# Simultaneous Allocation of Bundled Goods Through Auctions: Assessing the Case for Joint Bidding

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**Abstract:** We study the costs and benefits of allowing joint bidding in multiple simultaneous first price sealed bid auctions for bundled goods with private values. Joint bidding raises the prospect of higher allocative efficiency but also reduces the number of bidders resulting in an ambiguous net impact on seller revenue. The research was carried out using laboratory experiments in which groups of up to six buyers competed for eight bundles of two separable goods each. The main results show that in our experimental environment, allowing joint bidding increases efficiency by 11.3% and revenue by 9.4%. The research has immediate applications to the sale of public forest stands that arbor a mixture of species. For this reason, we explore how the results are affected by excess supply, the presence of dominant firms, and the removal of an allocation rule requiring multiple bidders under certain circumstances.

**Keywords:** Timber auctions; forest; joint bids; bidding rings; collusion; first price.

**JEL Classification:** Q23, Q28, D44, D47.

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Auctions have long been an important mechanism for buying and selling natural resources and agricultural products. They are found around the world at wholesale markets for fish (Guillotreaua and Jiménez-Toribio, 2011), cut flowers (Van den Berg, G. J., 2001), wheat (Banerji and Meenakshi, 2004), and hogs (Lame et al., 2000) among others. They are also the mechanism by which oil exploration leases (Hendricks and Porter, 1992) and pollution permits are sold. Several jurisdictions also use variants of the first price sealed bid auctions to allocate the rights to harvest publicly owned forests (e.g. U.S. National Forest Service; British Columbia, France and Romania; see for instance Athey and Levin, 2001; Athey Levin and Seira, 2011; Baldwyn, Marshall, and Richard, 1997; Li and Perrigne, 2003; Mead, 1968; Paarsch, 1992; Saphores et al., 2007).

In certain climes, wooded lots are hosts to more than one species to be processed by different mills. This is often the case in the North-American northeast, where mixed stands contain both hardwood and softwood. While cost effective logging and subsequent silvicultural practices dictate the harvesting of all trees, a hardwood mill may have little value for softwood and vice versa. For this reason, and the fact that there is no well-functioning forward market for the resale of trees that are not useful to the winner of a lot, the Government of Quebec has adopted an auction mechanism whereby it allows separate firms to bid jointly for the right to harvest a mixed stand. In this context, it is thought that joint bids 1) increase the total value of the lot to the joint bidders and thus could increase the amount of rents captured by the seller; 2) make it more likely that the values underlying joint bids are a fair representation of the market value of each species; and 3) increase the allocative efficiency of the auction mechanism by directly allocating each species of trees to a user who seeks it. Unfortunately, joint bidding also has downsides. 1) Given an initial number of potential bidders, joint bids reduce competition by turning two individual bids into a single bid. 2) Since the formation of binding joint bids requires explicit agreements between bidders, it is no longer possible to outlaw communication between bidders. Thus, an indirect effect of introducing joint bidding could be to facilitate the formation of bidding rings. This is an issue in timber auctions where the general consensus is that competition is often lacking (Brannman, 1996; Baldwyn, Marshall, and Richard, 1997; Jacobsen, 1999; and Froeb and McAfee, 1988). It is also a concern in auctions for other resource rights (Cramton, 2010; Crespi and Sexton, 2004; Banerji and Meenakshi, 2004), agricultural commodities, quotas, and permits where collusion has been a recurring challenge (Dia, 2011; DePiper, forthcoming; DePiper et al., 2013). Hence, the net impact of allowing joint bidding is ambiguous.[1]

The objective of this research is to study the impact of introducing joint bidding on the performance of first price sealed bid auctions when multiple bundled lots are offered simultaneously and to further test whether other changes in auction rules modify these results. Our primary interests are the auction's efficiency, seller revenue, and general bidding behavior.

Interest in joint bidding in auctions goes back nearly five decades (Mead, 1968). Although it is of direct relevance to procurement auctions where engineering and construction firms may submit a joint proposal (Iimi, 2004; Albano et al, 2009), it is interesting to note that much of what we know empirically about the effect of joint bidding comes from a series of studies of auctions for land leases and off-shore drilling rights for oil and gas by the U.S. federal government (Mead, 1968; DeBrock and Smith, 1983; Hendricks, Porter and Tan, 2008; Hendricks and Porter, 1992; Campo, Perrigne and Vuong, 2003). This line of research, however, adopts the common value framework because of the significant uncertainty about the real value of the object for sale. In this context, one of the advantages of bidding jointly is the pooling of information on the likely value of the object, which can help avoid the winner's curse and attract more small firms to the auction (Moody and Kruvant, 1988).[2] In timber auctions, the volume to be harvested is known with accuracy. Although there can be a common value component attributable to the volatility of future prices for fiber, timber auctions are normally thought of and modeled as independent private value auctions with much different implications.

Work on joint bidding is also of particular relevance in the emerging field of conservation auctions (Latacz-Lohmann and Schilizzi, 2005; Cason and Gangadharan,

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[1] Although engaging in market splitting or other forms of collusive strategies is still prohibited by Canadian competition laws (Canada Competition Act 1985), proving collusive behavior would be extremely difficult when communication between competitors is permitted for the purpose of forming joint bids.

[2] Entry effects can also be observed in Independent Private Value auctions. In fact, Athey, Levin and Seira (2011) show evidence supporting that they are present in U.S. timber auctions. However, these effects can only arise if there are costs to entering the auction. We abstract from this problem entirely in our experiment.

2004). In this context, the submission of joint tenders by adjacent landowners, who could coordinate the implementation of complementary projects, makes it possible to exploit economies of scale or increase the marginal effectiveness of conservation projects (Wang and Bennett, 2009; Romstad and Alfnes, 2011; Calel, 2010). The argument for allowing joint bidding is therefore the same as the one put forward for timber auctions: increasing efficiency by harnessing complementarities across bidders. However, Calel (2010) is similarly concerned by the potential reduction in the numbers of bidders that joint bidding implies. Interestingly, Latacz-Lohmann and Schilizzi (2005) identify economics experiments as a promising approach to inform the design of practical auction schemes. Our work indirectly informs these questions.[3]

We put in place a policy relevant experimental timber auction environment that replicates the main features of Quebec's new forest auction design for mixed stands. In our experiments, eight lots are offered simultaneously to six participants. Some lots are offered to all six players while others are offered to only three to reflect different degrees of competition and regional differences. All lots are composed of two goods sold together via first price sealed bid auctions. These two goods can only be allocated to different auction winners if a verified and binding joint bid was entered by two participants. In most treatments, all six bidders have a "soft" limit on their capacity to process the lots they win. This is implemented by imposing a cost on bidders who win more than two lots, reflecting the absence of a dependable resale market. Because we wish to isolate the impact of joint bidding, we always allow communication before each auction, whether or not joint bidding is permitted.

Our key result is that when joint bidding is allowed, bidders successfully form efficiency-enhancing joint bids. Joint bidders have higher average valuations and submit higher bids. Solo bidders (the bidders who are not making a joint bid) bid a higher fraction of their valuation when joint bids are allowed. Allowing joint bidding increases efficiency by 11.3% and revenue by 9.4%. We also observe that when joint bidding is not allowed,

[3] Part of the literature on the formation of joint ventures raises similar concerns regarding their net effect on efficiency (d'Aspremont and Jacquemin, 1988; Farrell and Shapiro 1990 and Kamien, Muller and Zang, 1992), with little evidence to reach a broad conclusion (Cassiman and Veugelers 2002; Gugler and Siebert 2007 and Duso, Roeller and Seldeslachts, 2014; Suetens, 2005 and 2008).

some of the groups were able to form bidding rings and were partially successful at implementing collusive agreements (as detected by low sham bids). Much fewer bidding rings were observed in the control treatment with joint bidding.

We are also interested in the role of other auction rules and characteristics of the auction environment. Specifically, we present additional data and discuss the impact of: i) doubling the number of lots offered in order to study the effect of offering “excess supply”. Excess supply resulted in the emergence of collusive bidding rings in three of the four groups and significantly decreased both bids and revenue. ii) Imposing a higher burden of coordination on bidding rings. The “two-bidder rule” is directly linked to Quebec’s auction and procurement regulations. It requires that if the highest bid for a lot lies between the seller’s private reserve price (below which the sale does not take place) and a publicly announced “starting price”, then the lot will only be awarded to the highest bidder if at least one other bid was received. In our experiment, however, the two bidder rule forces bidding rings to submit low sham bids that left a clear trace of collusive behavior in the data. We find that the rule increases auction revenue without affecting efficiency. iii) Introducing two players who, contrary to others, do not have a capacity constraint (they do not pay a penalty for winning more than two lots). When all bidders face this soft capacity constraint, the average bid decreases, but not the average winning bids. Thus, revenue is not affected. Overall, fears that allowing joint bidding might lead to lower bids due to decreased competition did not materialize in these experiments raising hope that they can be employed to increase the efficiency and revenue in auctions where complementarities across bidders exist.

Although we are guided by and we review relevant theory in Section 3, we do not seek to test theory or to perform a micro-behavioral analysis of bidding. The environment developed here is too complex to produce convincing theoretical predictions. Rather, we proceed in the tradition of “wind tunnel” experiments (Cason and Gangadharan, 2004) whereby the experiment itself can be viewed as a prototype of the policy being tested in a laboratory setting. The objective is to assess the mechanism’s performance as a whole and to explore directly how specific rules and components of the environment affect it. This, in turn, can help further refine the mechanism for applications outside of the laboratory.

### A Policy-Based Experimental Design

One hundred and fifty students from the University of Victoria (Canada) participated in experimental auctions in groups of six. Participants were inexperienced subjects, primarily from business and economics (third or fourth year undergraduate or graduate students). Each group participated in a total of 12 auctions (that we sometime refer to refer to as a "session"): 2 practice auctions without real payoffs and 10 paying auctions. Sessions lasted on average two hours and twenty minutes and carried unusually high payoffs for most economics experiments. Subjects received an average (confidential) cash payment of CA$82 for their efforts (ranging between CA$20 and CA$155), with those earnings based entirely on the profits they realized in the auctions.

A session began with oral instructions supported by a PowerPoint presentation. As part of the instructions, a full round of trading was completed in order to familiarize participants with the computer interface and computation of results. Each group of students was assigned to one of five treatments of ten computer-mediated auctions deployed on ZTree (Fischbacher, 2007). Communication between participants was allowed for up to 3.5 minutes per auction.

At the beginning of an auction, each participant was presented with a bidding screen presenting them with all of the data required for the auction. Key components are reproduced as figure 1. From Panel A, we observe that this subject could see 6 squares of private information. Each corresponds to a lot (labelled A to H) on which the participant could bid. The subject's private value for the lot is the sum of values for goods 1 and 2 (representing two different tree species). Each good value is an integer drawn independently from the set [1, 2,… 80] (expressed in Experimental Currency Units or ECU) with equal probability, to mimic a uniform distribution.

On the right side of the screen, a table revealed to everyone who of the six players could bid on each lot. The example of Panel B tells bidders that Lots C and F were offered to bidders 3, 4 and 6, and all others to bidders 1, 2 and 5. Thus, in this round, each lot is offered to three bidders. More generally, a lot was always offered to either all bidders or a subset of three participants. Providing this information is consistent with the realization that in timber auctions, both in Quebec and elsewhere, the likely bidders for any lot are largely determined by geographical location, and that this information is well known within the industry (Price, 2008).

Two other critical pieces of information appeared on the top left corner of the screen (not shown). First is a "penalty per lot in excess of two", equal to 20 ECU except in one of the robustness treatments. In our design, as in real auctions, subjects could bid on all lots they were offered. If lots were perfectly independent from one another, players should bid on every lot presented to them. However, this would have been a major departure from the policy context for timber auctions. In reality, mills have a fixed capacity and a regulatory obligation to harvest lots they win within a fixed time limit. Thus, winning "too many" lots at auction imposes additional transactions costs and exposes the firm to risks of having to harvest but be unable to recoup their purchase price on a thin informal secondary market. To simulate this soft capacity constraint, a penalty of 10 ECU per good (20 per lot) in excess of four was imposed on subjects who purchased more than four goods (corresponding to two full lots) in a given auction. For example, a subject who wins three full lots and one good in a joint bid (a total of 7 goods) would get a penalty of 30 deducted from his profits.

[[ Insert figure 1 approximately here ]]

The second piece of information is the "starting price" kept constant at 86 ECU throughout the experiment. This starting price is part of a central feature of the Quebec auctions that we mimic with the "two-bidder rule". Specifically, the allocation rule for our experiment is constructed around the starting price and a random reserve price drawn from [51, 52 … 60] with equal probability. Bidders know neither the distribution for the draws, nor the outcome in each auction. The reserve price is the absolute minimum at which the seller is willing to sell the lot. However, the two bidder rule states that if the highest bid falls between the reserve and starting prices, the allocation will take place only if at least two bids were received for the lot. Quebec's tendering law has a similar requirement thought to increase the cost of collusion and possibly increase the price in thin markets.

As they consulted their information screen, participants had the opportunity to copy key data to a sheet of paper that generically reproduced Panel A of the computer screen (i.e.

boxes for all eight possible lots but without values printed). They could then stand up and mingle in different parts of the lab in quiet discussions with others. The sheet of paper was added to the design to prevent players from credibly revealing their private values to others. Experimenters strictly enforced that all computer screens be turned off during the communication period. Subjects were also actively discouraged from showing their sheet of paper to one another but the rule was difficult to enforce perfectly. Thus we also suggested during the instructions that participants did not have to copy exact values (e.g. they could copy their real value minus a constant for instance) and could therefore be deceived if shown another participant's sheet. This was done to further reduce the credibility of information about values that was divulged in conversations, since such information cannot be verified in real auctions. For participants in joint bidding sessions, it was clear that finding joint bidding opportunities and concluding agreements was one of the possible goals of the communication period. However, all groups were told explicitly that they could use the communication period to discuss any aspect of their bidding strategies. They were not explicitly told that they could form bidding rings, however, as this would likely have interfered with their endogenous formation.

At the conclusion of each communication period, participants were asked to return to their workstation and enter their bids. Fields left blank were recorded as no bids (zeros in the data) and had no chance of winning. In the case of joint bids, joint bidders had to bid for both goods and also identify who is bidding on each good. These were binding agreements and bids were not accepted by the computer system until the two participants submitted identical bids on their respective data entry screens. Absent a perfect match of the four data fields, the server returned an error message indicating a mismatch.[4] Once all bids were acceptable, the server applied the allocation rules of the treatment (based on the sum of the bids for Goods 1 and 2) and returned the results to players. At the conclusion of an auction, all players received a table indicating the lots they won and their profits, as well as whether

[4] Experimenters monitored the data entry from the back of the lab and helped reconcile those errors. This prevented subjects from having to stand up at this stage of the round and possibly glance at other player's information. It also ensured that other players would not learn the lot for which a joint bid was being fixed nor the bid values required to fix the erroneous entry.

or not each of the other lots sold. Thus, the bid data from subjects remained private and no feedback other than "sold" or "did not sell" was given to a subject who did not win the lot.

[[Insert table 1 approximately here]]

Each auction implements one of four configurations of the lots that players can bid on (information displayed on Panel B of figure 1). These four configurations, presented in table 1, are meant to artificially represent different regional and inter-regional competitiveness scenarios.[5] Competitiveness is constant in region 1 (Column 2) but varies for inter-regional lots (Column 3) and in region 2(Column 4). Although there are 8 lots and 6 bidders in each scenario, competitiveness varies greatly at the lot level (Column 6). Participants were reassigned at random to region 1 and region 2 with each new auction. As such participants did not have a perfect ability to form stable coalitions since they could not count on the next offering to assemble the same subgroup of players. Though the reality in the field could allow more stable coalitions, it is also true that the geographical location of a lot relative to a mill is a strong determinant of who submits a bid. As such, a given mill can finds itself competing against different subsets of competitors for different lots, and making stable coalition formation more difficult.

The array of regional distribution scenarios replicates the decentralized timber management regime implemented in many jurisdictions, including Canadian provinces and in auctions conducted by the U.S. National Forest Service. The four scenarios reflect heterogeneity in the degree of competitiveness that is due to a geographically diverse offering. While such scenarios help us make the design more policy relevant, they also

[5] One can think of the regional distributions as various spatial representations of the lots offered at auction with 3 bidders located in each of two regions. Lots offered can generate an interest from bidders in either one of the regions, or in both (i.e. when they are located near the edge or between the two regions). For instance, scenario 1 has three bidders vying only for 2 lots located in Region 1, while three bidders compete for 6 lots offered in Region 2. No lot is offered that is of interest simultaneously to bidders in both regions. If we look at this auction from the perspective of competition for lots (the last column), we observe that all eight lots offered have 3 potential bidders. At the other extreme, 2 lots are offered exclusively to the three bidders of Region 1 and the other six are of interest to everyone. As a result, the two lots of region 1 can be bid on by 3 players, while the six lots of the inter region can be bid on by all six players.

introduce data limitations. The variation in the offering across the four scenarios inevitably modifies both the menu of lots that individuals can bid on and the degree of competition for the lots in ways that cannot readily be disentangled because of the systematic correlations that exists between these two variables. For this reason and others (e.g. endogenous joint bidding decisions, discontinuous penalties), the data is ill-suited to a fine analysis of bidding strategies at the individual level. Rather, it is built to gain an overall understanding of the effects of the various treatments and to analyze whether the treatments perform differently when deployed under different regional configuration scenarios. As such, the regional configurations can be viewed as an enhanced stress-test for the auction rules and environmental conditions of each treatment.

All the analysis is conducted by comparing moments of distributions across all auctions in a given regional distribution and across regional distributions. This is made possible by the fact that for all sessions, each regional configuration was played once (in random order) in the first four rounds, and once again in random order in rounds 5 to 8. Finally, scenarios 1 and 3 were played again in a random order in rounds 9 and 10. This keeps constant across all groups the number of repetitions of each scenario, the total number of lots offered to individuals, and the overall level of competition for lots. The randomization of each scenario's order of appearance should eliminate possible order effects. However, given the relatively small number of sessions over which we randomized, we chose to force each scenario to appear once in the first and second groups of four auctions in order to ensure that all groups faced all possible scenarios in the early part of their experiment. The analysis we perform, therefore, does not discuss the variations in regional scenarios other than in the robustness section where we show that the aggregate results hold when we look at the four regional distributions separately.

We conducted two main treatments to study the effect of joint bidding and three robustness treatments. The base treatment is the joint bid treatment [T0]. It corresponds most closely to the field conditions envisioned by the agency responsible for the management and sale of Quebec's public forests. All other treatments use the same design, except for the features mentioned.

- Joint Bid Treatment [T0(Control)]. Complete package of auction rules: (a) Eight lots are offered; (b) Joint bidding is permitted; (c) A penalty of 10 ECU is billed for each good won in excess of four goods; (d) The two bidder rule applies.
- No Joint Bid Treatment [T1(NoJ)]. Joint bidding is not allowed.
- Robustness Treatment [R1(x2)]: Excess Supply. 16 lots rather than 8 are offered in each auction and these sessions allow for 6.5 minutes of communication instead of 3.5. We will compare R1(x2) both with T0 and to another treatment identical to T0 but with 6.5 minutes session length. In doing so, we can separately measure the impact of excess supply.
- Robustness Treatment [R2(No2B)]: No Two-Bidder Rule. Lots are allocated to the highest bid greater than or equal to the random reserve price irrespective of the total number of bids.[6]
- Robustness Treatment [R3(Dom)]: Unconstrained Dominant Players. Two of the six players have unlimited capacity and therefore do not face a penalty if they purchase more than 2 lots (4 goods).

**Some Observations on Joint Bidding, Communication and Collusion**

Allowing joint bidding may change the auction outcomes through multiple channels. The experimental design allows players to interact, exchange information, and make both explicit joint bidding agreements and implicit collusive agreements. Unstructured interactions change bidder's information sets and influence bidding in ways that are difficult to capture with simple models. Nonetheless, we use this section to make some general guiding remarks on the impact of allowing joint bidding on bid levels and efficiency.

[6] The Government of Quebec's regulations require a total of three bids (rather than two) for the sale to be executed when the highest bid falls below the announced starting price. We require two bids instead of three since it would not be possible to allocate a lot at a price below the starting price when the lot is only offered to three players and two of them choose to bid jointly.

We also review the literature on collusive agreements in auctions and discuss implications for our experiments.[7]

*Efficiency Effect: Value Distributions*

As we alluded to earlier, allowing joint bids could result in substantial efficiency gains by allowing two potential bidders to combine their high values for the two species growing on a lot. Here, we illustrate for our experiment the underlying distributions of value that single and joint bidders bring to an auction. To keep the focus on bidding strategies, assume that joint bidders randomly match (they may in fact be able to form better than random matches, but the objective here is simply to illustrate the potential for efficiency gains).

In our experiment, the private value of the lot to player *i* is the sum $V_i = v_{i1} + v_{i2}$ where each of $v_{i1}$ and $v_{i2}$ is an iid random integer variable drawn from the interval [$v_{min}$, $v_{max}$]=[1,80]. This data generating process is analogous to rolling two six-sided dice and computing the sum. The probability of drawing the lowest possible total (*V*=2) is low, it increases until the mean (and median) *V*=81 (seven in the case of two dice) and decreases until the maximum value of 160). The resulting probability density function is symmetrical and the change in probability as *V* increases is stepwise linear. The cumulative density function (CDF) is drawn as a solid line in figure 2.

Now consider two players who meet randomly. Abstracting from all strategic considerations, suppose that if they find that they have complementary values ($v_{i1} > v_{j1}$ and $v_{i2} < v_{j2}$ or with both inequalities inverted), they form a joint bid selecting the two high values as the basis of their bid. If they do not have complementary values, they part ways and would bid individually. The two conditional distributions (conditioned on the event that values are complementary) are also shown in figure 2 from a simulation of 2.5 million pairs drawn. For our own experimental parameters, single bidders (no matching or after a failed match) have mean and median values at 81. However, the mean and median total value for joint bidders are 108 and 110 respectively.

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[7] DeBrock and Smith (1983) conduct a similar analysis in the case of incomplete information (common value auction) and without bundle goods. They find that the positive impact of joint bidding on efficiency likely dominates the negative aspects.

[[ Insert figure 2 approximately here ]]

It is clear that the distribution for successfully matched joint bidders stochastically dominates the other two distributions. As an entity, therefore, joint bidders gain a direct advantage over other bidders in the auction. One could admittedly construct other distributions based on different behavioral assumptions during the communication period. For instance, one could compute the best possible match in a group of three or six players, or consider more than one attempt at finding a match. In general, we would expect these distributions to create even better matches than a single random encounter. Thus, figure 2 can be viewed as the minimum shift in value that can occur when joint bids form endogenously with the goal of finding bidder complementarity.

The joint bidder distribution can also be viewed as a partial representation of the potential efficiency gains from joint bidding. If one assumes that there is no pre or post auction trading of timber resources, and therefore that joint bidding is the only mechanism that allows the best allocation of the two species found on a lot, the rightward shift of the distribution is representative of the higher values brought about by the partnership.

*Strategic Effects: Decrease in the Number of Bidders*

Joint bidding reduces the number of bids submitted and, everything else equal, bidders bid less aggressively when there are fewer bidders. To illustrate this point, assume a standard first price sealed bid auction for a single good (i.e. one without all of the rules added to our experiment), where $n$ symmetric bidders with an i.i.d valuation from the uniform distribution on [0,1]. This distribution of valuations is more convenient than the triangular distribution used in our experiment since it delivers a closed form solution. Vickrey (1961) was the first to derive the Nash equilibrium bidding strategy, from which is inferred that the equilibrium expected profit of a bidder with private value $v$ is equal to (Vickrey, 1961)

$$U(v,n) = \frac{v^n}{n} \tag{1}$$

Suppose now that two bidders with identical valuations make a joint bid and split the profits evenly. The number of bids decreases from $n$ to $n\text{-}1$. The bidders who make the joint bid will benefit if

(2) $$\frac{1}{2}U(v, n-1) > U(v, n)$$

or $v < \frac{n}{2(n-1)}$. For n=3 the inequality holds if $v$<3/4. For n=4, this inequality holds for any v<2/3. In other words, it is easy to find situations where joint bidding is beneficial to auction participants simply because it reduces the number of competitors. Keeping in mind that our distribution of valuations is triangular instead of uniform, defined over integers instead of a continuous interval, and has different supports, this nonetheless illustrates that reducing the number of bidders alone can be a strong motivation for joint bidding, independently of the degree of complementarity between bidders' valuations.

*Overall Effect on Bidding Strategies*

Let's return to the point that joint bidders have higher distributions of valuation than individual bidders. By virtue of their stochastically dominant value distribution, joint bidders become dominant bidders relative to individual bidders. Chermonaz (2012) derives the net impact of the two effects discussed above for simpler distributions: (a) a reduction in the number of bidders as discussed above and (b) an asymmetry in bidders' valuations. He considers joint bidding with three bidders. As in our experiment, joint bidding reduces the number of bidders to two. He leverages previous work by Lebrun (1999) and Maskin and Riley (2000) to show that (under general assumptions) the strong bidder (producing the joint bid) always bids a smaller fraction of her valuation than the weak (individual) bidder. In one example based on a different distribution of valuation than the one used in our experiment, Chermonaz shows that the bidding functions of the weak and strong bidders lie between the bidding functions used by two and three symmetric bidders. Thus, a joint bidder against an individual bidder bids less aggressively than three individual bidders but more aggressively than two individual bidders.

*Collusion, Communication, the Two Bidder Rule, and Low Bids*

An important concern with joint bidding is that some form of communication between bidders has to be allowed. Bidders can use these interaction opportunities to make implicit market splitting agreements. Pesendorfer (2000) and Klemperer (2004) note that few auction markets and indeed few markets of any kind are immune to tacit or explicit collusion.[8] There are many ways players could collude but a simple way to do so is to split the eight lots offered in an auction between the six players. Note that tacit collusion is possible even in the absence of explicit communication. In repeated auctions, for example, bidders can send signals through bid levels, both in our experiment and in real life. An important issue, thus, is whether allowing joint bidding changes the ability of auction participants to collude, independently of changes in the ability to communicate. For this reason, our design allows communication in all treatments, consistent with the inability of most regulators to control interactions between bidders who repeatedly meet.

The cost of this design choice is that bidding strategies may deviate from the one-shot Nash equilibrium benchmark that is used in the structural empirical auction literature to analyze independent auctions outcomes where it is reasonable to assume players are unlikely to interact again as in eBay auctions (Laffont and Vuong, 1996, Bajari and Hortacsu, 2005). However, the one-shot single-unit auction benchmark is not a realistic benchmark for our application. With multiple units and repetition, there is typically a large range of collusive equilibria, and folk theorem results apply as long as bidders care sufficiently about the future (Fudenberg, Levine and Maskin, 1994; Athey and Bagwell, 2001; Marshall and Marx, 2007).[9] In fact, the theoretical literature on collusion in auctions shows that under a variety of circumstances (type of auction, number of players and items auctioned, repetition, information conditions, etc…), there exists collusive equilibria whereby ring members find it in their interest to refrain from competing with each other (see for instance Graham and Marshall, 1987; Garratt, Tröger amd Zheng, 2009; Marshall and Marx, 2007). The complexity of collusion, however, greatly limits the power of theory. The literature is focused on proving the *existence* of collusive equilibria, characterizing the equilibria's efficiency, and analyzing the effect on auction prices.[10]

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[8]See also Isaac and Walker (1985), Burtraw, et al, 2009; Kwasnica (2000), and Dia (2011) for discussions of collusion in experiments.

[9] In our experiments, subjects were not told how many rounds of auctions they would be participating in, effectively making future interaction probabilistic from their perspective.

[10] Some form of communication between cartel members is always assumed in models of explicit collusion and adding pre-play communication can further expand the set of possible equilibria (Matthews and Postlewaite, 1988). The collusive mechanism requires some communication but without a structural model of this communication, the theory cannot provide guidance or testable hypotheses on the equilibrium selection process. There is also a vast literature where pre-play communication (cheap talk) is allowed in

In the absence of testable predictions, empirical work on the detection of collusion has employed reduced form analyses rather than structural models, and is focused on detecting bid distributions that depart from the better understood competitive equilibrium one-shot bidding strategies. For instance, low value bidders in a collusive agreement may submit low sham bids that are correlated and thus inconsistent with competitive behavior. Several papers follow this approach (Hendricks and Porter, 1989) and report results consistent with collusive behavior for the procurement of school milk program (Porter and Zona, 1999; Pesendorfer, 2000), highway construction contracts (Gupta, 2001 and Porter and Zona 1993), building construction (Bajari and Ye, 2003) and for logging rights (Baldwin et al, 1997; List, Millimet and Price, 2008).

We follow a similar descriptive approach here: we compare bids-to-value ratios across treatments and look for heterogeneity across groups within a treatment to document equilibrium multiplicity. In addition, the two bidder rule offers a unique window into collusion. With a collusive agreement, the two bidder rule forces the presence of a sham bid if the chosen winning bidder intends to bid below 86 ECU. The minimum acceptable bid in our auctions is 2 ECU (1 ECU for each good in a lot) since not bidding was allowed but actively submitting 0+0 or 0+1 was not. In the course of the experiments, we noticed many agreements leading to sham bids of 1+1=2.[11] These observations are confirmed in the data. Thus, the two bidder rule can help us detect some collusive behavior. Clearly, low bids can also be genuine attempts at scooping a lot in the event that both the demand and secret reserve price are very low. If low bids are collusive, however, we would expect that their presence on a lot would lead to other bids being lower than for similar lots where no collusive low bids have been submitted. This prediction differentiates the collusion and 'market scooping' hypothesis. Thus, the two bidder rule might leave a positive trace of market splitting collusion in the data, something rarely seen in experiments or field data.

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economics experiments. In some cases, the game played has multiple equilibria and communication can help coordination (e.g. in the battle of the sexes studied by Cooper et al, 1997).

[11] While it is possible that colluding bidders could enter sham bids above two, we find many bids equal to two and few low bids above. Being conservative, we use the number of bids equal to two as a proxy in our tests of collusion. We expand the analysis of bids of two below.

## Results

The main dataset is made up of 23 groups of six students each participating in 10 auctions (we will discuss two additional groups in relations to the amount of communication time allowed). Table 2 provides a breakdown of the data by treatment. A total of 2,160 (8x10x19+16x10x4) lots were offered at auction for a total of 8,910 lot-persons. In other words, if every subject had submitted an individual bid on every lot they could bid on, a total of 8,910 bids would have been made (we drew a total of 17,820 random values in our experiment).

We report tables and figures that aggregate the data at the treatment level (i.e. aggregated across all auctions and all four regional scenarios). Similar data broken down by regional scenarios (see table 1) are presented in the online appendix (when the number of observations warrants this breakdown). Aggregated and disaggregated results (in regional scenarios) show a high degree of conformity. For this reason, we provide the disaggregated data in the online appendix to the journal, but we only discuss them briefly in the robustness section.

We begin by comparing the base treatment with joint bids (T0) to the treatment without joint bids (T1NoJ) corresponding to the first two columns in tables 2 to 7. In the robustness section, we discuss the three additional treatments (last three columns of the tables). We start by describing bidding behavior and follow with an analysis of winning bids and their effect on auction revenue and efficiency.

*General Bidding Patterns*

When comparing columns one and two in table 2, a couple of preliminary observations are worth making. When joint bidding is allowed, about one out of five bids are joint. This demonstrates that players make extensive use of joint bids. Recall that joint bidders have to overcome two hurdles: (a) non-trivial search to find a player with 'strategically attractive' valuations in order to increase the gains from joint bidding (b) bargaining under asymmetric information in order to share the joint surplus. As a benchmark, note that if all possible joint bid opportunities were exploited, a session of ten auctions would produce 140 joint bids and 50 single bids (lots with three potential bidders necessarily force single bids). Thus, the maximum possible proportion of joint bids in the data is 73.7%. It is difficult to say whether the observation that 19.4% of joint bids submitted in T0 is high or low relative to that upper bound. What is important, however, is that this figure is large enough to have an economically significant impact on revenue and efficiency.

[[Insert table 2 approximately here ]]

As expected, joint bidders have higher combined valuations than individual bidders. Figure 3 plots the empirical cumulative distribution of lots valuations for individual and joint bidders. The former stochastically dominates the later. Taking averages, joint bidders have valuations that are about 30% higher than individual bidders (120.5 vs. 86.5). Several effects are at play. One effect was illustrated earlier with figure 2 under the assumption of random matching.

[[Insert figure 3 approximately here ]]

That's not the only effect, however. Joint bids are not drawn from a random sample of valuations. Instead, those who enter joint bidding agreements have private lot valuations (prior to agreeing to bid jointly) that are greater on average than individual bidders (88 versus 76 and the difference is statistically significant). In addition, each participant in a joint bid has valuations for the two goods that are more heterogeneous than individual bidders. The average of the absolute difference between the two good values ($|v_{1i} - v_{2i}|$) for players who make joint bids is 34, while it is 24 for individual bidders (the difference is highly significant). This supports the view that the formation of joint bids is driven by a search for complementarity among bidders who have at least one high value and a wide spread between their two valuations.

Turning to bidding behavior, note from table 2 that the percentage of bids equal to zero varies significantly across treatment. Since there are no entry costs, we should expect all bidding opportunities to be taken by participants. It is possible that subjects have understood that very low bids cannot win because of the existence of a reserve price or that some participants in collusive arrangements abstain entirely from bidding. Note however that the difference between the joint bid treatment, T0, and the no joint bid auctions T1(NoJ) is striking (23.3% versus 12.6%), and in the opposite direction of the difference in the percentage of bids equal to two (2.9% versus 19.6%). When players cannot make joint bids, they often make bids of two rather than not bid. The proportion of bids equal to the announced starting price of 86 is slightly higher when joint bids are not allowed. Bidders bid 86 to ensure that they are not subject to the two bidder rule. Thus, it would appear that prohibiting joint bidding increases the frequency of collusive behavior (measured by the frequency of bid of two; a sensible measure as argued in Subsection 4.3), but also leads to a greater number of bids where individuals without a market splitting agreement feel compelled to bid 86 to avoid the risk of being disqualified if no other player submitted a bid.

*Bids and bid-to-value ratios*

We now turn our attention to bid levels across T0 and T1(NoJ). Figure 4 plots all positive bids as a function of the bidder(s)' underlying total value for the lot. It allows for a bird's eye view of the dataset, with individual bids showing in clear dots and joint bids in dark dots. Several interesting patterns emerge. To start, most bids are below the 45 degree line. This shows that bids giving negative expected profits (that could be mistakes due to inattention, for example) are rare. Bids are increasing in valuation with a mild concave shape over high valuations. The graphs also reveal the high number of bids equal to two (horizontal line at two) previously noted.

Two further points emerge: there are very few data points between the line at two and the main cloud just below the 45 degree line. This further supports the collusion hypothesis. One would have expected more continuity between these two sets of points under the 'market scooping' hypothesis. Moreover, some of the players with very high valuations make bids equal to two and this is particularly pronounced in the no joint bid treatment T1(NoJ) and the Excess supply treatment R1(x2). This is surprising because these lots carry a high probability of a win and therefore high expected profits in a normal auction. Again, it is difficult to rationalize this behavior without appealing to a market splitting argument.

[[ Insert figure 4 approximately here ]]

Tables 3 and 4 more precisely describe the difference in bidding behavior between T0 and T1(NoJ), presenting individual and joint bids together and separately. Averages expressed in experimental dollars are presented in table 3, while table 4 is expressed as the bid-to-value ratios. We report statistics on all individual bids as well as those greater than 2 only in order to separate the effects of strategic bids.

[[ Insert table 3 and table 4 approximately here ]]

Table 3 reveals important differences in bidding behavior:

(1) Overall bids are much higher when joint bids are allowed (73.7 versus 55.0) and this holds even when we consider only bids above two (75.8 versus 67.9).

(2) In the joint bid treatment, joint bids are significantly higher than solo bids (93.0 versus 69.0).

(3) Even when we compare individual bids above two, we still find higher bids when joint bid are allowed (71.6 versus 67.9).

Allowing joint bids generates an asymmetry where joint bids dominate individual bids and it increases the overall aggressiveness of bids of both joint and individual bidders. Table 4 further establishes this point by looking at bid to value ratios. All bidders bid a larger fraction of their value when joint bids are allowed (79% versus 76%). Individual bidders also bid a larger fraction of their valuation in the joint bid treatment (they bid 76% in T0 versus 79% of their valuation in T1(NoJ)), consistent with standard predictions for weak bidders. However, joint bids in T0 are also more aggressive than individual bids in T0, a fact not easily reconciled with their dominant bidder position in an auction they know has one fewer potential bidder.

*Bid of two and the detection of Collusion*

One may question whether the bids of two are a sign of collusion. Under the collusion hypothesis, a bid of two is an umbrella to shield another (higher) collusive bid from the two bidder rule. Since we observe many bids of two in R2(No2B) where the two bidder rule was not in effect, the data clearly contains legitimate bids of two that are unrelated to collusive actions. However, if bids of two are collusive, they should happen in conjunction with less aggressive bids on the same lot.

This leads to the hypothesis that bids and bid-to-value ratios of bids greater than two should be lower when there is a bid of two on a lot than when there is not. This prediction is specific to the collusive hypothesis. To test it, we divide the bids greater than two into those for which another bidder has submitted a bid of two on the same lot, and those for which no bid of two was submitted. When joint bids are allowed in T0, we find that the average bid is 72.5 when there is a bid of two on the same lot and 76.0 when it's not the case. The difference for bid-to-value ratios is even more pronounced (70.9% versus 79.3%). Similar observations are made in T1(NoJ) where joint bids are not allowed. Bids average 64.4 when a bid of two is also submitted and 68.9 otherwise. The bid-to-value ratios are 68.5% and 76.7% respectively. The same pattern emerges if we look at the winner's average profit margins (value appropriation) measured by subtracting bid-to-value ratio from one.

Overall, we conclude that the presence of bids equal to two is often a signal of the existence of collusive bidding arrangements. Interestingly, the 2.9% and 19.6% fractions of bid of two in T0 and T1(NoJ) conceal significant heterogeneity within treatment across groups. Looking at the data at the group level, we find that the percentage of bids of two ranges from 0.0% to 14.9% across the six groups in T0 and from 0.0% to 52.3% across the four groups in T1(NoJ). If we take high frequencies of bids of two as an indicator of collusive bidding then, the large variations in the use of bids of two across groups suggests that collusion is possible but not an unavoidable curse. Still, it must be pointed out that the presence of collusion (measured by the fraction of bids of two) is significantly lower on average across all groups with joint-bidding. Without joint bidding, the group with the most collusion in T1(NoJ) had a profit margin averaging 23.6% of the value of the lot while the two least successful groups managed to appropriate only about 14%. To sum up, bidding rings have formed only in some groups and have significantly increased bidder profit margins.

*Auction Performance: Revenue*

The bid-to-value ratios identified above provide a representation of the competitive pressure felt by bidders. Ultimately, however, only the winning bids determine the overall performance of the auction in terms of the seller's revenue. Table 5 reports the bid-to-value ratio of lots won and allocated in the auctions. The data presented are to be interpreted as the descriptive statistics of the proportion of winner's value that is captured by the seller through the sale price (thus excluding lots not sold). For example, the seller appropriates 84% of the bidder's value in T0 while the bidder's profit margin, or information rent measured in percentage value terms, is 16%.

[[Insert table 5 approximately here ]]

Winners in T1(NoJ) bid on average the same proportion of value as winners in the base treatment (84% and 83% are not statistically different). Recall, however, that the distribution of valuation in T0 stochastically dominates the distribution of valuation in T1(NoJ). Thus, while the profit margins on the lots are equal, the total revenue in T1(NoJ) are bound to be lower since no value-enhancing joint bids can be formed. This is confirmed in the first line of table 6, showing that the absence of joint bids depresses winning bids: the mean auction revenue is 9.4 percent lower without joint bidding (673.9 versus 737.5).

The next row in table 6 shows that the maximum possible mean revenue is 1040.1 for the joint bid treatment but only 911.28 without joint bids. This is computed differently for the no joint bid treatment and all other treatments. For T1(NoJ) it is computed as the average across all auctions of the sum of the highest individual valuations across all potential bidders. This maximum total revenue, therefore, is simply the revenue the seller would have obtained if the bidder with the highest value won the lot and paid exactly that value. For the other four treatments, the maximum possible revenue is the sum over all lots of the highest possible total value, where the values of the two goods do not have to be from the same bidder (i.e. allowing of the highest values to come from joint bids whenever beneficial). The last line shows the mean over all auctions of the percentage of revenue in an auction divided by the maximum possible revenue (this mean of the ratios is close but not exactly the same as the ratio of the means obtained by dividing numbers in line 1 by those in line 2). The results confirm that when joint bids are prohibited, a similar proportion of potential revenue is actually achieved, but overall revenue are substantially smaller than when joint bids are allowed. This is the result of the inability of bidders to form welfare enhancing joint bids.

[[ Insert table 6 approximately here ]]

*Auction Performance: Efficiency*

Of importance to economists and policy makers is the ability of auctions to efficiently allocate the lots being sold. In the case of forestry auctions for bundled goods, one important criterion to judge the different auctions is their ability to allocate each lot and its component parts to the bidder with highest value (allocative efficiency). The benchmark used for computing the level of efficiency realized in our auctions is the optimal allocation of each good for that auction, net of the reserve price of the seller (forest plots are not lost if not sold), and accounting for the penalties imposed by allocating more than four lots per bidder.[12] We compare the gains in this benchmark allocation against the gains actually realized empirically by players in each auction. This is equal to the sum of the values realized by buyers for all of the goods sold minus the reserve price of sold lots and the penalties assessed on players. To normalize the results across auctions, we take the ratio of realized surplus to the surplus in the optimal allocation. The result is an efficiency index

[12] The benchmark is the socially optimal allocation of goods (i.e. half lots) for each auction. This benchmark was obtained by first allocating each good to the participant with the highest value for that good (but only if the sum of the highest of $v_1$ and $v_2$ across all buyers for that lot is higher than the lot's reserve price, otherwise it would be suboptimal to sell the lot since efficiency would call for the lot to remain unsold in the final allocation). Recall that penalties in our design are meant to represent true costs (transactions or otherwise) associated with purchasing stands in excess of capacity. As a result, penalties resulting from the initial allocation of goods were subtracted from the buyer values in the initial allocation. In a second stage, the presence of penalties triggered an algorithm exploring whether any good in an allocation that resulted in penalties for a player could be reassigned to the next highest value user. A modified allocation is superior to the initial one if a player can be found who has a value for the good no more than 10 below the value to the buyer in the initial allocation if the reallocation to the second buyer would, overall, eliminate a penalty of 10.

between zero and one that represents the proportion of the total surplus available in an auction that actually gets captured in the experiment.

Table 7 presents the descriptive statistics and figure 5 pictures the cumulative distributions of efficiency levels for the different treatments. Inspection of those results reveals a significant drop in efficiency when joint bids are not allowed. Looking at means, for example, reveals an efficiency level of 77.6% with joint bids and 69.7% without joint bids. The baseline level of efficiency of 69.7% is due to the facts that lots are sometimes unallocated, not allocated to the highest bidder, or the allocation results in higher penalties than in the optimal allocation. Despite these costs and the complexity or having 8 lots, T1(NoJ) captures a significant fraction of the potential surplus. The main point, however, is that allowing joint bids increases overall efficiency by 11.3 percentage points, which is an economically significant improvement.

[[ Insert table 7 and figure 5 approximately here ]]

**Robustness: No Two Bidder Rule, Excess Supply, and Capacity Constraint**

As we have seen, joint bidding has a significant and positive impact on bid levels, revenue and efficiency in the experimental setting of our auctions. Are these effects sensitive to the characteristics of the auction environment? Furthermore, it is worth asking whether those results hold across the various regional scenarios. The online appendix breaks down the results across the four regional distributions of players and lots. Each distribution has eight lots (sixteen in R1(x2)) and six players. When comparing T0 and T1(NoJ), all of our conclusions hold in each regional scenario in the sense that the direction of the impact of allowing joint bidding remain the same (though in some cases, the smaller sample sizes make the differences not statistically significant). In this section, therefore, we focus our attention to comparing the results in two sets of robustness treatments against the baseline treatment (T0). The first set of robustness checks looks at the effect of doubling the supply of lots and the role of the time constraint on communication (R1(x2) and T0 with long communication times). The second considers the removal of the two-bidder rule

(R2(No2B)), and the third removes the soft capacity constraint (penalties for buying more than 4 goods) on two players (one in each "region") (R3(DOM)).

*Excess Supply (R1(x2)), Long Communication Period, and Collusion*

The excess supply treatment (R1(x2)) differs from T0 in two dimensions: the number of lots offered in an auction was doubled from 8 to 16, and the length of the communication period was increased from 3.5 minutes to 6.5 minutes. Thus, we compare R1(x2) both with T0 and with two additional groups of T0 were we also allowed 6.5 minutes of communication (T0 Long).[13] A triangular comparison of T0, T0 Long and R1(x2) allows us to understand the role of the communication time constraint and excess supply.

Because subjects could use communication time to find joint bidding partners or to reach some form of collusive agreement, it is possible that with a tight time constraint the search for joint bidding partners might crowd out collusive agreements. This could explain why we observe less collusion (measured by the frequency of bids of two) when joint bids are allowed. To address this issue, we first compare T0 and T0 Long. We find that with extended communication time, (a) the fraction of joint bids increases by about 5.5 points (24.9 versus 19.4); (b) we do not find more bids of two in the long treatment relative to the short one; (c) the revenue as a fraction of winner's value is slightly lower in the long treatment relative to the short one although the difference is not significant, (d) the percentage of the maximum auction revenue captured by the seller is the same both treatments, (e) efficiency is about 7 percentage points higher in the long treatment and this difference is significant. Increasing the communication time increases the winning values (consistent with complementary matches) but does not decrease the bid-to-value ratio or the number of bids of two (no change in collusion). These findings are consistent with the casual observation that most participants in these two groups returned to their computer to enter their bids before the end of the communication period. They could have used the spare time to collude but they did not. Thus the earlier finding that collusion decreases with joint bidding cannot simply by the time constraint.

[13] We only collected data from two groups to make sure that results did not appear to hinge on the communication time. For this reason, we do not report detailed data in the tables.

Increasing the supply of lots offered significantly decreases the proportion of bids that are joint and increases the number of bids of two significantly (32% of bids are equal to two against 2.9% in T0). Again, we check the collusion hypothesis by comparing the average bid level and bid-to-value ratio for bids that are made on a lot where a bid of two is also entered and for lots where no such bid is made. Although bid levels are similar across the two groups, we find a significant difference in bid-to-value ratios (65.1% versus 71.2%). These results hint at a significant lack of competitive bidding and an increase in collusive behavior when there is excess supply. Consistent with this interpretation, table 5 shows that bidders bid a smaller fraction of their valuation and table 6 shows a significant decrease in revenue as a fraction of maximum possible revenue. Efficiency levels in this treatment are only marginally lower than in T0 and the difference is not statistically significant. It suggests that despite their anti-competitive nature, the bidding rings formed in this treatment are effective at allocating goods to the player with the highest value. To sum up, a decrease in the overall level of competition caused by excess supply induces more collusion, lower auction revenues, but does not change efficiency.

Overall, it is difficult to predict when collusion, measured by the percentage of bids of two, takes place. We observe very few bids of two with joint bidding (both in the regular treatment (T0) and in the two long sessions with the same number of lots). There are, however, a large fraction of such bids in T1(noJ) where joint bidding is not allowed, and in R2(x2) where joint-bidding is permitted and a large supply of lots is offered. Recall that collusion also greatly varies across groups in T1(NoJ) and T0 and this holds for the other treatments as well. Collusion is successful: it transfers surplus from the seller to bidders. But the variability in success across groups suggests that collusion is uncertain. Although the experimental evidence cannot allow us to reach definite conclusions on the determinants of collusion, it suggests that potentially complex interactions could be at play between joint bidding and the balance of supply and demand. It is also possible that, consistent with a multiple equilibrium scenario, collusion is a complex coordination problem that some groups manage to solve, while others simply don't.[14]

[14] From a theoretical perspective joint-bidding has two effects on collusion: (1) It introduces dominant bidders (see Figure 2); (2) it greatly increases the number of candidate deviations from a collusive agreement because incentive compatibility now applies to deviations by pairs of players in addition to individuals. One may speculate that

Treatment R1(x2) also points to the importance of maintaining a tight control over the supply of lots in an auction if the sellers' objective is to maximize the revenue per lot or to obtain bids that more closely reflect underlying values. It appears that excess supply is detrimental to both objectives as it makes it easier for players to divide the market and avoid competition for lots. In the context of field auctions, this makes it more difficult to properly manage public forests. On the one hand, supply must be sufficiently tight to create scarcity and competition on the auction market, but this runs the risk of choking the industry if the supply of timber is accidently set too low to allow proper functioning of the industry. In general, mills should be allowed to maintain private forest reserves or baseline access to public forests, making the auction the source of their marginal supply needs only. Auctions can be used as the instrument of marginal sales from which stumpage fees can be set for the baseline supply as well.

*No Two Bidder Rule (R2(No2B))*

Referring back to table 2, note that removing the two-bidder rule leads to an increase in the propensity to bid jointly (27% versus 19% of joint bids), a decrease in bids at the starting price of 86 and a small increase in the number of bids equal to two. We do not have a solid explanation for the increase in the proportion of bids submitted jointly, although it may be argued that if the two bidder rule is in place, joint bids below 86 for mid-value lots have a relatively small chance of success when there are only three potential bidders. The significant difference in the proportion of bids equal to 86 demonstrates that players understand the strategic value of bidding the starting price in order to escape the two bidder rule under T0 (bids at the starting price appear to be regular occurrence in Quebec timber auctions as well). More importantly, tables 4 and 5 show that players bid less aggressively in the absence of the two bidder rule. As a result, auction revenue is lower on average (700.5 versus 737.6) and the difference is not significant but this is partly explained by the fact that the number of observations drops dramatically when we aggregate data at the auction level. There is no significant change in efficiency, however. We conclude that

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these two channels could have a negative effect on collusion. However, we are not aware of any theory that addresses the issue.

the two bidder rule increases bid aggressiveness and auction revenue but does not affect efficiency.

*Unconstrained Players (R3(Dom))*

Unconstrained players do not face a penalty for purchasing more than two lots like other players do. De facto, these players can realize the full face value of a lot while the other players must adjust their bidding to account for expected losses once the two lot capacity has been reached. Much like the formation of joint bids creates strong and weak players, removing the penalties for two players in a group can be thought also as creating stronger bidders. The difference is that players are now asymmetric ex-ante, that is, before matching takes place. The treatment with unconstrained players has fewer joint bids relative to individual bids and a smaller percentage of 'no bids' relative to T0. This is consistent with the fact that dominant bidders face no penalty for purchasing more than two lots. We also find slightly more bids of two relative to T0. Bid-to-value ratios are significantly higher than in T0 (.80 versus .78), although the share of surplus appropriated by the seller does not change. Efficiency under R3(Dom) is slightly higher but this difference is not significant. The increase in efficiency is likely attributable to the lower overall penalties resulting from removing the capacity constraint on two players.

## Summary and Conclusions

We study the impact of allowing joint bidding in simultaneous multi-units first price sealed bid auctions for bundled goods on bidding behavior, revenue and efficiency. Joint bidding increased efficiency by 11.3% and revenue by 9.4%, and overall, winning bids came in as similar proportions of the underlying values. The efficiency gains from joint bidding clearly outweighed the reduction in competition that takes place when two bidders become one.

When no joint bids are allowed, we observed a significant increase in the number of collusive bids, and both total revenue and efficiency fell significantly. Collusion was also detected when a large number of lots were offered simultaneously and joint bidding was allowed but there is significant heterogeneity in the ability of different groups to collude. The overall results suggest that permitting joint bidding can result in substantial efficiency gains and increase revenue. Yet, the fact that some groups of students managed to collude should give pause to policy makers and point to the need to carefully monitor anomalous bidding patterns in field auctions.

We also explore the robustness of the results to characteristics of the auction environment that are relevant in the timber auctions context. Excess supply produces the most collusion: while efficiency remained high, winning bids and auction revenues were substantially lower when supply was doubled. The removal of capacity constraints and the removal of the two bidder rule have less impact on the results.

The research has immediate applications to forest stands that arbor a mixture of species. The auction treatments capture important environmental conditions and auction rules in the complex but policy relevant context of timber auctions implemented in Quebec. Overall, the results are cautiously supportive of the set of rules considered by the government of Quebec in its timber auctions. Although there is little evidence that rules requiring a minimum number of bids are effective at discouraging collusion in the laboratory, the results suggest that these rules can help detect collusive bidding.

While joint bidding was generally beneficial in our experiments, the specific context and rules deployed here prevent a direct transfer of those results to other settings. However, several insights from this research (joint-bidding increases efficiency and revenue, using a "two-bidder" rule to detect collusion, warning about excess supply, to name just a few) are relevant not only to timber markets but also extend to joint bidding schemes already existing in procurement auctions and contemplated in environmental conservation programs. As Latacz-Lohmann and Schilizzi (2005) suggest, and as we demonstrated here, experiments can be an effective first step to gain traction of the multiple impacts of joint-bidding and help identify possible faults to guide further mechanism refinements.

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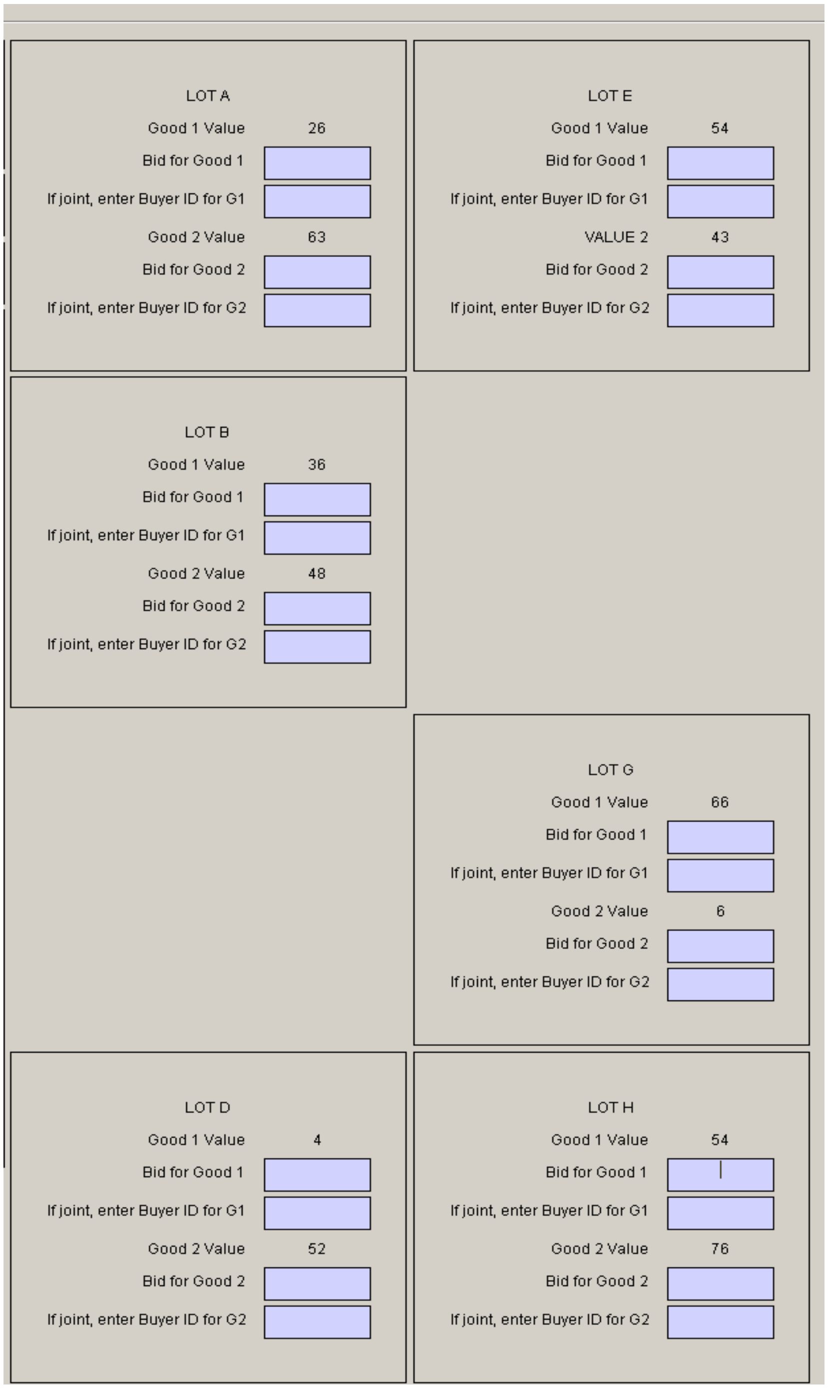
**Panel A**




**Panel B**

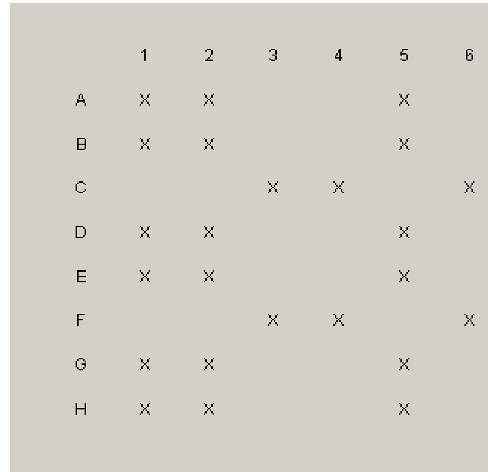



**Figure 1. Participant information and bidding screen**

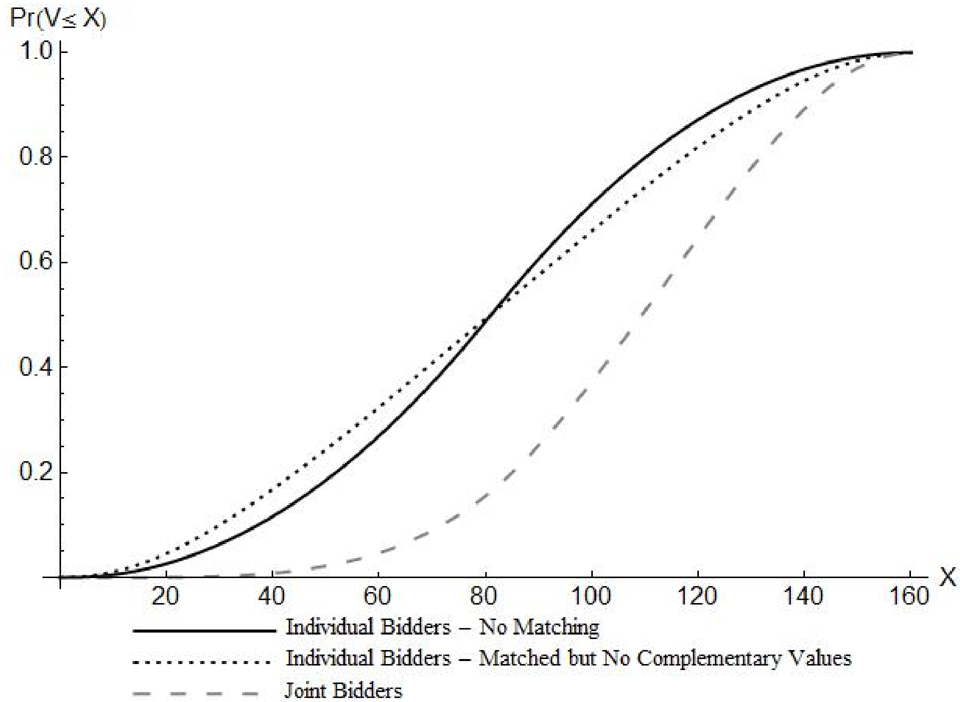



**Figure 2. CDF of induced values for an individual bidder and a joint bidder**

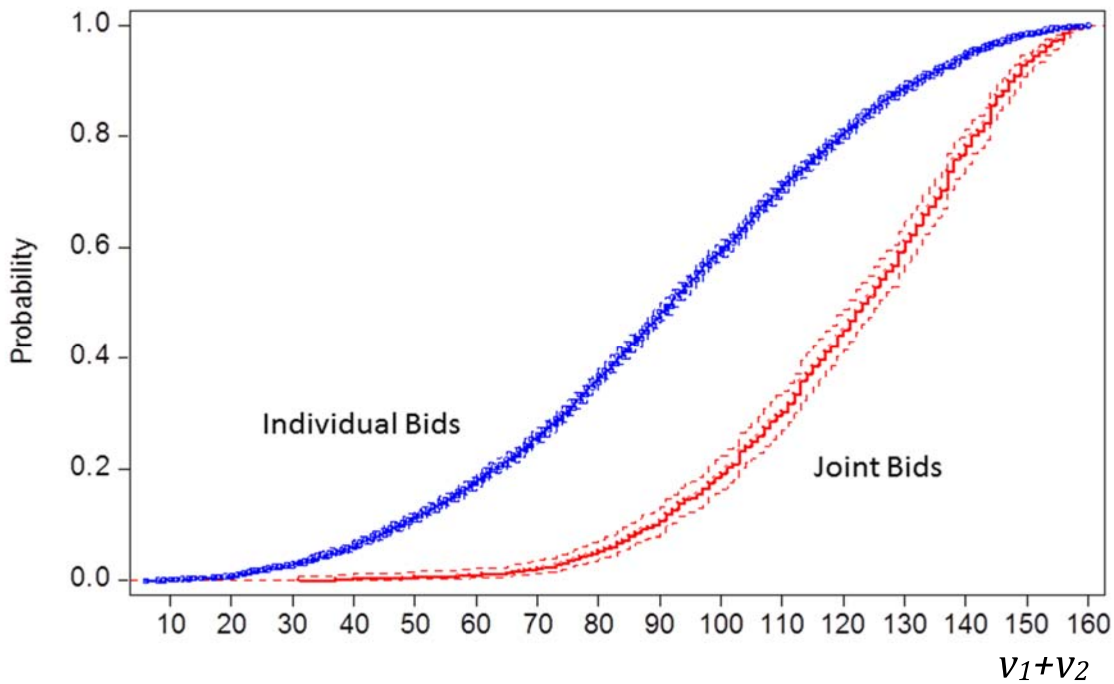



**Figure 3. Empirical CDF (with confidence intervals) of individual and joint bidder values**

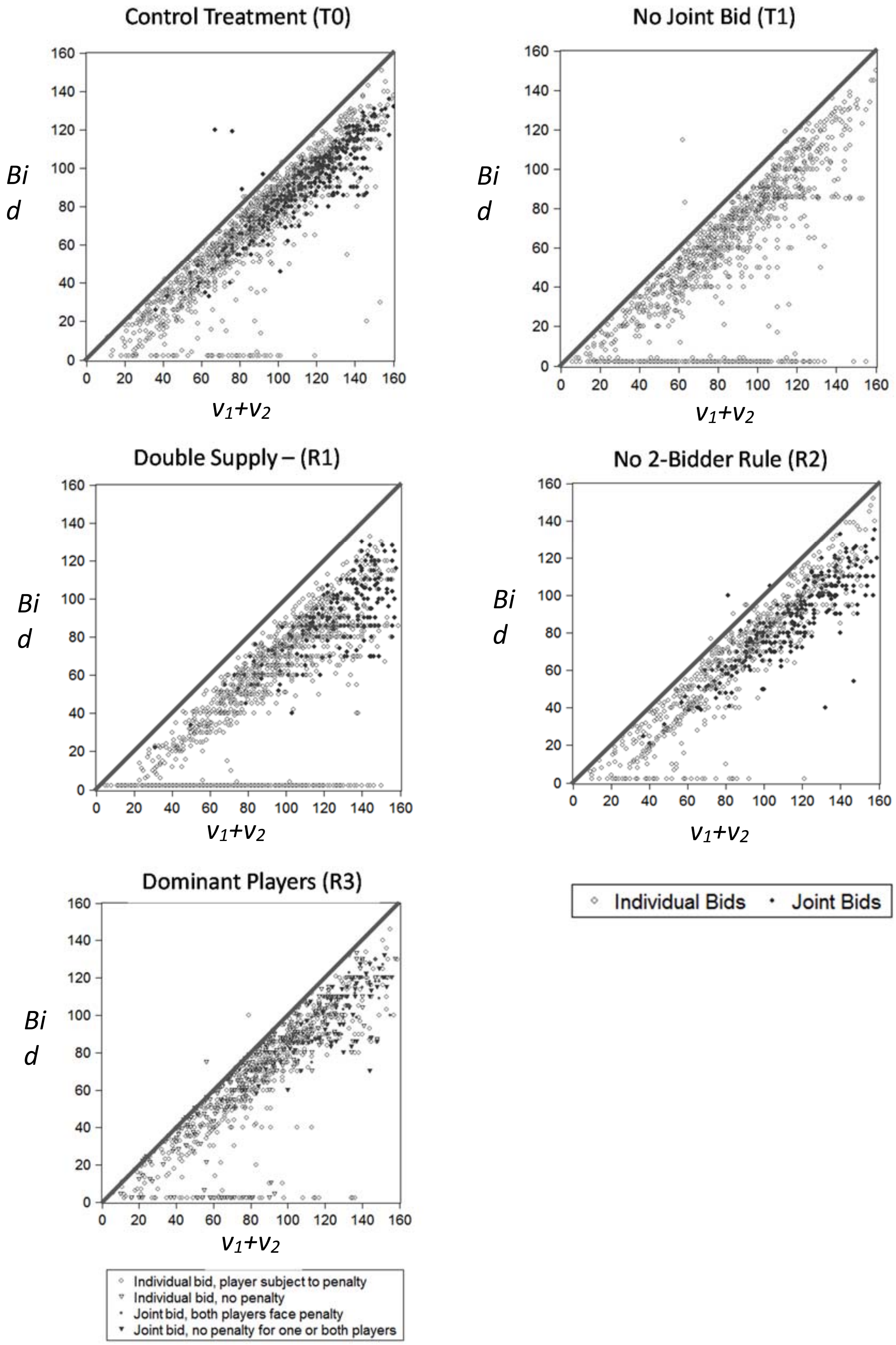



**Figure 4. Individual and joint bids by treatment**

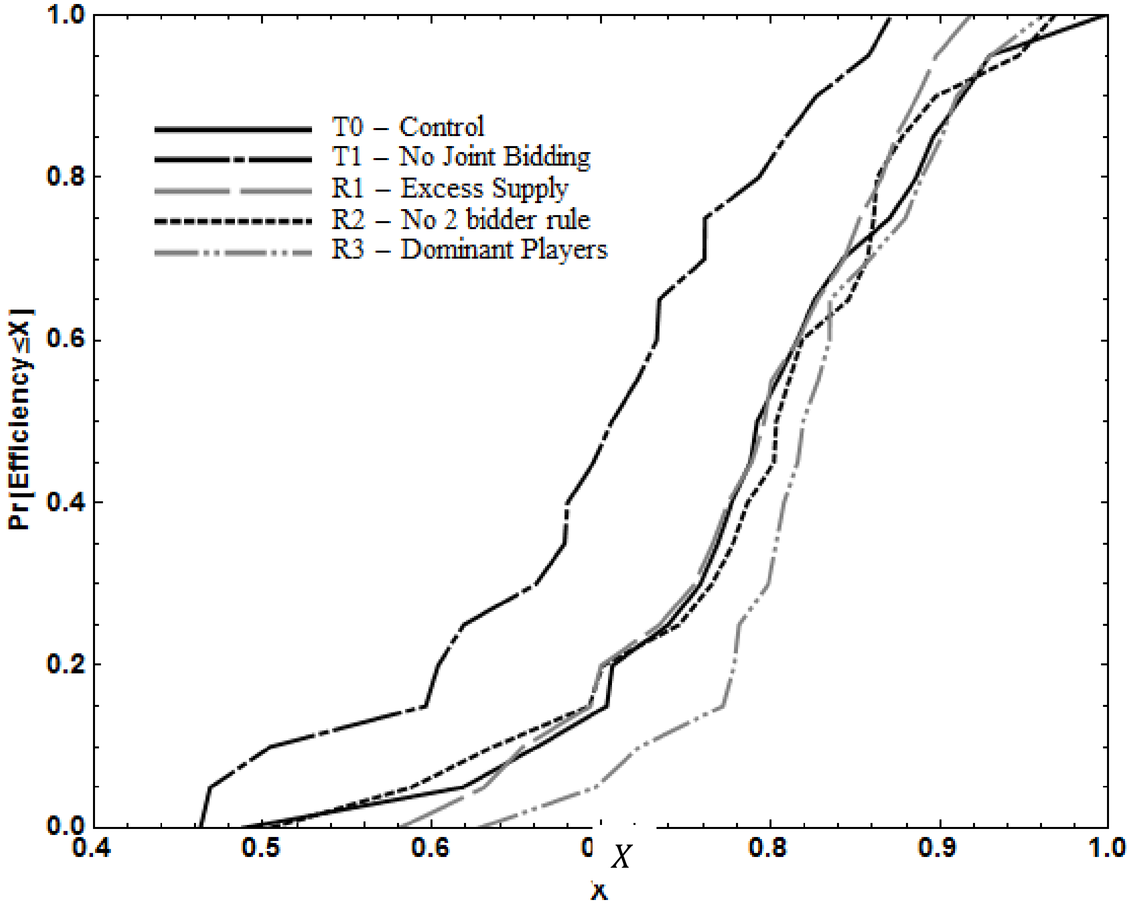



**Figure 5. CDF of auction efficiency results by treatment**

**Table 1. "Regional Distributions" of Auctioned Lots**

| Scenario Number | Number of Lots Exclusive to Region 1 | Number of Lots Common to Regions 1 and 2 | Number of Lots Exclusive to Region 2 | Player Bidding Opportunities | Competition at the Lot Level |
|---|---|---|---|---|---|
| 1 | 2 | 0 | 6 | (2,6) | 8 lots with 3 bidders |
| 2 | 2 | 3 | 3 | (5,6) | 5 lots with 3 bidders 3 lots with 6 bidders |
| 3 | 2 | 4 | 2 | (6,6) | 4 lots with 3 bidders 4 lots with 6 bidders |
| 4 | 2 | 6 | 0 | (8,6) | 2 lots with 3 bidders 6 lots with 6 bidders |

Note: The first (second) number in column 5 denote the number of lots that the three bidders in region 1 (2) can bid on.

**Table 2. Summary of Observations and Bid Types Per Treatment**

| | T0 | T1 (NoJ) | R1 (x2) | R2 (No2B) | R3 (Dom) |
|---|---|---|---|---|---|
| Number of groups | 6 | 4 | 4 | 5 | 4 |
| Total number of lot-person offered | 1980 | 1320 | 2640 | 1650 | 1320 |
| Total number of bids submitted | 1272 | 1154 | 1745 | 1007 | 988 |
| Percentage of individual bids | 80.6% | 100.0% | 88.1%*** | 73.1%*** | 89.9%*** |
| Percentage of joint bids | 19.4% | - | 11.9%*** | 26.9%*** | 10.1%*** |
| Percentage of "no bids" | 23.3% | 12.6%*** | 26.1%** | 22.3% | 17.5%*** |
| Percentage of bids equal to 2 | 2.9% | 19.6%*** | 32.0%*** | 4.5%** | 6.3%*** |
| Percentage of bids equal to 86 | 2.2% | 3.6%** | 3.5%*** | 0.7%*** | 3.2% |

Note: *, **, and *** indicate 10%, 5% and 1% significance levels when compared to T0

**Table 3. Descriptive Statistics of Bids**

| | | T0 | T1(NoJ) | R1(x2) | R2(No2B) | R3(Dom) |
|---|---|---|---|---|---|---|
| **All Ind. Bids** | **Mean** | 69.04 | 54.99*** | 44.16*** | 64.98** | 67.39 |
| | **Median** | 70 | 60 | 49 | 69 | 72 |
| | **Std. Dev.** | 31.76 | 37.17 | 37.64 | 33.75 | 32.69 |
| | **Obs.** | 1025 | 1154 | 1538 | 735 | 887 |
| **Ind. Bids >2** | **Mean** | 71.56 | 67.89*** | 68.16*** | 69.09* | 72.31 |
| | **Median** | 72 | 69 | 70 | 71 | 75 |
| | **Std. Dev.** | 29.52 | 29.45 | 25.22 | 30.62 | 28.34 |
| | **Obs.** | 988 | 928 | 980 | 690 | 825 |
| **Joint Bids** | **Mean** | 92.96 | NA | 90.46 | 85.85*** | 100.14*** |
| | **Median** | 96 | NA | 90 | 85.5 | 101 |
| | **Std. Dev.** | 21.59 | NA | 19.508 | 21.68 | 16.89 |
| | **Obs.** | 247 | 0 | 207 | 272 | 101 |
| **All Bids** | **Mean** | 73.69 | 54.99*** | 49.65*** | 70.62** | 70.74** |
| | **Median** | 77 | 60 | 57 | 75 | 75 |
| | **Std. Dev.** | 31.50 | 37.17 | 38.97 | 32.30 | 32.97 |
| | **Obs.** | 1272 | 1154 | 1745 | 1007 | 988 |
| **All Bids>2** | **Mean** | 75.84 | 67.89*** | 72.05*** | 73.83 | 75.34 |
| | **Median** | 78 | 69 | 74 | 76 | 79 |
| | **Std. Dev.** | 29.38 | 29.45 | 25.741 | 29.35 | 28.66 |
| | **Obs.** | 1235 | 928 | 1187 | 962 | 926 |

Note: *, **, and *** indicate 10%, 5% and 1% significance levels when compared to T0

**Table 4. Descriptive statistics of Bid-to-Value ratios for bids greater than two**

| | | T0 | T1(NoJ) | R1(x2) | R2(No2B) | R3(Dom) |
|---|---|---|---|---|---|---|
| **Ind. Bids** | **Mean** | 0.79 | 0.76*** | 0.69*** | 0.76*** | 0.81*** |
| | **Median** | 0.82 | 0.79 | 0.71 | 0.80 | 0.83 |
| | **Std. Dev.** | 0.14 | 0.16 | 0.13 | 0.15 | 0.15 |
| | **Obs.** | 988 | 928 | 980 | 690 | 825 |
| **Joint Bids** | **Mean** | 0.80 | NA | 0.72*** | 0.75*** | 0.79 |
| | **Median** | 0.81 | NA | 0.74 | 0.76 | 0.79 |
| | **Std. Dev.** | 0.11 | NA | 0.01 | 0.09 | 0.09 |
| | **Obs.** | 247 | 0 | 207 | 272 | 101 |
| **All bids** | **Mean** | 0.79 | 0.76*** | 0.69*** | 0.76*** | 0.80** |
| | **Median** | 0.82 | 0.79 | 0.71 | 0.78 | 0.83 |
| | **Std. Dev.** | 0.14 | 0.16 | 0.13 | 0.14 | 0.14 |
| | **Obs.** | 1235 | 928 | 1187 | 962 | 926 |

Note: *, **, and *** indicate 10%, 5% and 1% significance levels when compared to T0

**Table 5. Descriptive Statistics; Revenue per lot as a fraction of winner's value**

| | T0 | T1(NoJ) | R1(x2) | R2(No2B) | R3(Dom) |
|---|---|---|---|---|---|
| **Mean** | 0.84 | 0.83 | 0.73*** | 0.81*** | 0.84 |
| **Median** | 0.84 | 0.83 | 0.74 | 0.81 | 0.85 |
| **S. D.** | 0.10 | 0.12 | 0.10 | 0.09 | 0.09 |
| **Obs** | 563 | 289 | 530 | 366 | 299 |

Note: *, **, and *** indicate 10%, 5% and 1% significance levels when compared to T0

**Table 6. Average Auction Revenue as a fraction of Maximum Possible Revenue**

| | T0 | T1(NoJ) | R1(x2) | R2(No2 B) | R3(Dom) |
|---|---|---|---|---|---|
| **Mean Auction Revenue** | 737.55 | 673.95 | 1223.38 | 700.52 | 753.50 |
| **Mean Maximum Revenue Possible** | 1040.08 | 911.28 | 2046.20 | 1011.68 | 1026.60 |
| **Mean % of Max Revenue Achieved** | 70.83% | 73.60% | 59.62%*** | 69.01% | 73.36% |
| **Obs** | 60 | 40 | 40 | 50 | 40 |

Note: *, **, and *** indicate 10%, 5% and 1% significance levels when compared to T0.

**Table 7. Efficiency Level per Auction**

| | T0 | T1(NoJ) | R1(x2) | R2(No2B) | R3(Dom) |
|---|---|---|---|---|---|
| **Mean** | 0.78 | 0.70*** | 0.79 | 0.79 | 0.82 |
| **Median** | 0.78 | 0.71 | 0.80 | 0.81 | 0.82 |
| **S.D.** | 0.10 | 0.11 | 0.08 | 0.10 | 0.07 |
| **Min** | 0.49 | 0.46 | 0.58 | 0.50 | 0.63 |
| **Max** | 0.95 | 0.87 | 0.92 | 0.97 | 0.96 |
| **Obs** | 60 | 40 | 40 | 50 | 40 |

Note: *, **, and *** indicate 10%, 5% and 1% significance levels when compared to T0.

## Appendix

**Table A1**
**Bids Submitted Jointly**

| | | | T0 (Control) | T1(NoJ) | R1(x2) | R2(No2B) | R3(Dom) |
|---|---|---|---|---|---|---|---|
| Regional Scenario | 2-0-6 | % of bids=joint | 0.19 | NA | 0.10*** | 0.20 | 0.09*** |
| | | # of bids=joint | 57 | NA | 43 | 50 | 21 |
| | | Total # of Bids | 304 | 264 | 420 | 247 | 235 |
| | 2-3-3 | % of bids=joint | 0.19 | NA | 0.14* | 0.28** | 0.12** |
| | | # of bids=joint | 50 | NA | 45 | 57 | 23 |
| | | Total # of Bids | 258 | 229 | 333 | 202 | 197 |
| | 2-4-2 | % of bids=joint | 0.22 | NA | 0.13*** | 0.30*** | 0.11*** |
| | | # of bids=joint | 88 | NA | 72 | 96 | 33 |
| | | Total # of Bids | 408 | 374 | 567 | 318 | 314 |
| | 2-6-0 | % of bids=joint | 0.17 | NA | 0.11** | 0.29*** | 0.10** |
| | | # of bids=joint | 52 | NA | 47 | 69 | 24 |
| | | Total # of Bids | 302 | 287 | 425 | 240 | 242 |
| | All | % of bids=joint | 0.19 | NA | 0.12*** | 0.27*** | 0.10*** |
| | | # of bids=joint | 247 | NA | 207 | 272 | 101 |
| | | Total # of Bids | 1272 | 1154 | 1745 | 1007 | 988 |

Level of statistical significance when compared to T0: *:p< 0.1; **:p< 0.05; and ***: p<0.01.

**Table A2**
**Data on Bids Equal to 2**

| | | | T0 (Control) | T1(NoJ) | R1(x2) | R2(No2B) | R3(Dom) |
|---|---|---|---|---|---|---|---|
| | 2-0-6 | % of Bids=2 | 6.58 | 26.14*** | 35.48*** | 4.45 | 16.60*** |
| | | # of Bids=2 | 20 | 69 | 149 | 11 | 39 |
| | | Total # of Bids | 304 | 264 | 420 | 247 | 235 |
| | 2-3-3 | % of Bids=2 | 3.88 | 18.34*** | 28.83*** | 3.47 | 2.54 |
| | | # of Bids=2 | 10 | 42 | 96 | 7 | 5 |
| | | Total # of Bids | 258 | 229 | 333 | 202 | 197 |
| Regional Scenario | 2-4-2 | % of Bids=2 | 0.98 | 16.31*** | 31.22*** | 3.77** | 4.78*** |
| | | # of Bids=2 | 4 | 61 | 177 | 12 | 15 |
| | | Total # of Bids | 408 | 374 | 567 | 318 | 314 |
| | 2-6-0 | % of Bids=2 | 0.99 | 18.82*** | 32.00*** | 6.25*** | 1.24 |
| | | # of Bids=2 | 3 | 54 | 136 | 15 | 3 |
| | | Total # of Bids | 302 | 287 | 425 | 240 | 242 |
| | All | % of Bids=2 | 2.91 | 19.58*** | 31.98*** | 4.47** | 6.28*** |
| | | # of Bids=2 | 37 | 226 | 558 | 45 | 62 |
| | | Total # of Bids | 1272 | 1154 | 1745 | 1007 | 988 |

Level of statistical significance when compared to T0: *:p< 0.1; **:p< 0.05; and ***: p<0.01.

**Table A3**
**Data on Bids Equal to 86**

| | | | T0 (Control) | T1(NoJ) | R1(x2) | R2(No2B) | R3(Dom) |
|---|---|---|---|---|---|---|---|
| | 2-0-6 | % of Bids=86 | 3.29 | 3.41 | 5.24 | 0.81** | 4.68 |
| | | # of Bids=86 | 10 | 9 | 22 | 2 | 11 |
| | | Total # of Bids | 304 | 264 | 420 | 247 | 235 |
| | 2-3-3 | % of Bids=86 | 2.71 | 4.80 | 3.00 | 0.50* | 4.06 |
| | | # of Bids=86 | 7 | 11 | 10 | 1 | 8 |
| | | Total # of Bids | 258 | 229 | 333 | 202 | 197 |
| Regional Scenario | 2-4-2 | % of Bids=86 | 1.96 | 4.01* | 2.65 | 0.63 | 2.55 |
| | | # of Bids=86 | 8 | 15 | 15 | 2 | 8 |
| | | Total # of Bids | 408 | 374 | 567 | 318 | 314 |
| | 2-6-0 | % of Bids=86 | 0.99 | 2.44 | 3.29** | 0.83 | 2.067 |
| | | # of Bids=86 | 3 | 7 | 14 | 2 | 5 |
| | | Total # of Bids | 302 | 287 | 425 | 240 | 242 |
| | All | % of Bids=86 | 2.20 | 3.64** | 3.50** | 0.70*** | 3.24 |
| | | # of Bids=86 | 28 | 42 | 61 | 7 | 32 |
| | | Total # of Bids | 1272 | 1154 | 1745 | 1007 | 988 |

Level of statistical significance when compared to T0: *:p< 0.1; **:p< 0.05; and ***: p<0.01.

**Table A4**
**Descriptive Statistics**
**All Bids >2**

| | | | T0 (Control) | T1(NoJ) | R1(x2) | R2(No2B) | R3(Dom) |
|---|---|---|---|---|---|---|---|
| | 2-0-6 | Mean | 75.31 | 66.61 | 69.17 | 71.81 | 74.07 |
| | | S.D. | 28.16 | 28.80 | 22.93 | 30.47 | 28.86 |
| | | Obs. | 284 | 195 | 271 | 236 | 196 |
| | 2-3-3 | Mean | 75.88 | 69.53 | 74.03 | 69.90 | 72.43 |
| | | S.D. | 27.96 | 28.04 | 25.96 | 28.82 | 28.74 |
| Regional Scenario | | Obs. | 248 | 187 | 237 | 195 | 192 |
| | 2-4-2 | Mean | 76.61 | 66.98 | 72.80 | 75.43 | 78.03 |
| | | S.D. | 30.82 | 30.20 | 26.12 | 29.25 | 26.48 |
| | | Obs. | 404 | 313 | 390 | 306 | 299 |
| | 2-6-0 | Mean | 75.26 | 68.88 | 72.10 | 77.16 | 75.37 |
| | | S.D. | 29.80 | 30.17 | 27.39 | 28.38 | 30.87 |
| | | Obs. | 299 | 233 | 289 | 225 | 239 |
| | All | Mean | 75.84 | 67.89 | 72.05 | 73.83 | 75.34 |
| | | S.D. | 29.38 | 29.45 | 25.74 | 29.35 | 28.66 |
| | | Obs. | 1235 | 928 | 1187 | 962 | 926 |

Level of statistical significance when compared to T0: $^{*}$:p< 0.1; $^{**}$:p< 0.05; and $^{***}$: p<0.01.

**Table A5**
**Descriptive Statistics for Bid/Value**
**Winning Bids Only**

| | | | **T0 (Control)** | **T1(NoJ)** | **R1(x2)** | **R2(No2B)** | **R3(Dom)** |
|---|---|---|---|---|---|---|---|
| Regional Scenario | 2-0-6 | Mean | 0.83 | 0.83 | 0.71*** | 0.82 | 0.82 |
| | | S.D. | 0.12 | 0.10 | 0.10 | 0.10 | 0.10 |
| | | Obs. | 123 | 76 | 143 | 105 | 87 |
| | 2-3-3 | Mean | 0.84 | 0.82 | 0.743*** | 0.81** | 0.85 |
| | | S.D. | 0.06 | 0.12 | 0.11 | 0.08 | 0.08 |
| | | Obs. | 84 | 62 | 103 | 70 | 59 |
| | 2-4-2 | Mean | 0.85 | 0.84 | 0.72*** | 0.80* | 0.84 |
| | | S.D. | 0.11 | 0.13 | 0.11 | 0.08 | 0.08 |
| | | Obs. | 130 | 91 | 171 | 113 | 93 |
| | 2-6-0 | Mean | 0.85 | 0.81*** | 0.74*** | 0.80*** | 0.84 |
| | | S.D. | 0.07 | 0.11 | 0.10 | 0.07 | 0.07 |
| | | Obs. | 86 | 60 | 113 | 78 | 60 |
| | All | Mean | 0.84 | 0.83 | 0.73*** | 0.81*** | 0.84 |
| | | S.D. | 0.10 | 0.12 | 0.10 | 0.09 | 0.09 |
| | | Obs. | 423 | 289 | 530 | 366 | 299 |

Level of statistical significance when compared to T0: *:p< 0.1; **:p< 0.05; and ***: p<0.01.