	(0.006)
SRA_OA_sig					0.606**	0.676**
					(0.155)	(0.156)
$SRA\_OA\_sig^2$					-0.018**	-0.018**
					(0.003)	(0.003)
HRA_EA_sig					0.736**	0.755**
					(0.242)	(0.246)
$HRA\_EA\_sig^2$					-0.020**	-0.019**
					(0.006)	(0.006)
SRA_EA_sig					0.367**	0.364**
					(0.162)	(0.161)
$SRA\_EA\_sig^2$					-0.011**	-0.008**
					(0.004)	(0.003)
Period Effects	No	Yes	Yes	Yes	Yes	Yes
Sigma_U	2.344	2.511	2.981	2.944	2.828	2.687
Sigma_E	8.421	7.927	5.573	5.518	5.333	4.879
Log Likelihood	-3220.605	-3171.527	-2883.937	-2874.892	-2843.842	-2108.307

Note: Cell entries indicate the marginal effect of model covariates (see text for description of covariates) on recorded bid level. For example, in row 2 of Column E the estimated marginal effect of being in the OA treatment is an increase of $5.293 on bids, ceteris paribus. SRA (HRA) indicates a slightly (highly) risk averse agent, where the baseline group is risk neutral agents.

Table 7: Random Effects Regression of Absolute Difference in Predicted Risk Neutral Bid and Actual Bid

	Model (A)	*Model (B)*
Constant	5.06**	5.37**
	(0.36)	(0.438)
SRA	2.88**	
	(0.71)	
SRA_mid		2.28**
		(0.72)
HRA	5.52**	
	(1.09)	
HRA_mid		5.01**
		(1.07)
SRA_signal	-0.096**	
	(0.019)	
SRA_mid_signal		-0.089**
		(0.019)
HRA_signal	-0.180**	
	(0.033)	
HRA_mid_signal		0.181**
		(0.031)
Log Likelihood	-2590.21	-2589.52
Sigma_U	1.47	1.48
Sigma_E	4.13	4.12

Note: The table provides results of a random effects regression model, where the absolute difference in predicted risk-neutral and observed bids is regressed on treatment effects, individual risk preference, and an interaction of individual risk preference and signals. Standard errors are in parentheses. **denotes significance at the 95 percent level. Entries in the table can be interpreted as follows. From Column 1, Rows 5 and 9, we see that highly risk averse agents submit bids that on average diverge from an associated risk-neutral prediction by $5.52, with this difference decreasing by $0.18 for a dollar increase in signals. Both of these differences are significant at the $p < 0.05$ level.

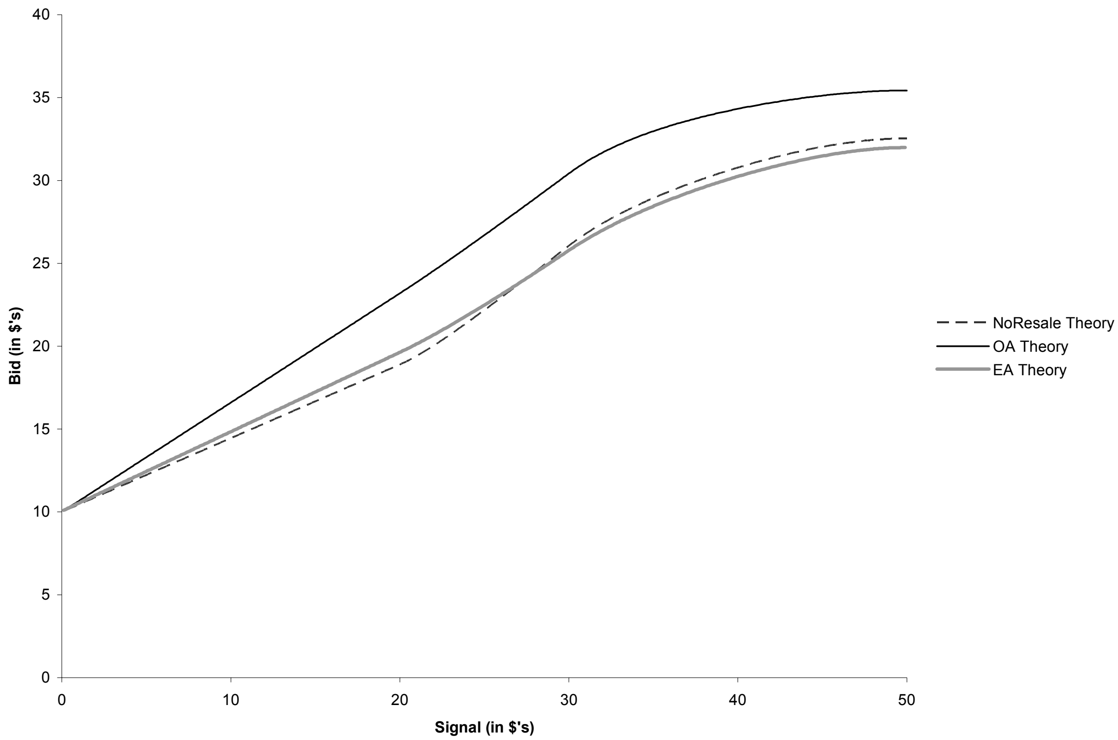

Figure 1: Risk-Neutral Predictions for Bids

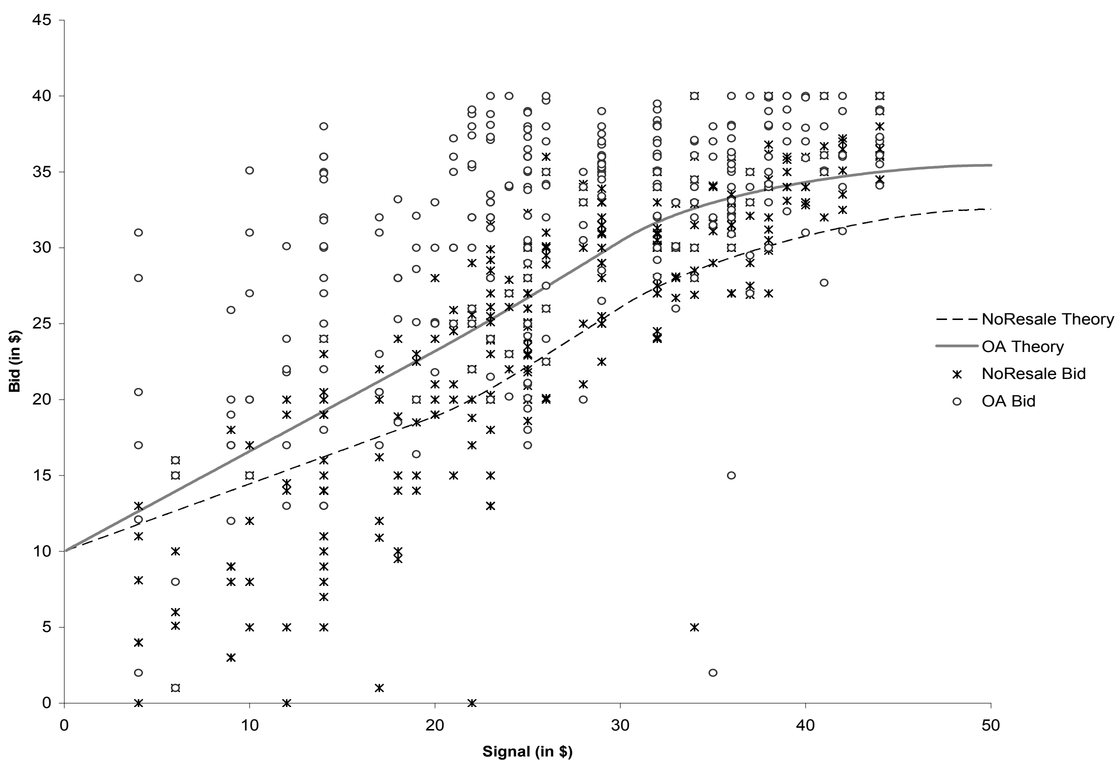

Figure 2: No Resale vs. OA Bids

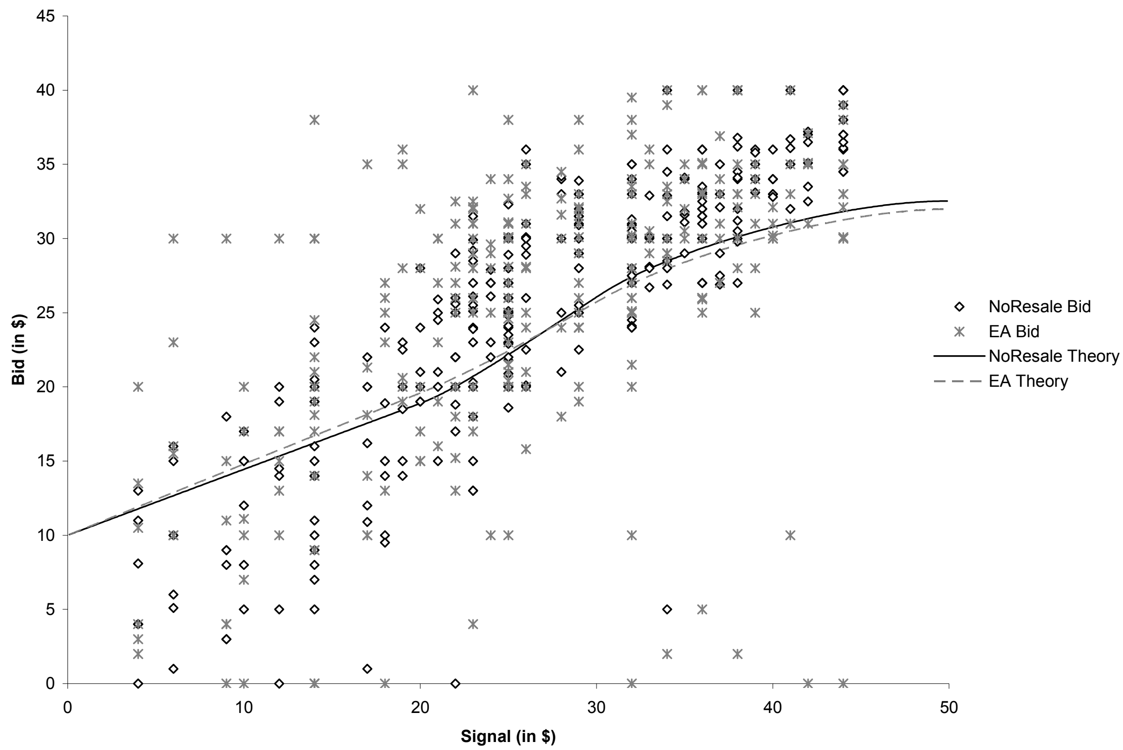

Figure 3: Bids No-Resale vs. EA Treatment

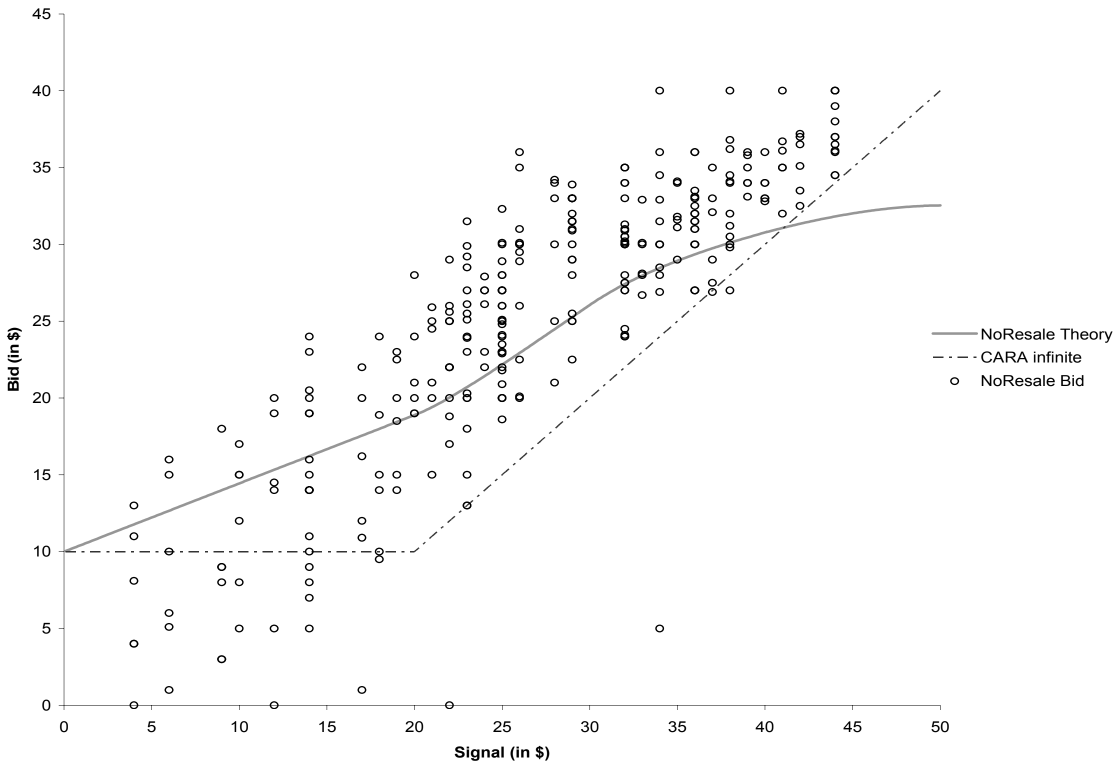

Figure 4: All Bids No-Resale Treatment

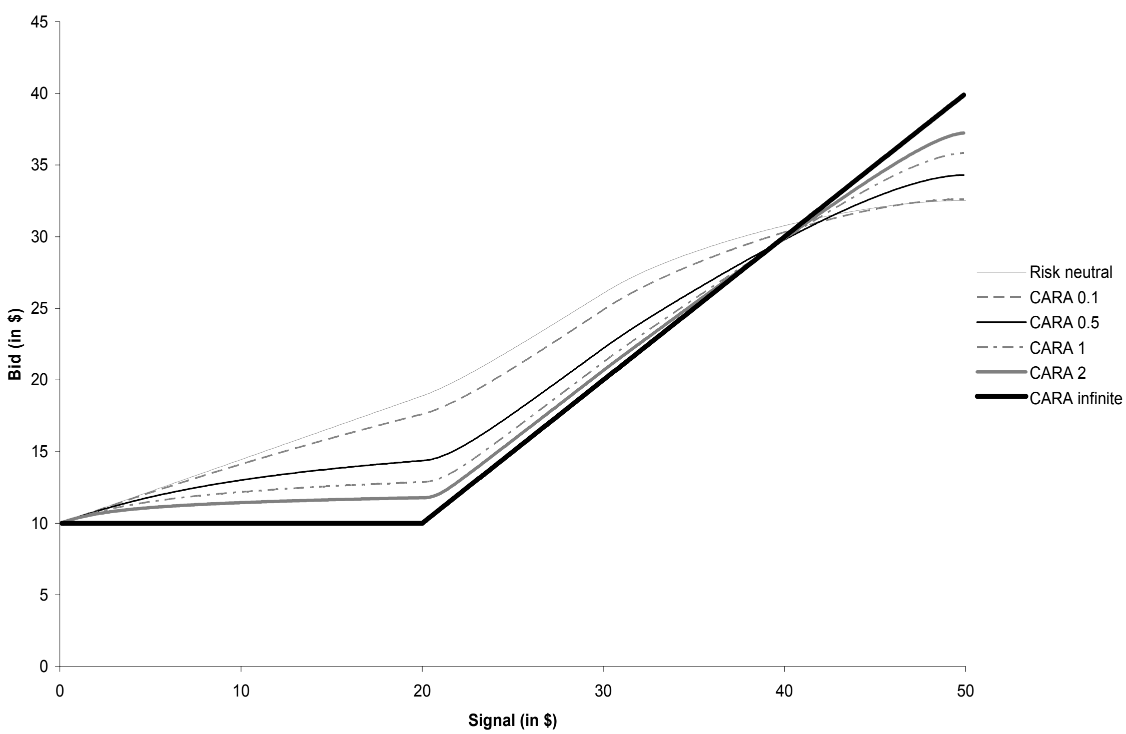

Figure 5: Predicted Bids No-Resale Treatment by Risk Preference

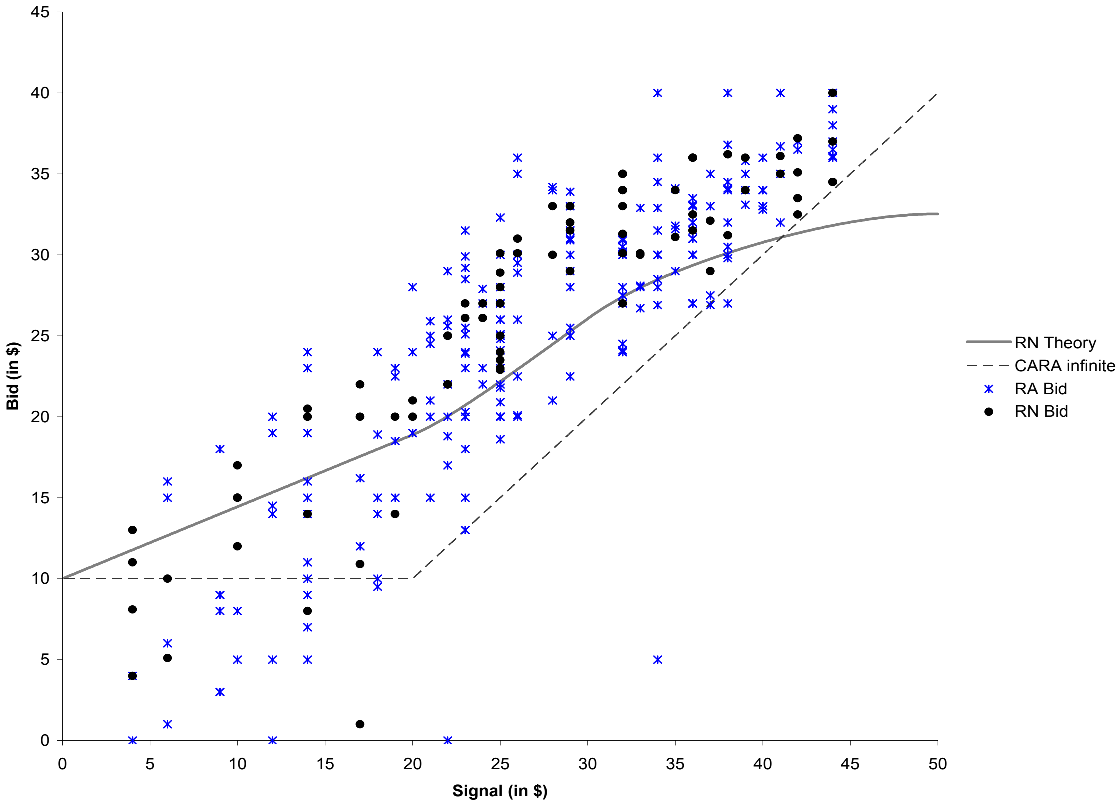

Figure 6: Bids by Risk Posture – No-Resale Treatment

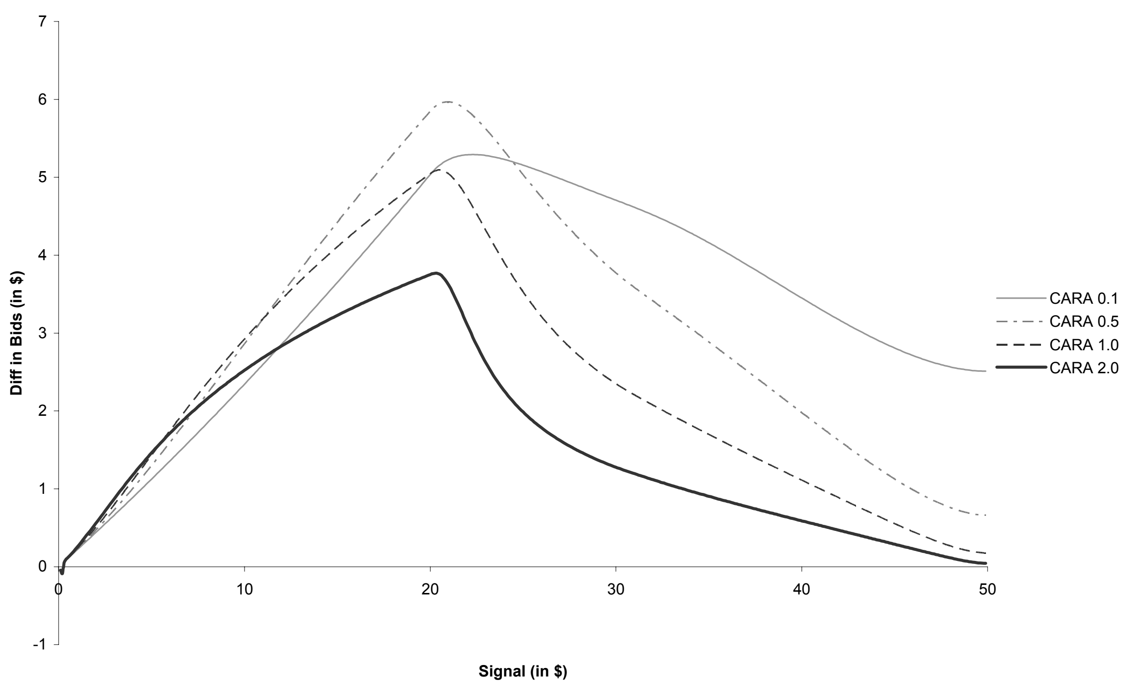

Figure 7: Predicted Differences OA vs. No-Resale by Risk Preference

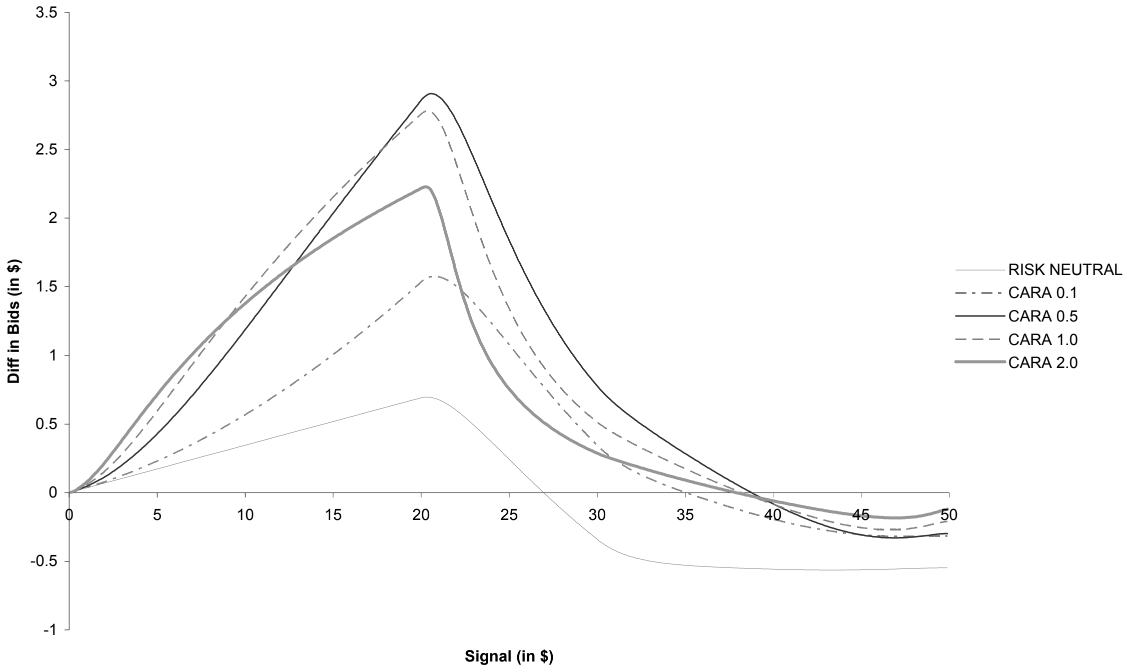

Figure 8: Predicted Differences EA vs. No-Resale by Risk Preference

APPENDIX A. Theoretical Derivations

In the proofs, we use the following characteristic of stochastic dominance:

Lemma 1:

For any given strictly increasing function ϕ *and distributions* $H_1(u)$ *and* $H_2(u)$ *on* $u \in [u_{\min}, u_{\max}]$, where $H_1(u)$, *which stochastically dominates* $H_2(u)$, $\int_{u_{\min}}^{u_{\max}} \phi(u) dH_1(u) > \int_{u_{\min}}^{u_{\max}} \phi(u) dH_2(u)$ *whenever the expectation exists.*

Proof of Proposition 1 (Optimal bid without resale):

We must ensure that $b_N(x)$ is increasing in x and that the first-order condition describes an optimum. For the latter (with standard arguments in Haile 2003 and Milgrom and Weber 1982), it is sufficient to show that $\frac{\partial^2 EU}{\partial x \partial \tilde{x}}(x = \tilde{x}) > 0$ where, *EU* refers to the expected utility given *x* and *y*.

$$
\begin{aligned}
& b_N'(x) > 0 \\
\Leftrightarrow\ & \frac{d}{dx} \frac{1}{F(x)^{n-1}} \int_{x_l}^{x} \frac{1}{K_N(z)} dF(z)^{n-1} < 0 \\
\Leftrightarrow\ & \frac{1}{K_N(x)} F(x)^{n-1} - \int_{x_l}^{x} \frac{1}{K_N(z)} dF(z)^{n-1} < 0
\end{aligned}
$$

which follows since $K_N(x)$ is increasing in x (from Lemma 1).

$$
\begin{aligned}
& \frac{\partial^2 EU}{\partial x \partial \tilde{x}}(x = \tilde{x}) \\
& \quad = \left[\left(\frac{F(x)^{n-1}}{\rho(b_N(x))} \right)' K_N'(x) \right] \rho(0) \\
& \quad = (F(x)^{n-1})' / \underbrace{K_N(x)}_{<0} \underbrace{K_N'(x)}_{\geq 0} \underbrace{\rho(0)}_{<0} \\
& \quad \geq 0
\end{aligned}
$$

Optimal bid for risk-neutral players without resale as a limit for $\lim_{\sigma \to 0} b_N(x)$**:**

$$\lim_{\sigma\to 0} b_N(x) = \lim_{\sigma\to 0} \frac{1}{\sigma}\log\left[\int_{x_l}^{x} \frac{1}{\int \exp(-\sigma u)dG(u\mid z)} dF(z)^{n-1}\right]$$

$$= \lim_{\sigma\to 0} \frac{\int_{x_l}^{x} \frac{\int \exp(-\sigma u)udG(u\mid z)}{\left(\int \exp(-\sigma u)dG(u\mid z)\right)^2} dF(z)^{n-1}}{\int_{x_l}^{x} \frac{1}{\int \exp(-\sigma u)dG(u\mid z)} dF(z)^{n-1}} = \int_{x_l}^{x}\int udG(u\mid z)dF(z)^{n-1}$$

Optimal bid for risk-neutral players without resale as a limit for $\lim_{\sigma\to\infty} b_N(x)$:
Analogously to the limit $\sigma \to 0$,

$$\lim_{\sigma\to\infty} b_N(x) = \lim_{\sigma\to\infty} \frac{\int_{x_l}^{x} \frac{\int \exp(-\sigma(u-u_{\min}(x)))udG(u\mid z)}{\left(\int \exp(-\sigma(u-u_{\min}(x)))dG(u\mid z)\right)^2} dF(z)^{n-1}}{\int_{x_l}^{x} \frac{1}{\int \exp(-\sigma(u-u_{\min}(x)))dG(u\mid z)} dF(z)^{n-1}} = u_{\min}(x)$$

Lemma 2: *$G_1(u\mid x,y)$ and $G_2(u\mid x,y)$ are decreasing in x and y.*

Proof of Lemma 2:
Since $G(u\mid x)$ is decreasing in *x* by assumption, the same property follows immediately for $G_i(u\mid x,y)$, *i*=1,2. To see that $G_i(u\mid x,x)$ is also decreasing in *x*,

$$\frac{\partial}{\partial y}\bar{G}_1(u\mid y)$$
$$= \frac{\partial}{\partial y}G(u\mid y)M(u\mid y)^{n-2} + G(u\mid y)(n-2)M(u\mid y)^{n-3}\frac{\partial M(u\mid y)}{\partial y}$$

where both summands are negative since $G(u\mid y)$ and $M(u\mid y)$ are decreasing in *y*.
Similarly, using $G(u\mid y) \le M(u\mid y)$:

$$\frac{\partial}{\partial y}\bar{G}_2(u\mid y)$$
$$= \frac{\partial}{\partial y}G(u\mid y)(n-2)M(u\mid y)^{n-3}(1-M(u\mid y))$$
$$+G(u\mid y)(n-2)M(u\mid y)^{n-4}\left[M(u\mid y)+G(u\mid y)(n-3)-G(u\mid y)(n-2)M(u\mid y)\right]\frac{\partial M(u\mid y)}{\partial y}$$
$$\le \frac{\partial}{\partial y}G(u\mid y)(n-2)M(u\mid y)^{n-3}(1-M(u\mid y))$$
$$+G(u\mid y)(n-2)^2M(u\mid y)^{n-4}G(u\mid y)\left[1-M(u\mid y)\right]\frac{\partial M(u\mid y)}{\partial y}$$
$$\le 0$$

Assumption 1 (A1): We assume that $G(u \mid x)$ satisfies $\frac{d^2}{dxdu}\log G(u \mid x) \geq 0$.

Lemma 3: $\frac{\overline{G}_2(u \mid x)}{\overline{G}_1(u \mid x)}$ is decreasing in u.

Proof:

$$\frac{\overline{G}_2(u \mid x)}{\overline{G}_1(u \mid x)} = \frac{M(u \mid x)^{n-2} + (n-2)G(u \mid x)M(u \mid x)^{n-3}\left[1 - M(u \mid x)\right]}{G(u \mid x)M(u \mid x)^{n-2}}$$
$$= \frac{1}{G(u \mid x)} + \frac{(n-2)}{M(u \mid x)} - (n-2)$$

where the first two terms are decreasing in u.

Lemma 4: Given (A1), $\frac{\overline{G}_1(u \mid x)}{\int_{u_l}^{u} \rho'(-z)d\overline{G}_1(z \mid x)}$ is decreasing in u.

Proof:

$$\frac{d}{du}\frac{\overline{G}_1(u \mid x)}{\int_{u_l}^{u} \rho'(-z)d\overline{G}_1(z \mid x)} < 0$$

$$\Leftrightarrow \frac{d}{du}\overline{G}_1(u \mid x)\int_{u_l}^{u} \rho'(-z)d\overline{G}_1(z \mid x) - \overline{G}_1(u \mid x)\rho'(-u)\frac{d}{du}\overline{G}_1(u \mid x)$$

$$= \frac{d}{du}\overline{G}_1(u \mid x)\left[\int_{u_l}^{u} \underbrace{\rho'(-z)}_{<\rho'(-u)} d\overline{G}_1(z \mid x) - \overline{G}_1(u \mid x)\rho'(-u)\right] < 0$$

Lemma 5: Let $\phi_1(u)$ and $\phi_2(u)$ be positive and decreasing functions and $\mu(u)$ a positive function on $u \in [u_{\min}, u_{\max}]$. Then

$\int_{u_{\min}}^{u_{\max}} \phi_1(u)\phi_2(u)\mu(u)du \int_{u_{\min}}^{u_{\max}} \mu(u)du > \int_{u_{\min}}^{u_{\max}} \phi_1(u)\mu(u)du \int_{u_{\min}}^{u_{\max}} \phi_2(u)\mu(u)du$ *whenever the expectations exist.*

Proof: Define $\overline{\mu}(u) = \mu(u) / \int_{u_{\min}}^{u_{\max}} \mu(z)dz$ and let $\tilde{u}$ solve $\phi_2(\tilde{u}) = \int_{u_{\min}}^{u_{\max}} \phi_2(z)\overline{\mu}(z)dz$**.** Then we have

$$\int_{u_{\min}}^{u_{\max}} \phi_1(u)\phi_2(u)\bar{\mu}(u)du - \int_{u_{\min}}^{u_{\max}} \phi_1(u)\bar{\mu}(u)du \int_{u_{\min}}^{u_{\max}} \phi_2(u)\bar{\mu}(u)du$$

$$= \int_{u_{\min}}^{u_{\max}} \phi_1(u)\bar{\mu}(u) \underbrace{\left[\phi_2(u) - \int_{u_{\min}}^{u_{\max}} \phi_2(z)\bar{\mu}(z)dz \right]}_{>0 \Leftrightarrow u<\tilde{u}} du$$

$$\geq \int_{u_{\min}}^{u_{\max}} \phi_1(\tilde{u})\bar{\mu}(u) \underbrace{\left[\phi_2(u) - \int_{u_{\min}}^{u_{\max}} \phi_2(z)\bar{\mu}(z)dz \right]}_{>0 \Leftrightarrow u<\tilde{u}} du = 0$$

Lemma 6: $\dfrac{K_R(x,x)}{L_R(x,x)}$ is increasing in x for R=OA. Given (A1), $\dfrac{K_R(x,x)}{L_R(x,x)}$ is also increasing in *x* for R=EA.

Proof: $K_R(x,y)$ is increasing in both arguments, whereas $L_R(x,y)$ is constant for R=OA and decreases in *x* but increases in *y* for R=EA (from Lemma 2). It remains to show that $\dfrac{\partial}{\partial x}\dfrac{K_R(x,y)}{L_R(x,y)}|_{y=x} \geq 0$ for R=EA.

For this, we consider the derivative w.r.t. x and show that $\dfrac{\partial}{\partial x}K_R(x,x)L_R(x,x) - K_R(x,x)\dfrac{\partial}{\partial x}L_R(x,x) \geq 0$. Using the definitions of K_R and L_R, we have:

$$K_{EA}(x,y) = \int_{u_l}^{u_u} \rho(u)dG_2(u \mid x,y) = \rho(u_{\max}(x)) - \int_{u_l}^{u_{\max}(x)} \rho'(u)G(u \mid x)\bar{G}_2(u \mid y)du$$

$$\frac{\partial}{\partial x}K_{EA}(x,x) = -\int_{u_l}^{u_{\max}(x)} \rho'(u)\frac{\partial}{\partial x}G(u \mid x)\bar{G}_2(u \mid y)du$$

$$L_{EA}(x,y) = \int_{u_l}^{u_u} \left[\rho'(u)\int_{u_l}^{u} \rho'(-z)d\bar{G}_1(z \mid y) + (1-\bar{G}_1(u \mid y)) \right] dG(u \mid x)$$

$$= \rho'(u_{\max}(x))\int_{u_l}^{u_u} \rho'(-z)d\bar{G}_1(z \mid y) - \int_{u_l}^{u_{\max}(x)} \left[\rho''(u)\int_{u_l}^{u} \rho'(-z)d\bar{G}_1(z \mid y) \right] G(u \mid x)du$$

$$\frac{\partial}{\partial x}L_{EA}(x,x) = -\int_{u_l}^{u_{\max}(x)} \left[\rho''(u)\int_{u_l}^{u} \rho'(-z)d\bar{G}_1(z \mid y) \right] \frac{\partial}{\partial x}G(u \mid x)du$$

and, therefore,

$$\frac{\partial}{\partial x}K_R(x,x)L_R(x,x)-K_R(x,x)\frac{\partial}{\partial x}L_R(x,x)$$

$$=-\rho'(u_{\max}(x))\int_{u_l}^{u_{\max}(x)}\rho'(u)\frac{\partial}{\partial x}G(u|x)\left[\bar{G}_2(u|x)\int_{u_l}^{u_u}\rho'(-z)d\bar{G}_1(z|x)-\int_{u_l}^{u}\rho'(-z)d\bar{G}_1(z|x)\right]du$$

$$-\sigma\left[\int_{u_l}^{u_{\max}(x)}\rho'(u)\frac{\partial}{\partial x}G(u|x)\bar{G}_2(u|x)du\right]\left[\int_{u_l}^{u_{\max}(x)}\left[\rho'(u)\int_{u_l}^{u}\rho'(-z)d\bar{G}_1(z|x)\right]G(u|x)du\right]$$

$$+\sigma\left[\int_{u_l}^{u_{\max}(x)}\rho'(u)\int_{u_l}^{u}\rho'(-z)d\bar{G}_1(z|x)\frac{\partial}{\partial x}G(u|x)du\right]\left[\int_{u_l}^{u_{\max}(x)}\rho'(u)G(u|x)\bar{G}_2(u|x)du\right]$$

We can apply Lemma 5 to the last two summands with $\mu(u)=\rho'(u)\int_{u_l}^{u}\rho'(-z)d\bar{G}_1(z|y)G(u|x)$, $\phi_1(u)=\frac{\bar{G}_2(u|x)}{\int_{u_l}^{u}\rho'(-z)d\bar{G}_1(z|x)}$ and $\phi_2(u)=-\frac{\frac{\partial}{\partial x}G(u|x)}{G(u|x)}$, where we use (A1), Lemma 3, and Lemma 4 to guarantee the required properties Lemma 5. We then obtain:

$$\frac{\partial}{\partial x}K_R(x,x)L_R(x,x)-K_R(x,x)\frac{\partial}{\partial x}L_R(x,x)$$

$$\geq-\rho'(u_{\max}(x))\int_{u_l}^{u_{\max}(x)}\rho'(u)\frac{\partial}{\partial x}G(u|x)\underbrace{\left[\bar{G}_2(u|x)\int_{u_l}^{u_u}\rho'(-z)d\bar{G}_1(z|x)-\int_{u_l}^{u}\rho'(-z)d\bar{G}_1(z|x)\right]}_{>0\text{ (Lemma 3,4)}}du$$

$$\geq 0$$

Lemma 7: $\frac{\frac{\partial K_R}{\partial x}(x,y)}{K_R(x,y)}$ is increasing in y for R=EA.

Proof of Proposition 2 (Optimal bid function with resale)

With standard arguments (Haile 2003 and Milgrom and Weber 1982): Existence and optimality is given if $b_R'(x)>0$ and $\frac{\partial^2 EU}{\partial x\partial\tilde{x}}(x=\tilde{x})\geq 0$. We have:

$$b_R'(x)>0\Leftrightarrow\left(\frac{1}{\rho(b_R(x))}\right)'<0$$

$$\Leftrightarrow L_R(x,x)-\frac{K_R(x,x)}{\rho(b_R(x))}>0$$

From Lemma 6 we have that $\frac{K_R(x,x)}{L_R(x,x)}$ is increasing in x. We therefore obtain:

$$\frac{K_R(x,x)}{\rho(b_R(x))}$$

$$\leq \int_{x_l}^{x} \exp\left(\int_{x}^{z} K_R(y,y)/\int_{x_l}^{y} K_R(y,w)dF(w)^{n-1}dF(y)^{n-1}\right)\frac{K_R(z,z)(F(z)^{n-1})'}{\int_{x_l}^{z} K_R(z,y)dF(y)^{n-1}} L_R(x,x)dz$$

$$= L_R(x,x)\left[1-\exp\left(\int_{x}^{x_l} K_R(y,y)/\int_{x_l}^{y} K_R(y,w)dF(w)^{n-1}dF(y)^{n-1}\right)\right]$$

$$< L_R(x,x)$$

Further, we have to show:

$$\frac{\partial^2 EU}{\partial x \partial \tilde{x}}(x=\tilde{x})$$

$$= \left[\left(\frac{1}{\rho(b_R(x))}\right)' \int_{x_l}^{x} \underbrace{\frac{\partial K_R}{\partial x}(x,z)}_{>0} dF(z)^{n-1} + \left[\frac{1}{\rho(b_R(x))}\frac{\partial K_R}{\partial x}(x,x) - \frac{\partial L_R}{\partial x}(x,x)\right](F(x)^{n-1})' \right] \underbrace{\rho(0)}_{<0}$$

$$> 0$$

Optimal auction **(R=OA)**

The claimed relationship follows immediately as we have already shown that $\left(\frac{1}{\rho(b_R(x))}\right)' < 0$ and further that $\frac{1}{\rho(b_R(x))}\frac{\partial K_R}{\partial x}(x,x) \leq 0$ and $\frac{\partial L_R}{\partial x}(x,x) = 0$.

English auction **(R=EA)**

Using (7'), we have to show that

$$\frac{\int_{x_l}^{x} \frac{\partial K_R}{\partial x}(x,z)dF(z)^{n-1}}{\int_{x_l}^{x} K_R(x,z)dF(z)^{n-1}} \underbrace{\left[\frac{K_R(x,x)}{\rho(b_R(x))} - L_R(x,x)\right]}_{<0} > \frac{1}{\rho(b_R(x))}\frac{\partial K_R}{\partial x}(x,x) - \frac{\partial L_R}{\partial x}(x,x).$$

From Lemma 7 we know $\frac{\int_{x_l}^{x} \frac{\partial K_R}{\partial x}(x,z)dF(z)^{n-1}}{\int_{x_l}^{x} K_R(x,z)dF(z)^{n-1}} < \frac{\frac{\partial K_R}{\partial x}(x,x)}{K_R(x,x)} < 0$. Therefore:

$$\frac{\int_{x_l}^{x}\frac{\partial K_R}{\partial x}(x,z)dF(z)^{n-1}}{\int_{x_l}^{x}K_R(x,z)dF(z)^{n-1}}\underbrace{\left[\frac{K_R(x,x)}{\rho(b_R(x))}-L_R(x,x)\right]}_{<0}-\left[\frac{1}{\rho(b_R(x))}\frac{\partial K_R}{\partial x}(x,x)-\frac{\partial L_R}{\partial x}(x,x)\right]$$

$$\geq -L_R(x,x)\frac{\frac{\partial K_R}{\partial x}(x,x)}{K_R(x,x)}+\frac{\partial L_R}{\partial x}(x,x)$$

$$\geq 0$$

where the last inequality was proven in Lemma 6.

Optimal bid for risk-neutral players with resale: $\lim_{\sigma\to 0} b_R(x)$ **and** $\lim_{\sigma\to\infty} b_R(x)$**:**

Note that $\exp\left(\int_x^z K_R(y,y)/\int_{x_l}^{y} K_R(y,w)dF(w)^{n-1}dF(y)^{n-1}\right)\to\frac{F(z)^{n-1}}{F(x)^{n-1}}$ for $\sigma\to 0$. The proof is therefore analogous to that of the no-resale case (see above).

$$\lim_{\sigma\to 0} b_R(x)$$

$$=\lim_{\sigma\to 0}\frac{\int_{x_l}^{x}\frac{F(z)^{n-1}}{F(x)^{n-1}}\frac{\frac{\partial}{\partial\sigma}L_R(z,z)\int_{u_l}^{z}(-\sigma)K_R(z,y)dF(y)^{n-1}-L_R(z,z)\int_{u_l}^{z}\frac{\partial}{\partial\sigma}((-\sigma)K_R(z,y))dF(y)^{n-1}}{\left((-\sigma)\int_{u_l}^{z}K_R(z,y)dF(y)^{n-1}\right)^2}dF(z)^{n-1}}{\int_{x_l}^{x}\frac{F(z)^{n-1}}{F(x)^{n-1}}\frac{L_R(z,z)}{(-\sigma)\int_{u_l}^{z}K_R(z,y)dF(y)^{n-1}}dF(z)^{n-1}}$$

$$=\int_{x_l}^{x}\frac{1}{F(x)^{n-1}}\frac{\left[\lim_{\sigma\to 0}\frac{\partial}{\partial\sigma}L_R(z,z)\right]F(z)^{n-1}-\int_{u_l}^{z}\left[\lim_{\sigma\to 0}\frac{\partial}{\partial\sigma}(-\sigma)K_R(z,y)\right]dF(y)^{n-1}}{F(z)^{n-1}}dF(z)^{n-1}$$

from which one obtains the claimed relationships. The proof for $\sigma\to\infty$ is similar.

Appendix B: Experimental Instructions – OA Resale Treatment

Welcome to Lister's Auctions! You have the opportunity to bid in a series of experimental auctions today and you can earn cash by participating.

Auction Rules:
In this auction you will bid against four (4) other people and the person with the highest bid is the winner, and pays the amount of their bid for the "fictitious" commodity. The auction is a sealed bid auction so you don't know the bids of the other participants. We will repeat the auction for 10 rounds. At the end of the session, your earnings from this experiment and another unrelated experiment will be summed and paid to you in cash.

There are six steps in the auction process, each of which are explained in detail below. The six steps include: (i) determining your signal of the value of the fictitious commodity, (ii) determining your bid, (iii) determining your use value for the fictitious good, (iv) determining the winner, (v) the resale market, and (vi) determining your payouts for the round.

1. **Determining your signal of the good's value:** At the beginning of each period, a monitor will hand you a card numbered from zero dollars ($0) to fifty dollars ($50) in one dollar ($1) increments. The value on the card handed to you will be a signal of your use value for the fictitious good. The other bidders in your auction will have their signals determined in exactly the same way. Signals are private and independent across buyers, and your signal will change across rounds.

   Signals and Use Values

   Use values, V, in each round are drawn from a uniform distribution on the interval [10, 40]. That is, every dollar value between 10 and 40 is equally likely to be drawn as your use value. These values are independently drawn for each subject and will differ across periods.

   The signal you will receive is determined by adding a random number drawn on the interval [-10, 10] to your use value. Again, each dollar value between -10 and 10 is equally likely to be drawn and added to your use value. Your first-stage signal, S, is hence given by:

   $$S = V + random\ number$$

   Your signal, S, is thus distributed on the interval [$0, $50].

   Given your signal, you can compute the expected use value. For example, if you were to receive a signal of $30 in the first stage, you know that your final use value must lie somewhere in the interval [$20, $40]. Since each of these values is equally likely to have been selected as your use value, on average your use value is $30. However, any value in this range could have been assigned as your use value.

2. Determining your bid value: After receiving your signal, you will choose your bid value for the fictitious good. In order to choose your bid, consider how your earnings for each period are calculated. If you are the person with the highest bid you are the winner of the auction. Your earnings are equal to your use value minus your bid amount if you have the highest end use value:

Earnings = your good's use value (V) – your bid

If you are the person with the highest bid but do not have the highest use value, your earnings are equal to the highest use value of all participants minus your bid amount:

Earnings = highest use value – your bid

If you are not the high bidder in a round, your earnings for the period are zero. If there is a tie, the winner will be determined by the flip of a coin (if more than two people tie we will draw a card to determine the winner). Your bid can be any amount in the range from zero ($0) to forty dollars ($40) in ten cent ($0.10) increments.

3. Determining your use value: Once all bids have been received, a monitor will hand you a second slip of paper numbered from ten dollars ($10) to forty dollars ($40) that gives your final use value, V. Your use value will lie within $\pm$$10 of your signal, S.

4. Determining the auction winner: All bids will be publicly announced and recorded by a monitor on the blackboard. Your bid will be compared with those of the four other participants in the auction. The person with the highest bid amount is the winner.

5. The resale market: In the resale market, each participant can see the use values for all other participants. The highest bidder in the auction market will sell the "fictitious" commodity to the individual with the highest use value. In this experiment this happens automatically. The payoff for the winner is the highest use value of all participants minus his/her bid amount. If you did not win the auction, your payout for the period will be zero. The payout for the auction winner can be positive even if your bid was greater than your use value.

6. Determining your payouts: If you are the auction winner, you will receive the difference between the highest use value and your bid. If you did not win the auction, you receive zero for that period. Your total earnings for this experiment is the sum of your earnings for each of the 10 periods.

Do you have any questions about the auction process?

Appendix C: Experimental Instructions for Risk Aversion Experiment

Record your subject number from the previous part on your decision sheet. Your decision sheet shows ten decisions listed on the left. Each decision is a paired choice between OPTION A and OPTION B. You will make ten choices and record these in the final column, but only one of them will be used in the end to determine your earnings. Before you start making your ten choices, please let me explain how these choices will affect your earnings for this part of the experiment.

We will use part of a deck of cards to determine payoffs; cards 2-10 and the Ace will represent "1". After you have made all of your choices, we will randomly select a card twice, once to select one of the ten decisions to be used, and a second time to determine what your payoff is for the option you chose, A or B, for the particular decision selected. (After the first card is selected, it will be put back in the pile, the deck will be reshuffled, and the second card will be drawn.) Even though you will make ten decisions, only one of these will end up affecting your earnings, but you will not know in advance which decision will be used. Obviously, each decision has an equal chance of being used in the end.

Now, please look at Decision 1 at the top. OPTION A pays $2.00 if the Ace is selected, and it pays $1.60 if the card selected is 2-10. OPTION B yields $3.85 if the Ace is selected, and it pays $0.10 if the card selected is 2-10. The other decisions are similar, except that as you move down the table, the chances of the higher payoff for each option increase. In fact, for Decision 10 in the bottom row, the cards will not be needed since each option pays the highest payoff for sure, so your choice here is between $2.00 or $3.85.

To summarize, you will make ten choices: for each decision row you will have to choose between OPTION A and OPTION B. You may choose A for some decision rows and B for other rows, and you may change your decisions and make them in any order. When you are finished, we will come to your desk and pick a card to determine which of the ten decisions will be used. Then we will put the card back in the deck, shuffle, and select a card again to determine your money earnings for the OPTION you chose for that decision. Earnings for this choice will be added to your previous earnings, and you will be paid all earnings in cash when we finish.

So now please look at the empty boxes on the right side of the record sheet. You will have to write a decision, A or B in each of these boxes, and then the card selection will determine which one is going to count. We will look at the decision that you made for the choice that counts, and circle it, before selecting a card again to determine your earnings for this part. Then you will write your earnings in the blank at the bottom of the page.

Are there any questions? Now you may begin making your choices. Please do not talk with anyone else while we are doing this; raise your hand if you have a question.