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Jump bidding does not reduce prices: Field-experimental evidence from online auctions[☆]

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ABSTRACT

One feature of online auctions that has attracted much interest is jump bidding, whereby a bidder raises the price by more than what is needed to become the highest bidder. The effects of jump bidding on the final selling price are unknown because past observational studies could not separate bidder interest from bidder behavior. Our study involves an in vivo experiment during live auctions on a large online auction platform. We intervened early in auctions at low, non-competitive price levels, either through jump bidding or through incremental bidding, and randomly varied the magnitude of our intervention. In contrast to leading theories in the auction literature, which predict a negative effect of jump bidding on the final selling price, we find that our jump bidding intervention has no effect on the final selling price.

1. Introduction

The emergence of worldwide English auctions on publicly accessible online platforms has increased interest in understanding bidding behaviors and their relationship to the final selling price. A common bidding strategy in auctions is that of jump bidding, in which a bidder places a bid that is greater than what is required to become the current highest bidder. Even though the phenomenon of jump bidding has been studied extensively, it has remained unclear whether this bidding strategy has a favorable effect on final prices for bidders engaging in it. This study aims to examine the impact of jump bids on final prices using an in vivo experiment in live auctions on a large online auction platform.

Traditionally, auction theory has focused on identifying equilibrium bidding strategies in standard auctions such as the English auction (e.g., McAfee and McMillan, 1987). Standard theories of auctions do not allow for jump bids and consider jump bidding irrational behavior (e.g., Milgrom and Weber, 1982). Bidders are predicted to increase bidding levels by the smallest amount allowed until the bidder with the highest valuation has outbid the bidder with the second-highest valuation.

More recent auction literature rationalizes jump bidding as a mechanism for bidders to achieve a lower selling price. One theoretical approach proposes that bidders use jump bids to signal their superior valuation of the item for sale (e.g.,

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Avery, 1998; Daniel and Hirshleifer, 2018; Hörner and Sahuguet, 2011; Khazal et al., 2020), thus discouraging competition. Alternatively, jump bids may be made to prevent opponents from aggregating information (e.g., Ettinger and Michelucci, 2016a; 2016b), again leading to a lower selling price.

Available evidence points to jump bids having a positive or neutral effect on final selling prices (e.g., Bapna et al., 2003; Khazal et al., 2020; Sommervoll, 2020). However, a key limitation of all prior empirical studies is that they lack a controlled comparison of jump bids with incremental bids to assess their causal effect. A number of lab and field experiments have evaluated the impact of minimum bid size on final prices by systematically varying online auction rules (e.g., Isaac et al., 2005; Carpenter et al., 2011; Lim and Xiong, 2021). However, these studies cannot isolate the effect of a jump bid on a given auction while holding auction rules constant.

Our strategy for studying the effect of jump bidding on auction outcomes is an in vivo experiment where we take part in actual online auctions as bidders. We randomly place early jump bids of different sizes on hundreds of items. We compare the auctions ensuing after these jump bids with those initiated instead with an automated sequence of incremental bids, as well as with a control condition in which we do not intervene. We test whether the final selling price differs between experimental conditions. By doing so, our experiment provides the first controlled evidence for the effect of jump bids on final selling prices. In contrast to existing empirical studies, which rely on endogenous variation in bidding behavior, we are able to generate an exogenous source of jump bidding by directly intervening on the online auction platform ourselves. Moreover, we are able to do so in a setting of high external validity.

Despite finding positive effects of our jump bidding treatment on the number of bidders and number of bids in treated auctions, we find that these effects are offset by a reduction in the size of subsequent jump bids by these bidders. As a result, we fail to reject the null hypothesis that jump bidding has no effect on the final selling price, thereby rejecting the leading auction theories regarding the effects of jump bidding.

The remainder of this paper is organized as follows. In Section 2, we relate our contributions to the literature. Section 3 outlines our experimental set-up and online auction platform setting. Section 4 describes the data and Section 5 presents our results. We discuss our findings and conclude in Section 6.

2. Literature

A number of studies in economics document the prevalence of jump bidding and analyze its effect on the auction's outcome in FCC auctions (e.g., Plott and Salmon, 2004; Börgers and Dustmann, 2005; Isaac et al., 2007; Cramton, 1997), real-state auction markets (e.g., Sommervoll, 2020; Khazal et al., 2020), laboratory auctions (e.g., McCabe et al., 1988; Coppinger et al., 1980; Banks et al., 2003), and online auctions (e.g., Easley and Tenorio, 2004; Grether et al., 2015; He and Leszczyc, 2013). However, the rational foundations for jump bidding in ascending auctions are an unresolved matter in the auction literature (e.g., Milgrom and Milgrom, 2004). Adding to the problem is that empirical estimates of its actual effect on final selling prices are based on observational data and thus uncertain. We first review the main theoretical arguments and then existing empirical evidence.

2.1. Theoretical studies of jump bids

The theoretical literature has proposed two motivations to jump bid, each implying reduced final selling prices. The first account is that the strongest bidder uses jump bids strategically to indicate his superior valuation and intimidate rivals (Avery, 1998; Daniel and Hirshleifer, 2018; Easley and Tenorio (2004); Hörner and Sahuguet, 2011). Early jump bidding thus serves as a signaling device that achieves a lower selling price and reduces the risk of a winner's curse. The second explanation is that bidders have an incentive to manipulate the quality of the information that other bidders can aggregate. Thus, more informed bidders place a jump bid to prevent the less informed bidders from aggregating precise information (Ettinger and Michelucci, 2016b).

Avery (1998) suggests a two-stage model with affiliated values in which an auctioned item has both a private and a common value component. Jump bids can then be employed to select the bidder with the highest private value prematurely, avoiding a costly arms race: the strongest bidder places the biggest jump bid in the first stage to signal their superior valuation. This signal thus helps players to coordinate upon the asymmetric equilibrium to be played in a second stage: the weaker bidders drop out.

Similarly, Daniel and Hirshleifer, 2018 propose a model of sequential auctions with private values and a costly bidding process, where the first bidder has a monotonic bidding strategy that signals their high value. If the signal is sufficiently high and when bidding is costly, the second bidder may be intimidated and thus want to quit early to reduce bidding costs.

Hörner and Sahuguet (2011) consider a first-price sealed-bid auction and a pure private value structure. They suggest a non-monotonic equilibrium: bidders use a mixture of aggressive and cautious bidding, intimidate competitors (bluffing), or lower the competition by giving a false sense of security (sandbag).

Easley and Tenorio (2004) develop a theoretical model for online auctions where bidding is costly. They argue that jump bids are used as entry deterrence strategies and are more likely earlier in auctions.[1]

[1] For related theories of takeover bidding see Fishman (1988); Hirshleifer and Png (1989); Bhattacharyya et al. (1990).

Ettinger and Michelucci (2016b) propose that bidders have an incentive to manipulate the quality of the information that other bidders can aggregate. That is, jump bids may manipulate information about which bidders are active or inactive at any given price. "[...] when a jump bid is not matched by some of the bidders, the remaining active bidders can aggregate only coarser information of the private information of the bidders who did not match the jump bid" (Ettinger and Michelucci, 2016b, p.1484). In particular, a more informed bidder places a jump bid to prevent the less informed bidders from aggregating precise information. The less informed bidders need to take into account the winners' curse (Ettinger and Michelucci, 2016a) and this decreases their willingness to pay. Therefore, as a result of hiding information, the more informed bidder buys the item at a lower price, and the seller revenue decreases.

In sum, prior theoretical work, while disagreeing on the exact mechanism, suggests that jump bidding reduces an item's final selling price.

2.2. Empirical studies of jump bids

Contradicting these theoretical predictions, empirical studies generally find that jump bids have no or a small positive effect on final selling prices (Isaac et al., 2007; 2005; Isaac and Schnier, 2005; Carpenter et al., 2010; Lim and Xiong, 2021). At the same time, previous empirical and experimental studies of jump bidding are limited in their ability to assess the effect of jump bidding on auction outcomes, as they do not control the act of jump bidding.

In experiments that vary auction eligibility rules, Banks et al. (2003) find that jump bidding is prevalent and tends to increase final selling prices. Plott and Salmon (2004) and Börgers and Dustmann (2005) find that jump bids are observed early on in auctions yet have no discernible effect on the outcome or prices. Isaac and Schnier (2005), who study jump bidding behavior in charity silent auctions in observational and laboratory settings, find that jump bids decrease as bids approach to value, yet also find that jump bids have little effect on final prices. Similarly, Raviv (2008), who studies the characteristics of bids in second-hand car oral auctions, finds that the biggest jumps happen early and the smallest ones happen late in the auction. Isaac et al. (2007) come to a similar conclusion when examining field data from 41 spectrum license auctions conducted by the US Federal Communications Commission (FCC) and the 3G spectrum auction in the UK. They find that jump bids do not impact the final price much, except when they result from impatience, in which case final prices tend to increase slightly. However, on many online auction platforms, including the one we study here, bidders can use automated bidding up to a set level so that impatience cannot plausibly play much of a role.

Kwasnica and Katok (2007) investigate the effect of timing on auction using a laboratory experiment by varying the opportunity cost of bidders. Higher opportunity costs produce more jump bids, but these are not significantly impacting the final price. Haruvy and Leszczyc (2010) study the effect of online auctions' duration on other selling prices. They show that shorter durations lead to higher selling prices and that this effect is mediated by bigger jump bids, suggesting a positive effect of jump bidding on the final price. Grether et al. (2015) study jump bids in a field experiment of an online company selling second-hand cars, varying the size of the jumps that are permitted. They find the effect of jump bids on the final price to be ambiguous. Sommervoll (2020) study the effect of jump bids on auctions in the Norwegian housing market and find it increases the final price. Finally, in a laboratory experiment Lim and Xiong (2021) find that jump bidding increases seller revenue, but only to a limited extent.

Our main contribution to this literature is that we isolate the effect of jump bidding on the final price in an in vivo experiment, combining the causal inference potential provided by randomization of jump bidding behavior with the external validity of a leading auction platform as a research site.

3. Experiment

3.1. Setting

The experiment was conducted on an online auction platform that is specialized in buying and selling novelty items and collectibles such as stamps, arts, antique cars, and gemstones. The platform provides services to a large number of sellers and bidders located in 42 countries. Auctions are scheduled to start and end at varying times and days of the week, and have a flexible deadline, meaning that if a bid is placed within the last hour of the scheduled duration, extra time is added to the auction.

Bidders can join an auction at any time and may additionally view the items in upcoming auctions. Every item is provided with information about the seller, shipping cost, item details, pictures, and a certificate (if any), including in-depth details of the item. An important feature of the platform is its experts' service. The platform has hundreds of experts who help evaluate and arrange lots submitted by the sellers.[2] As a result, most of the items sold on the platform are presented along with a range of estimated values of the item made by one or multiple experts.

After making an account, interested parties may place a bid manually or may use the platform's automatic or proxy bidding system. When placing a bid manually, bidders may place any bid that is greater than or equal to the minimum bid

[2] The platform refers to auctioned items as lots, where multiple lots together constitute an auction. In this paper, we follow the literature in using the term auction to refer to a single lot, rather than a combination of lots.

increment.[3] When placing a proxy bid, the platform places bids on behalf of the bidder, i.e., bids are raised automatically with the minimum increment up to a maximum amount set by the bidder, without any further action on the part of the bidder.

The bidding process is anonymous from the bidders' perspective; in each auction, every bidder is identified by a unique code assigned to them by the platform. This code changes in the next auction, and there is no way for sellers or bidders to trace a bidder in more than one auction on the website without having access to the raw data. Sellers, on the other hand, are identified with a nick- or company name. In addition, they have their own profiles with information about their membership date, location, and reviews. Sellers may also apply for a pro icon indicating that they are professionals if they regularly offer, buy and (re)sell items and earn at least 50,000 euros a year on the platform.

Sellers may decide to list a reserve or minimum price below which the item will not be sold. This reserve price may also be secret, i.e., it is not visible to bidders. At the end of the auction, the item is sold to the highest bidder as long as its bid meets the optional reserve price. The winning bidder pays the winning bid plus an auction fee of 9% of the winning bid. In addition, the seller pays a commission fee of 12.5% of the winning bid to the platform.

Within the Diamonds & Gems category, mixed diamonds auctions are held frequently. In these auctions, loose and unpolished diamonds are offered, usually bought by small retailers, artists who use them in their artwork, or collectors who seek diamonds in varying colors and crystal forms. To ensure quality, all diamonds are provided with an authenticity certificate, and they are also always supervised by professional diamond experts. These diamonds can be characterized as affiliated value goods: they have both a private value component, as well as a common value component, where the common value of each item is the same for all bidders, but the underlying estimate of the value differs between different bidders.

3.2. Design and procedures

The experiment was conducted over 13 weeks between April 19 and August 23, 2019. We specifically collected data from mixed diamond auctions, as these items are frequently offered on the platform. Moreover, the auctions in this category satisfy the assumption of affiliated values, on which the theoretical models by Avery (1998) and Ettinger and Michelucci (2016a) rely. We selected auctions with an experts' estimate only, as this allowed us to bid at levels far below what we expected the item to sell for, thus minimizing the risk of having to buy the item. Finally, we focused on auctions that did not list a reserve or minimum price below which the item will not be sold, as this guarantees that the item will be sold and the low bids we make are credible. As a result, we are confident that the selected auctions provide an excellent setting to test the theoretical prediction that jump bidding reduces an item's selling price.

Shortly before the start of weekly auctions, we selected relevant auctions, i.e., mixed diamond auctions without a minimum price, from the list of "auctions opening on a specific date". We then randomly assigned each auction to one of the three experimental conditions: the treatment or jump bidding (T) condition, the proxy bidding (P) condition, and the no bidding (N) condition.

In the T and P conditions, we made groups of five items and assigned a different bid size to each item. As soon as the auctions began, we placed the first bid on the items based on the rules of the treatments they had been randomly assigned to. In the T condition, we placed a jump bid. In the P condition, we placed a proxy bid to create an artificial control group in which all first bids are incremental. In the N condition, we did not intervene in the bidding.

In both T and P conditions, the amount of the bid was uniformly randomly drawn without replacement from the set {30, 35, 40, 45, 50}. These amounts were chosen based on data of 373 auctioned diamonds collected during a trial. The minimum selling price for these items was 55 euros, and the size of the first bid on more than 80% of auctions was less than 10 euros. A first jump bid between 30 and 50 thus allowed us to place bids that were large enough to be perceived as jumps, yet small enough to ensure that we would not buy many items ourselves.

We placed our bids in the first one-and-a-half hour of an auction. We made sure that our bids were the first bids in every auction. If another bidder had already bid on one of our listed items, we did not bid on the item. On some dates, we were prohibited from bidding on all items due to credit card restrictions. To ensure that the number of auctions in each treatment remained balanced, we decided to run two sessions in which we only randomized across the T and P conditions.[4]

This study was approved by the Ethics Committee of the Faculty of Social and Behavioural Sciences of Utrecht University (reference number FETC19-016). Sellers and bidders were not informed about the experiment and had no way of identifying the experimenters. If we unexpectedly ended up having to buy the item at the price of our bid, which happened in 13 cases, we paid our bid plus 9% buyer's fee and shipping costs which varied from 0 to 200 euros per item. Regarding our activities as bidders, we complied with the platform's Terms of Use. After all auctions ended, we requested the platform for the data.

4. Data

In the experiment, 2,063 auctions were observed: 724 were assigned to the T condition, 720 to the P condition, and 619 to the N condition. Seven auctions had to be excluded because we were not able to retrieve the data from the auction

[3] The size of the minimum bid increment changes during an auction, as it depends on the level of the current bid (see Table A1 in Appendix A).

[4] Neither excluding the auctions in weeks 11 and 12 nor including week fixed effects affects our main results.

Table 1
Intention to treat vs. As treated.

	Treatment assigned			
Treatment received	T	P	N	Total
Jump bidding (T)	568	11	0	579
Proxy bidding (P)	1	523	0	524
No bidding (N)	61	81	520	662
Total	630	615	520	1,765

platform (1 in the T condition, 5 in the P condition, and 1 in the N condition). Furthermore, in line with the criteria defined in our experimental design, four additional auctions were removed because we did not manage to intervene before other bidders placed a bid.

Due to time pressure, we inadvertently included some auctions that did not meet the selection criteria as defined in Section 3.2. In roughly 10% of the auctions in our sample, experts did not provide lowest and highest estimates of the value of the item for sale. These experts' estimates are highly correlated with the final selling price. Moreover, in line with the linkage principle (Milgrom and Weber, 1982), we observe that auctions that do not have experts' estimates on average lead to lower final prices than auctions that have such an estimate. The reasoning behind this might be that there is greater uncertainty about the value of the item (Easley et al., 2010; Clemons, 2007). We therefore exclude all auctions without an experts' estimate.[5] We also exclude any auctions that had a secret reserve price.[6] Furthermore, we exclude the 13 auctions in which the experimenters bought the item for sale; as for these items, it is not clear what the maximum willingness to pay of other bidders would have been.[7]

Finally, note that by intervening, we restricted the bidding space in the T condition and, to a lesser extent, in the P condition. The restricted bidding space may lead to biased results when analyzing outcome variables such as the number of bids and the number of bidders. To correct for any such bias, we therefore choose to exclude bids that were placed up to the level of our intervention in the P condition. That is, we exclude all bids that were placed before the maximum price of our proxy bid was reached in the P condition. We also created a counterfactual intervention by assigning a random number of the set {30,35,40,45,50} to each auction in the N condition. Any bids that were placed below this counterfactual intervention, are then excluded from analyses. This results in the exclusion of 6 auctions in the N condition, as the winning bids in these auctions were below the counterfactual intervention.[8]

Our final sample thus consists of 1,765 auctions: 630 assigned to the T condition, 615 assigned to the P condition, and 520 assigned to the N condition. Table 1 presents the treatment assignment versus the actual treatment that was received. Because of the fast-paced and non-automated nature of our interventions, inevitably not all auctions received the treatment that they were intended to. First, attempting to be the first to bid required the experimenters to rush, which led to a few *cross-over* mistakes when placing bids, e.g., placing a jump bid when it should have been a proxy bid.[9] Second, as described in Section 3.2, it occasionally happened that another bidder had already placed a bid before us, which meant that we were no longer able to intervene. Third, we did not manage to bid in all auctions due to credit card restrictions.

To deal with the discrepancies between the treatment assignment and the treatment received, we follow the literature on randomized controlled trials by presenting three analyses: (i) intention-to-treat (ITT) analysis, in which we analyze auctions according to the treatment they were assigned, (ii) per-protocol (PP) analysis, in which we only analyze auctions that received the treatment they were assigned, and (iii) as-treated (AT) analysis, in which we analyze auctions according to the treatment they received. In the main text, we will present the AT analysis; the results for the ITT and PP analysis are qualitatively similar and can be found in the Appendix.

Treatment assignment was balanced across all relevant covariates: average experts' estimated values, uncertainty in experts' estimated values (operationalized as the difference between the highest and lowest estimated value divided by the

[5] Note that 11 out of 13 items that were bought by the experimenters (6 in the T condition and 7 in the P condition) did not have experts' estimates. As a result, we exclude auctions without an experts' estimate from the analyses presented in the main text (227 in total: 81 assigned to the T condition, 79 assigned to the P condition, and 67 assigned to the N condition). However, including these auctions and adding a dummy variable for missing experts' estimates does not lead to qualitatively different results.

[6] We included several items that had a secret reserve price (10 which were assigned to the T condition, 17 assigned to the P condition, and 26 assigned to the N condition). Only in a few of these auctions did the final bid exceed the reserve price so that the item was sold (this happened in 2 auctions in the T condition, in 1 in the P condition, and 6 in the N condition). In the paper, we present the analyses for which we excluded all auctions with a secret reserve price. However, robustness tests show that including the auctions with a secret reserve price that ended up in a sale does not affect our results.

[7] Results are robust to the inclusion of these items, either using the experimenters' bid or the second-highest bid.

[8] Since 9 auctions in the N condition had a final selling price below 50, this means that the number of observations may differ depending on the exact randomization that is used. Our results are robust to (i) using a different randomization, (ii) excluding all 9 auctions with a selling price below 50, and (iii) not excluding any of these auctions.

[9] Also, in the T condition it occurred twice that we placed a bid of 45 when it should have been 40, and in the P condition we once bid 40 instead of 35. We deal with such cross-over in a similar way to cross-over regarding treatment. However, note that this may lead to a slight discrepancy between the number of observations when considering the T, P, and N conditions as a whole and the number of observations when considering the conditions by bid size.

Table 2
Final selling prices.

Bid size	Obs	Mean	SD	Min	Max
Jump bidding (T)					
30	127	229.1	176.8	35	1,000
35	113	297.3	580.8	40	6,000
40	112	325.0	279.1	45	1,800
45	112	363.1	272.0	55	1,400
50	115	322.4	255.7	55	1,900
Total	579	305.4	341.0	35	6,000
Proxy bidding (P)					
30	111	269.4	249.6	45	1,600
35	103	286.3	317.7	41	2,400
40	107	296.7	321.3	45	2,600
45	103	289.4	246.9	50	1,200
50	100	346.0	459.1	57	4,200
Total	524	296.8	325.8	41	4,200
No bidding (N)					
Total	662	335.7	323.0	45	3,200

lowest estimated value), average shipping cost, and scheduled time of the auction. When considering which treatment was received, we find no statistically significant differences between the T and P conditions. However, we find that items in the T and P conditions have statistically significantly lower estimated values than those in the N condition. Moreover, we find that the scheduled time of the auction is shorter in the P condition than in the N condition. As the literature is divided on whether such imbalances should be controlled for in analyses of experimental data (or even be investigated to begin with), we present both results with and without these controls in our further analyses. Finally, the distribution of jump and proxy bids placed by the experimenters (see Table 2 for the exact number of observations by bid size) was balanced across the T and P conditions.[10] Experimenters placed a single bid in auctions in the T condition and placed up to ten bids (with an average of 4.33 bids) in the P condition. More information on covariate balance is available in Appendix B.

5. Results

Table 2 presents the average final selling prices (i.e., winning bids, excluding auction fees or shipping costs) in the auctions, categorized into the different treatments and the size of the bids placed by the experimenters.[11] On average, the final price across all 1,765 auctions equals 314.21 euros. Figure D1 in Appendix D shows the distribution of final prices. This is highly skewed, which is why we log-transform the variable in further analyses.

To examine the effect of our interventions on final prices, we ran linear regression models with the log-transformed final price as a dependent variable. The treatment effect was estimated by comparing the situation in which we place a jump bid at the start of the auction (T condition) (i) to the situation in which we place a proxy bid (P condition), thereby ensuring that the opening bid is always equal to 1; and (ii) to the situation in which we do not intervene (N condition), thereby allowing for opening bids varying between 1 and 900, with a mean of 9.144 and median of 1 (see Table C1 in Appendix C for an overview of all opening bids). We also examined the effect of our interventions while controlling for any information included in the auction listing, which may have affected bidders' behaviors. In particular, we controlled for the log-transformed average experts' estimated value, the log-transformed uncertainty in the experts' estimated value, the log-transformed average shipping cost, and the scheduled duration of the auction.

Table 3 shows the main treatment effect of placing a jump bid on the final selling price; a visual representation can also be found in the upper part of Figure 1. We find no significant effect of jump bidding in any analysis, neither when comparing jump bidding to proxy bidding (P condition, see models (1) and (2) in Table 3) nor when comparing jump bidding to not bidding (N condition, see models (7) and (8) in Table 3). We thus fail to reject the null hypothesis that jump bidding has no effect on the final selling price. This leads us to reject the theoretical prediction that jump bidding reduces an item's selling price.

This prediction was derived from two core theoretical arguments made in prior literature: (i) jump bids would prevent arms races towards higher prices through early discouragement of bidders entering the auction, and (ii) they would prevent information exchange at low bidding levels, leaving new bidders considering to enter the auction with less information to base their decision on. To better understand the lack of an effect in light of these theoretical arguments, we examined the role of two potential moderators: value and value uncertainty.

[10] Chi-squared tests show that there are no significant differences in the bids placed by experimenters across the T and P conditions for any of our analyses (ITT: $\chi^2(4, N = 1,245) = 1.5503$, $p = 0.818$; PP: $\chi^2(4, N = 1,088) = 0.2656$, $p = 0.992$; AT: $\chi^2(4, N = 1,103) = 0.3343$, $p = 0.987$).

[11] Table D1 presents the final selling prices for ITT and PP.

Table 3
The effect of placing a jump bid on the final selling price.

Control group	P					
Model	(1)	(2)	(3)	(4)	(5)	(6)
Treatment effect	0.020	0.029	-0.067	-0.093	-0.110	0.157
	(0.045)	(0.030)	(0.291)	(0.289)	(0.140)	(0.096)
Interaction effects						
Avg estimated value (log)			0.013	0.017		
			(0.040)	(0.040)		
Uncertainty (log)					0.092	-0.089
					(0.093)	(0.064)
Avg estimated value (log)		0.763***	0.721***	0.754***		0.765***
		(0.022)	(0.029)	(0.031)		(0.022)
Uncertainty (log)		0.121***		0.121***	-0.423***	0.178***
		(0.034)		(0.034)	(0.073)	(0.053)
Controls	No	Yes	No	Yes	No	Yes
Constant	5.399***	-0.191	0.174	-0.125	6.005***	-0.288
	(0.032)	(0.202)	(0.214)	(0.255)	(0.109)	(0.214)
Obs	1,103	1,103	1,103	1,103	1,103	1,103
R-squared	0.000	0.556	0.550	0.556	0.058	0.557
Control group	N					
Model	(7)	(8)	(9)	(10)	(11)	(12)
Treatment effect	-0.093*	0.025	-0.006	-0.029	-0.864***	-0.133
	(0.043)	(0.027)	(0.250)	(0.250)	(0.141)	(0.096)
Interaction effects						
Avg estimated value (log)			0.004	0.007		
			(0.034)	(0.034)		
Uncertainty (log)					0.571***	0.113+
					(0.096)	(0.065)
Avg estimated value (log)		0.747***	0.730***	0.744***		0.742***
		(0.019)	(0.022)	(0.023)		(0.019)
Uncertainty (log)		0.039		0.040	-0.902***	-0.039
		(0.034)		(0.034)	(0.078)	(0.056)
Controls	No	Yes	No	Yes	No	Yes
Constant	5.512***	0.200	0.113	0.222	6.759***	0.344+
	(0.030)	(0.184)	(0.164)	(0.209)	(0.111)	(0.202)
Obs	1,241	1,241	1,241	1,241	1,241	1,241
R-squared	0.004	0.610	0.608	0.610	0.123	0.611

NOTES: Coefficients from OLS regressions on the log-transformed final selling price; standard errors in parentheses. Additional controls include the log-transformed average shipping cost and scheduled time of the auction. The complete regression results including ITT and PP analyses can be found in Tables D2 - D4 in Appendix D. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

In auctions for items with lower experts' estimated values, our jump bid is relatively more competitive, as indeed we ended up buying a few of these items. These jump bids arguably had a stronger discouraging effect and took out a larger fraction of the bidding space. Models (3), (4), (9) and (10) of Table 3 reject this, showing no significant interaction between treatment and average estimated values in their effects on final prices, with or without controls and regardless of whether P or N is analyzed as the contrasting condition.

One may also suspect low uncertainty about the item's value to be responsible for the lack of a strong treatment effect. We find no interaction between treatment and value uncertainty in models (5) and (6) in Table 3, where jump bidding is compared to proxy bidding. We do find a positive interaction in model (11), where jump bidding is compared to not bidding, but this effect vanishes once the average estimated value is controlled for in model (12). This suggests that the model (11) estimates are spurious due to the natural positive correlation between value and value uncertainty that is not properly controlled for.

Both theoretical mechanisms operate through a reduction in the number of bidders and bids. We evaluated whether the reason the hypothesis of a lower selling price is rejected in the data is perhaps that no such reduction in participation took place. Multivariate models (2), (4), (6), and (8) of Table 4, however, all find significantly positive treatment effects on both the number of bidders as well as on the number of bids made in an auction, both when compared to the P and N condition. These outcome variables exclude the experimenter (T and P conditions) as well as any bidders and bids below the maximum experimenter proxy bid (P condition) and below the counterfactual level of the jump bid had we made it (N condition). The size of these estimates indicates that our jump bids increased the number of bidders by about 1/2 and the number of bids by 1.

These positive effects on bidders and bids strongly reject both the argument that jump bids discourage bidding by signaling high valuations as well as by eliminating bidding space for information exchange. Our jump bids instead invited more

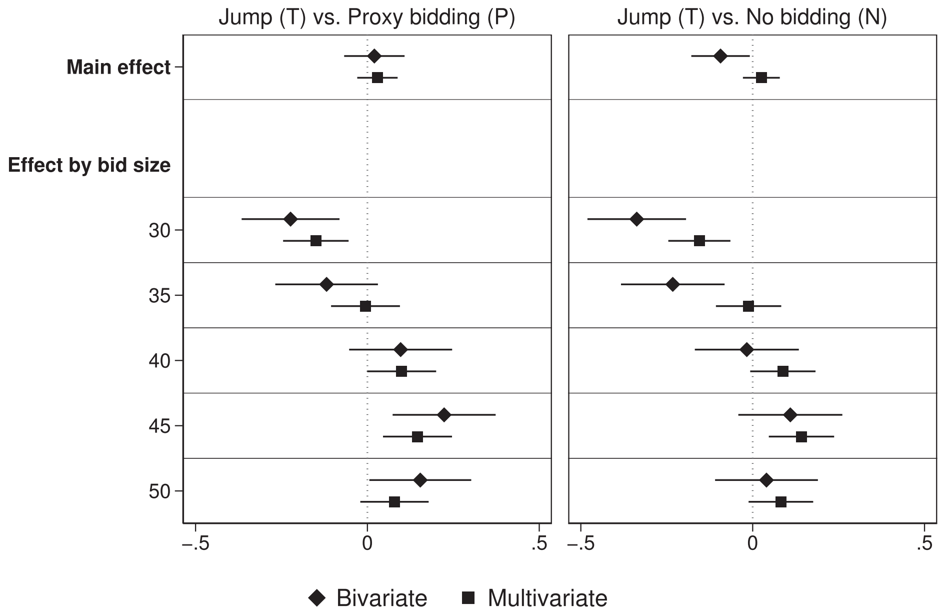

Fig. 1. The effect of placing a jump bid on the final selling price. Notes: Coefficients from OLS regressions on the log-transformed final selling price. The multivariate models control for log-transformed average estimated value, log-transformed uncertainty in the estimated value, log-transformed average shipping cost, and scheduled time of the auction. Tables D2 and D5 in Appendix D presents the full regression results. Squares and diamonds describe the point estimates; bars describe 95% confidence intervals.

Table 4
The effect of placing a jump bid on other auction outcomes.

Control group	P							
Outcome	Nr bidders		Nr bids		Nr jump bids		Avg size jump (log)	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment effect	0.361+	0.415*	1.061*	1.202**	0.070	0.078	-0.086***	-0.089***
	(0.199)	(0.173)	(0.529)	(0.430)	(0.107)	(0.095)	(0.026)	(0.026)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Constant	7.275***	-6.136***	17.429***	-29.665***	2.008***	-6.502***	0.441***	-0.627***
	(0.144)	(1.171)	(0.383)	(2.908)	(0.077)	(0.641)	(0.019)	(0.173)
Obs	1,103	1,103	1,103	1,103	1,103	1,103	1,103	1,103
R-squared	0.003	0.247	0.004	0.346	0.000	0.215	0.010	0.049
Control group	N							
Outcome	Nr bidders		Nr bids		Nr jump bids		Size jump bids (log)	
Model	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Treatment effect	0.305	0.637***	-0.053	1.048*	-0.070	0.105	-0.130***	-0.114***
	(0.193)	(0.170)	(0.515)	(0.415)	(0.110)	(0.097)	(0.028)	(0.028)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Constant	7.331***	-5.291***	18.544***	-26.647***	2.148***	-6.392***	0.484***	-0.628***
	(0.132)	(1.140)	(0.352)	(2.787)	(0.075)	(0.654)	(0.019)	(0.186)
Obs	1,241	1,241	1,241	1,241	1,241	1,241	1,241	1,241
R-squared	0.002	0.237	0.000	0.360	0.000	0.223	0.017	0.072

Notes: Coefficients from OLS regressions on different outcome variables; standard errors in parentheses. Additional controls include log-transformed average estimated value, log-transformed uncertainty in the estimated value, log-transformed average shipping cost, and scheduled time of the auction. The full regression results including ITT and PP analyses can be found in Tables E2 - E5 in Appendix E; descriptive statistics regarding these auction outcomes can be found in Table E1. *** $p<0.001$, ** $p<0.01$, * $p<0.05$, + $p<0.1$

bidders and bids. Why then did this not result in higher final selling prices? Table 4 provides a two-prong answer: the extra bid our jump bid on average generated was an incremental bid, not a jump bid (see models (5), (6), (13) and (14)), and moreover it reduced the size of subsequent jump bids (see models (7), (8), (15) and (16)). As a net result, then, the final price did not increase.

Finally, in order to better understand the bidding dynamics producing the main null finding, we also considered the effect of the size of our jump bids. While the original purpose of randomly varying bid size was to avoid the artificiality of the same bid across many auctions, and the range of variation is low, we can nonetheless exploit its random nature for causal inference about the size of the initial bid in an auction. To our surprise, we found a strongly significant non-monotonic effect of first bid size. As Figure 1 shows, as compared to placing a proxy bid (where all bid sizes are lumped together) or no bid, the final price is lower when we placed a jump bid of 30, and it is higher when we placed a jump bid of 40, 45 or 50. That is, for "low" bids (i.e., bids of 30) by the experimenters in the T condition, we find a negative effect on the final selling price. Conversely, for "high" bids (i.e., bids of 40 or higher) we find a positive effect on the final selling price. In models predicting the final selling price in auctions in the T condition, a linear term for bid size is highly statistically significant (see Table D7 in Appendix D). It is somewhat odd that the small variation in bid size within the narrow range between 30 and 50 can produce such strong effects. We are therefore cautious to consider the possibility of incidental findings and not overinterpret them. Nonetheless, the result is again inconsistent with the two arguments in auction theory that we reviewed, which predict greater rather than smaller reductions in final selling price following larger jumps.

6. Discussion and conclusion

Our in vivo experiment provides the first controlled evidence for the effect of jump bids on final selling prices in auctions. It does so for a setting of high external validity in which thousands of auctions take place each week. Our results qualitatively alter our understanding about the effects of jump bidding. In contrast to prior theorizing, we do not find that jump bids uniformly reduce final selling prices and seller revenue. Moreover, neither the estimated value of an item nor the uncertainty about this value moderate the impact of our treatment, again in contrast to what existing auction theory predicts. We find that our jump bids raise the number of bidders as well as the number of bids, but because these effects are offset by a reduction in the size of subsequent jump bids by others, they have no net effect on final selling prices.

Interestingly, we found that the effect of our jump bid strongly and highly significantly depends on the size of the jump, where larger jumps have a more positive effect on final selling price than smaller jumps. This result contrasts with prior theory which predicts that larger jumps are associated with reduced final selling prices. One interpretation for the positive jump size effect is that under uncertainty about the item's value, bidders make positive inferences about it from the size of others' jump bids. This interpretation is consistent with analyses where we find that uncertainty positively moderates the effect of jump bid size on the final selling price (see Table D6 in Appendix D). Given the incidental nature of this finding and the narrow range of jump bids explored, we are reluctant to overinterpret and invite others to replicate, exploring a wider range of jump bid sizes, and propose alternative theoretical accounts.

Data availability

The authors do not have permission to share data. The code used for data analysis is available at https://osf.io/qfsm6/.

Appendix A. Setting

Table A1
Minimum bid increments.

Bid range	Minimum increment
€ 0-€ 10	€ 1
€ 10-€ 100	€ 5
€ 100-€ 200	€ 10
€ 200-€ 500	€ 20
€ 500-€ 1000	€ 50
€ 1,000-€ 2,000	€ 100
€ 2,000-€ 5,000	€ 200
€ 5,000-€ 10,000	€ 500
€ 10,000-€ 20,000	€ 1,000
€ 20,000-€ 50,000	€ 2,000
€ 50,000-€ 100,000	€ 5,000
€ 100,000-€ 1,000,000	€ 10,000

Appendix B. Balance checks

Table B1 provides information on the auction listing, such as the average estimated value according to the online auction platform's experts and average shipping costs of the item for sale, as well as the scheduled duration of the auction, divided into our three experimental conditions. Kruskal-Wallis tests, corrected for tied ranks, and pairwise post-hoc Dunn tests with Bonferroni corrections are used to evaluate differences across the conditions. These results can be found in Table B2.

Table B1
Listing information, summary statistics.

	T					P					N				
	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max
ITT															
Avg estimated value	630	1923.6	1588.1	232.5	12600	615	1973.8	1665.1	225	12600	520	2141.3	1859.5	210	13125
Uncertainty	630	10.76	4.386	0	100	615	10.70	3.116	3.245	60	520	10.58	3.578	9.910	72.86
Avg shipping cost	630	50.86	27.90	0	200	615	50.60	27.53	0	150	520	48.73	26.38	0	150
Scheduled time (hours)	630	180.0	37.73	98	248	615	178.3	38.68	98	248	520	180.0	37.71	98	248
PP															
Avg estimated value	568	1837.7	1445.1	232.5	10500	523	1842.7	1502.4	225	12600	520	2141.3	1859.5	210	13125
Uncertainty	568	10.80	4.611	0	100	523	10.74	3.348	3.245	60	520	10.58	3.578	9.910	72.86
Avg shipping cost	568	50.27	28.02	0	200	523	50.00	28.23	0	150	520	48.73	26.38	0	150
Scheduled time (hours)	568	179.6	37.56	98	248	523	176.0	39.50	98	248	520	180.0	37.71	98	248
AT															
Avg estimated value	579	1835.0	1454.8	232.5	10500	524	1841.3	1501.3	225	12600	662	2283.9	1988.4	210	13125
Uncertainty	579	10.79	4.568	0	100	524	10.74	3.345	3.245	60	662	10.55	3.203	4.476	72.86
Avg shipping cost	579	50.43	27.97	0	200	524	50.08	28.28	0	150	662	49.93	26.01	0	150
Scheduled time (hours)	579	179.7	37.32	98	248	524	176.0	39.47	98	248	662	181.8	37.38	98	248

Table B2
Listing information, mean difference testing.

	Kruskal-Wallis	T vs. P	T vs. N	P vs. N
ITT				
Avg estimated value	0.245	1	0.157	0.322
Uncertainty	0.270	1	0.172	0.368
Avg shipping cost	0.305	1	0.265	0.262
Scheduled time (hours)	0.723	0.644	1	0.911
PP				
Avg estimated value	0.047	1	0.046	0.049
Uncertainty	0.356	0.986	0.237	0.513
Avg shipping cost	0.664	1	0.623	0.677
Scheduled time (hours)	0.225	0.233	1	0.174
AT				
Avg estimated value	0.0003	1	0.0006	0.001
Uncertainty	0.658	1	0.550	0.879
Avg shipping cost	0.989	1	1	1
Scheduled time (hours)	0.017	0.242	0.225	0.007

NOTES: P-values of the Kruskal-Wallis tests, corrected for tied ranks, and corresponding pairwise post-hoc Dunn tests, with Bonferroni corrections

The platform's experts estimate that the items for sale in our sample have average values ranging from 210 euros to 13125 euros. Most of the items are in the lower end of this scale. Figure B1 confirms that the average estimated values are log-normally distributed.

Table B2 reveals that there are no statistically significant differences in the average estimated values between assigned treatments (ITT). However, the estimated values differ significantly between per-protocol (PP) and received (AT) treatments; whereas there are no differences between the T and P conditions, both the T and P conditions have statistically significantly lower estimated values than the N condition. We conjecture that this is due to the fact that we had to exclude some auctions from the T and P conditions after we assigned the treatment, e.g., because another bidder beat us to it and already placed the first bid or because we were prohibited from bidding due to credit card restrictions. Indeed, if we consider only auctions that were not bid on (N condition, AT), we see that there is a negative correlation between the estimated values and the time the first bid was placed ($r(660) = -0.3243$, $p < 0.001$). It is not clear how credit card restrictions have contributed to this result, but we consider the possibility that the list of auctions was ordered by estimated value.

On average, an item's highest estimated value is 10% greater than its lowest estimated value. We interpret this measure as the uncertainty regarding the estimated value. This is not statistically significantly different across experimental conditions.

Each listing includes a list of shipping costs that have to be paid by the winning bidder, and that may differ depending on the winner's country of residence. The variable average shipping cost is constructed by taking the simple average of the shipping costs of the eight countries in which most of the platform's bidders reside. Though different shipping costs may apply to bidders outside of these countries, most sellers charge the same shipping cost for all countries outside of their own. The average shipping cost is the same across all conditions and ranges between free shipping and 200 euros.

At any point during the auction, bidders know that the auction is scheduled to end after some set time. On average, the auctions in our sample are scheduled to last roughly a week, with a minimum of 4 days and 2 hours, and a maximum of

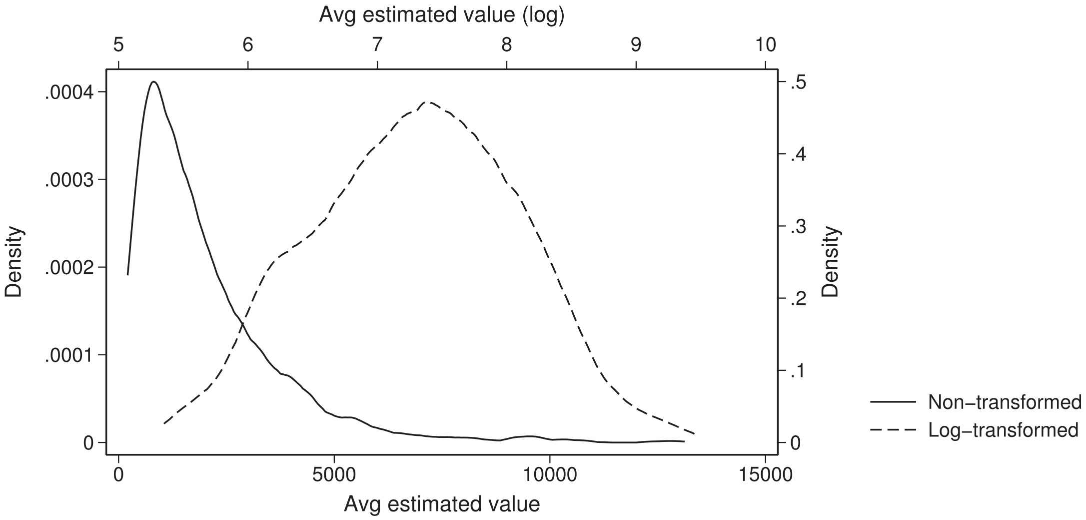

Fig. B1. Distribution plots of average experts' estimated values.

10 days and 8 hours. There is no difference across conditions for the ITT and PP analyses. However, in the AT analysis, the scheduled duration of the auctions in the N condition appears to be greater than those in the P condition.

Appendix C. Treatment delivery

Table C1
First bids, as treated (AT).

	T	P	N	Total
1	0	524	511	1,035
2	0	0	45	45
3	0	0	32	32
4	0	0	3	3
5	0	0	9	9
8	0	0	2	2
9	0	0	1	1
10	0	0	13	13
15	0	0	5	5
20	0	0	7	7
25	0	0	4	4
30	127	0	0	127
35	113	0	0	113
40	112	0	1	113
45	112	0	0	112
50	115	0	9	124
60	0	0	2	2
90	0	0	1	1
100	0	0	6	6
120	0	0	2	2
150	0	0	2	2
200	0	0	2	2
250	0	0	1	1
300	0	0	1	1
500	0	0	1	1
639	0	0	1	1
900	0	0	1	1
Total	579	524	662	1,765

Appendix D. Treatment effects on final selling prices

Table D1
Final selling prices.

	T					P					N				
	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max
ITT															
Total	630	319.5	357.5	35	6,000	615	311.2	337.1	35	4,200	520	311.3	284.6	45	2,660
Bid size															
30	135	248.4	193.2	35	1,000	132	277.5	245.4	35	1,600					
35	128	345.5	616.6	40	6,000	115	316.6	372.1	41	2,400					
40	126	336.1	277.1	45	1,800	119	327.4	363.5	45	2,600					
45	114	360.3	270.5	55	1,400	127	305.6	259.2	50	1,300					
50	127	315.7	255.7	55	1,900	122	332.8	424.4	57	4,200					
PP															
Total	568	306.3	342.3	35	6,000	523	297.2	326.0	41	4,200	520	311.3	284.6	45	2,660
Bid size															
30	122	234.5	177.5	35	1,000	111	269.4	249.6	45	1,600					
35	113	297.3	580.8	40	6,000	103	286.3	317.7	41	2,400					
40	112	325.0	279.1	45	1,800	105	299.8	323.6	45	2,600					
45	106	363.4	270.4	55	1,400	103	289.4	246.9	50	1,200					
50	113	320.4	256.5	55	1,900	100	346	459.1	57	4,200					
AT															
Total	579	305.4	341.0	35	6,000	524	296.8	325.8	41	4,200	662	335.7	323.0	45	3,200
Bid size															
30	127	229.1	176.8	35	1,000	111	269.4	249.6	45	1,600					
35	113	297.3	580.8	40	6,000	103	286.3	317.7	41	2,400					
40	112	325.0	279.1	45	1,800	107	296.7	321.3	45	2,600					
45	112	363.1	272.0	55	1,400	103	289.4	246.9	50	1,200					
50	115	322.4	255.7	55	1,900	100	346	459.1	57	4,200					

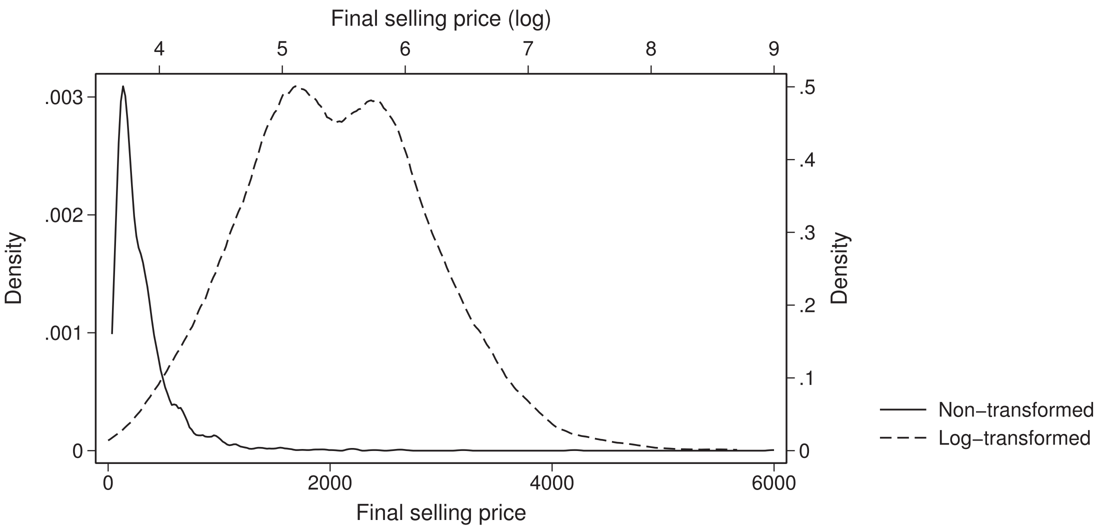

Fig. D1. Distribution plots of final selling prices.

Table D2
The effect of jump bidding on the final selling price.

Control group	P						N					
Analysis	ITT		PP		AT		ITT		PP		AT	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment effect	0.028	0.044	0.026	0.031	0.020	0.029	0.003	0.058*	-0.029	0.046	-0.093*	0.025
	(0.043)	(0.028)	(0.045)	(0.030)	(0.045)	(0.030)	(0.045)	(0.029)	(0.045)	(0.029)	(0.043)	(0.027)
Avg estimated value (log)		0.769***		0.757***		0.763***		0.740***		0.738***		0.747***
		(0.020)		(0.022)		(0.022)		(0.020)		(0.020)		(0.019)
Uncertainty (log)		0.116***		0.119***		0.121***		0.038		0.041		0.039
		(0.033)		(0.034)		(0.034)		(0.034)		(0.034)		(0.034)
Avg shipping cost (log)		-0.041+		-0.047+		-0.051+		-0.054*		-0.053*		-0.046+
		(0.024)		(0.026)		(0.026)		(0.026)		(0.027)		(0.025)
Scheduled time (hours)		0.000		0.000		0.000		-0.000		-0.000		-0.001
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Constant	5.431***	-0.194	5.400***	-0.162	5.399***	-0.191	5.455***	0.245	5.455***	0.216	5.512***	0.200
	(0.030)	(0.190)	(0.032)	(0.204)	(0.032)	(0.202)	(0.033)	(0.189)	(0.033)	(0.194)	(0.030)	(0.184)
Obs	1,245	1,245	1,091	1,091	1,103	1,103	1,150	1,150	1,088	1,088	1,241	1,241
R-squared	0.000	0.579	0.000	0.550	0.000	0.556	0.000	0.595	0.000	0.589	0.004	0.610

NOTES: Coefficients from OLS regressions on the log-transformed final selling price; standard errors in parentheses.
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table D3
Effect of jump bidding on the final selling price, interacted with average experts' estimated value.

Control group	P						N					
Analysis	ITT		PP		AT		ITT		PP		AT	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment effect	0.103	0.090	-0.002	-0.034	-0.067	-0.093	-0.040	-0.063	-0.012	-0.038	-0.006	-0.029
	(0.263)	(0.262)	(0.293)	(0.292)	(0.291)	(0.289)	(0.261)	(0.261)	(0.270)	(0.270)	(0.250)	(0.250)
Interaction with avg estimated value (log)	-0.008	-0.006	0.005	0.009	0.013	0.017	0.013	0.017	0.008	0.012	0.004	0.007
	(0.036)	(0.036)	(0.040)	(0.040)	(0.040)	(0.040)	(0.036)	(0.035)	(0.037)	(0.037)	(0.034)	(0.034)
Avg estimated value (log)	0.739***	0.772***	0.721***	0.753***	0.721***	0.754***	0.718***	0.732***	0.718***	0.732***	0.730***	0.744***
	(0.025)	(0.027)	(0.029)	(0.031)	(0.029)	(0.031)	(0.025)	(0.026)	(0.025)	(0.027)	(0.022)	(0.023)
Uncertainty (log)		0.116***		0.119***		0.121***		0.039		0.042		0.040
		(0.033)		(0.034)		(0.034)		(0.034)		(0.034)		(0.034)
Avg shipping cost (log)		-0.041+		-0.047+		-0.051+		-0.055*		-0.053*		-0.046+
		(0.024)		(0.026)		(0.026)		(0.026)		(0.027)		(0.025)
Scheduled time (hours)		0.000		0.000		0.000		-0.000		-0.000		-0.001
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Constant	0.044	-0.218	0.177	-0.127	0.174	-0.125	0.187	0.306	0.187	0.255	0.113	0.222
	(0.187)	(0.231)	(0.214)	(0.256)	(0.214)	(0.255)	(0.188)	(0.230)	(0.188)	(0.231)	(0.164)	(0.209)
Obs	1,245	1,245	1,091	1,091	1,103	1,103	1,150	1,150	1,088	1,088	1,241	1,241
R-squared	0.574	0.579	0.544	0.550	0.550	0.556	0.593	0.595	0.587	0.589	0.608	0.610

NOTES: Coefficients from OLS regressions on the log-transformed final selling price; standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table D4
Effect of jump bidding on the final selling price, interacted with uncertainty.

Control group	P						N					
Analysis	ITT		PP		AT		ITT		PP		AT	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment effect	-0.224	0.155+	-0.119	0.155	-0.110	0.157	-0.483***	-0.071	-0.584***	-0.099	-0.864***	-0.133
	(0.136)	(0.093)	(0.139)	(0.097)	(0.140)	(0.096)	(0.146)	(0.098)	(0.146)	(0.099)	(0.141)	(0.096)
Interaction with uncertainty (log)	0.180*	-0.078	0.103	-0.087	0.092	-0.089	0.359***	0.092	0.409***	0.103	0.571***	0.113+
	(0.091)	(0.062)	(0.092)	(0.064)	(0.093)	(0.064)	(0.099)	(0.067)	(0.099)	(0.067)	(0.096)	(0.065)
Avg estimated value (log)		0.772***		0.760***		0.765***		0.737***		0.734***		0.742***
		(0.020)		(0.022)		(0.022)		(0.020)		(0.020)		(0.019)
Uncertainty (log)	-0.549***	0.166**	-0.422***	0.175**	-0.423***	0.178***	-0.728***	-0.026	-0.728***	-0.031	-0.902***	-0.039
	(0.071)	(0.052)	(0.073)	(0.053)	(0.073)	(0.053)	(0.082)	(0.058)	(0.081)	(0.058)	(0.078)	(0.056)
Avg shipping cost (log)		-0.043+		-0.049+		-0.052*		-0.053*		-0.052+		-0.045+
		(0.024)		(0.026)		(0.026)		(0.026)		(0.027)		(0.025)
Scheduled time (hours)		0.000		0.000		0.000		-0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Constant	6.210***	-0.283	6.004***	-0.257	6.005***	-0.288	6.469***	0.349+	6.469***	0.338	6.759***	0.344+
	(0.106)	(0.203)	(0.109)	(0.215)	(0.109)	(0.214)	(0.118)	(0.204)	(0.118)	(0.209)	(0.111)	(0.202)
Obs	1,245	1,245	1,091	1,091	1,103	1,103	1,150	1,150	1,088	1,088	1,241	1,241
R-squared	0.076	0.580	0.057	0.551	0.058	0.557	0.096	0.596	0.094	0.590	0.123	0.611

NOTES: Coefficients from OLS regressions on the log-transformed final selling price; standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table D5
The effect of jump bidding on the final selling price, by bid size.

Control group	P						N					
Analysis	ITT		PP		AT		ITT		PP		AT	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment effect												
30	-0.175*	-0.117*	-0.249***	-0.147**	-0.224**	-0.150**	-0.200**	-0.103*	-0.292***	-0.138**	-0.337***	-0.155***
	(0.071)	(0.046)	(0.074)	(0.048)	(0.073)	(0.049)	(0.072)	(0.046)	(0.074)	(0.047)	(0.073)	(0.046)
35	-0.043	0.017	-0.180*	-0.016	-0.119	-0.006	-0.067	0.027	-0.224**	-0.010	-0.232**	-0.012
	(0.073)	(0.047)	(0.076)	(0.050)	(0.076)	(0.051)	(0.074)	(0.047)	(0.077)	(0.048)	(0.077)	(0.048)
40	0.106	0.112*	0.035	0.086+	0.097	0.100+	0.082	0.121*	-0.008	0.090+	-0.017	0.088+
	(0.074)	(0.048)	(0.076)	(0.050)	(0.076)	(0.051)	(0.074)	(0.047)	(0.077)	(0.048)	(0.077)	(0.048)
45	0.183*	0.134**	0.169*	0.124*	0.223**	0.146**	0.159*	0.152**	0.126	0.137**	0.110	0.142**
	(0.077)	(0.050)	(0.078)	(0.051)	(0.076)	(0.051)	(0.078)	(0.049)	(0.079)	(0.050)	(0.077)	(0.048)
50	0.097	0.093+	0.084	0.064	0.154*	0.079	0.072	0.114*	0.041	0.082+	0.040	0.082+
	(0.073)	(0.048)	(0.076)	(0.050)	(0.076)	(0.051)	(0.074)	(0.047)	(0.077)	(0.048)	(0.076)	(0.048)
Avg estimated value (log)		0.766***		0.764***		0.755***		0.737***		0.742***		0.741***
		(0.020)		(0.020)		(0.022)		(0.019)		(0.019)		(0.019)
Uncertainty (log)		0.115***		0.114***		0.118***		0.037		0.037		0.037
		(0.033)		(0.033)		(0.034)		(0.034)		(0.033)		(0.033)
Avg shipping cost (log)		-0.044+		-0.043+		-0.053*		-0.058*		-0.049*		-0.048*
		(0.024)		(0.024)		(0.026)		(0.026)		(0.025)		(0.024)
Scheduled time (hours)		0.000		0.000		0.000		-0.000		-0.001		-0.001
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Constant	5.431***	-0.160	5.460***	-0.135	5.399***	-0.120	5.455***	0.284	5.504***	0.252	5.512***	0.260
	(0.030)	(0.189)	(0.029)	(0.191)	(0.032)	(0.202)	(0.033)	(0.188)	(0.029)	(0.183)	(0.029)	(0.183)
Observations	1,245	1,245	1,245	1,245	1,103	1,103	1,150	1,150	1,242	1,242	1,241	1,241
R-squared	0.015	0.587	0.021	0.586	0.028	0.567	0.016	0.604	0.023	0.618	0.027	0.619

NOTES: Coefficients from OLS regressions on the log-transformed final selling price; standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table D6
The effect of jump bidding on the final selling price, by bid size and interacted with uncertainty.

Control group	P						N					
Analysis	ITT		PP		AT		ITT		PP		AT	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment effect												
30	-0.748***	0.165	-0.939***	0.109	-0.631***	0.142	-1.007***	-0.090	-1.390***	-0.159	-1.385***	-0.165
	(0.168)	(0.118)	(0.169)	(0.119)	(0.170)	(0.121)	(0.174)	(0.121)	(0.171)	(0.120)	(0.171)	(0.120)
35	1.559***	-0.165	0.826+	-0.412	1.157**	-0.322	1.300***	-0.300	0.375	-0.595*	0.403	-0.588*
	(0.396)	(0.276)	(0.426)	(0.294)	(0.423)	(0.298)	(0.393)	(0.272)	(0.421)	(0.286)	(0.421)	(0.285)
40	1.111**	0.435+	0.813*	0.399+	1.143**	0.470+	0.852*	0.249	0.361	0.184	0.389	0.191
	(0.341)	(0.234)	(0.351)	(0.241)	(0.349)	(0.244)	(0.340)	(0.232)	(0.348)	(0.235)	(0.348)	(0.234)
45	0.003	0.082	-0.173	0.042	0.203	0.113	-0.256	-0.132	-0.624**	-0.191	-0.551*	-0.170
	(0.229)	(0.157)	(0.231)	(0.158)	(0.230)	(0.160)	(0.232)	(0.158)	(0.232)	(0.157)	(0.230)	(0.156)
50	-0.175	-0.017	-0.313	-0.058	0.033	-0.004	-0.434*	-0.224	-0.764***	-0.280*	-0.721***	-0.268+
	(0.207)	(0.142)	(0.208)	(0.143)	(0.208)	(0.145)	(0.210)	(0.144)	(0.209)	(0.142)	(0.209)	(0.141)
Interaction with uncertainty (log)												
30	0.408***	-0.194**	0.493***	-0.175*	0.288**	-0.199**	0.587***	-0.006	0.802***	0.019	0.767***	0.012
	(0.107)	(0.075)	(0.106)	(0.075)	(0.107)	(0.076)	(0.112)	(0.078)	(0.110)	(0.077)	(0.110)	(0.077)
35	-1.168***	0.133	-0.714*	0.283	-0.910**	0.227	-0.989***	0.236	-0.405	0.417*	-0.431	0.411*
	(0.280)	(0.196)	(0.297)	(0.206)	(0.295)	(0.209)	(0.279)	(0.193)	(0.294)	(0.200)	(0.294)	(0.200)
40	-0.766**	-0.236	-0.594*	-0.228	-0.790**	-0.268	-0.587*	-0.096	-0.285	-0.070	-0.311	-0.076
	(0.245)	(0.169)	(0.251)	(0.172)	(0.249)	(0.174)	(0.244)	(0.167)	(0.249)	(0.168)	(0.250)	(0.168)
45	0.136	0.034	0.253+	0.055	0.020	0.020	0.315*	0.198+	0.562***	0.229*	0.500**	0.218*
	(0.151)	(0.103)	(0.151)	(0.104)	(0.151)	(0.105)	(0.154)	(0.105)	(0.153)	(0.103)	(0.152)	(0.103)
50	0.208	0.071	0.299*	0.079	0.097	0.052	0.387**	0.231*	0.608***	0.248**	0.576***	0.240**
	(0.132)	(0.091)	(0.133)	(0.091)	(0.133)	(0.092)	(0.136)	(0.093)	(0.135)	(0.092)	(0.135)	(0.091)
Avg estimated value (log)		0.780***		0.779***		0.770***		0.742***		0.745***		0.744***
		(0.021)		(0.021)		(0.023)		(0.020)		(0.019)		(0.019)
Uncertainty (log)	-0.549***	0.173***	-0.619***	0.160**	-0.423***	0.182***	-0.728***	-0.022	-0.928***	-0.041	-0.902***	-0.035
	(0.070)	(0.051)	(0.069)	(0.052)	(0.071)	(0.053)	(0.080)	(0.058)	(0.076)	(0.056)	(0.076)	(0.056)
Avg shipping cost (log)		-0.044+		-0.042+		-0.053*		-0.055*		-0.046+		-0.046+
		(0.024)		(0.024)		(0.026)		(0.026)		(0.024)		(0.024)
Scheduled time (hours)		0.000		0.000		0.000		-0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Constant	6.210***	-0.347+	6.336***	-0.311	6.005***	-0.328	6.469***	0.313	6.787***	0.327	6.759***	0.322
	(0.103)	(0.207)	(0.101)	(0.209)	(0.107)	(0.218)	(0.115)	(0.208)	(0.108)	(0.205)	(0.108)	(0.204)
Obs	1,245	1,245	1,245	1,245	1,103	1,103	1,150	1,150	1,242	1,242	1,241	1,241
R-squared	0.125	0.591	0.124	0.591	0.112	0.572	0.150	0.608	0.169	0.623	0.169	0.624

Notes: Coefficients from OLS regressions on the log-transformed final selling price; standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table D7
The effect of the size of the treatment on the final selling price in treated auctions (T condition).

Analysis	ITT		PP		AT	
Model	(1)	(2)	(3)	(4)	(5)	(6)
Size of treatment	0.015***	0.011***	0.020***	0.012***	0.022***	0.013***
	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)
Avg estimated value (log)		0.750***		0.736***		0.745***
		(0.028)		(0.031)		(0.030)
Uncertainty (log)		0.069		0.072+		0.074+
		(0.043)		(0.043)		(0.043)
Avg shipping cost (log)		-0.049		-0.046		-0.053
		(0.038)		(0.040)		(0.039)
Scheduled time (hours)		-0.000		0.000		0.000
		(0.001)		(0.001)		(0.001)
Constant	4.847***	-0.325	4.621***	-0.367	4.544***	-0.445
	(0.170)	(0.282)	(0.175)	(0.293)	(0.174)	(0.289)
Obs	630	630	566	566	579	579
R-squared	0.021	0.569	0.037	0.553	0.043	0.567

Notes: Coefficients from OLS regressions on the log-transformed final selling price; standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Appendix E. Treatment effects on other auction outcomes

Table E1
Other auction outcomes.

	T					P					N				
	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max
ITT															
Nr bidders	630	7.625	3.333	1	18	615	7.328	3.356	1	20	520	7.260	3.386	1	18
Nr bids	630	18.69	8.953	1	50	615	17.74	8.915	1	57	520	18.13	8.945	1	50
Nr jump bids	630	2.143	1.847	0	9	615	2.033	1.786	0	9	520	2.071	2.007	0	15
Avg size jump	630	7.317	50.67	0	989.2	615	5.713	12.40	0	148	520	5.392	11.15	0	148
PP															
Nr bidders	568	7.646	3.279	1	18	523	7.279	3.285	1	20	520	7.260	3.386	1	18
Nr bids	568	18.60	8.864	1	50	523	17.45	8.647	1	57	520	18.13	8.945	1	50
Nr jump bids	568	2.092	1.791	0	9	523	2.008	1.745	0	9	520	2.071	2.007	0	15
Avg size jump	568	5.302	41.95	0	989.2	523	5.409	11.49	0	148	520	5.392	11.15	0	148
AT															
Nr bidders	579	7.636	3.302	1	18	524	7.275	3.283	1	20	662	7.331	3.460	1	18
Nr bids	579	18.49	8.887	1	50	524	17.43	8.648	1	57	662	18.54	9.189	1	50
Nr jump bids	579	2.078	1.790	0	9	524	2.008	1.744	0	9	662	2.148	2.040	0	15
Avg size jump	579	5.316	41.57	0	989.2	524	5.409	11.48	0	148	662	7.575	32.66	0	638

Table E2
The effect of jump bidding on the number of bidders.

Control group	P						N					
Analysis	ITT		PP		AT		ITT		PP		AT	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment effect	0.297	0.356*	0.367+	0.406*	0.361+	0.415*	0.366+	0.548**	0.387+	0.616***	0.305	0.637***
	(0.190)	(0.167)	(0.199)	(0.174)	(0.199)	(0.173)	(0.199)	(0.174)	(0.202)	(0.177)	(0.193)	(0.170)
Avg estimated value (log)		2.108***		2.188***		2.203***		2.089***		2.112***		2.077***
		(0.120)		(0.128)		(0.126)		(0.120)		(0.122)		(0.116)
Uncertainty (log)		0.197		0.204		0.203		0.163		0.147		0.136
		(0.199)		(0.196)		(0.196)		(0.207)		(0.205)		(0.209)
Avg shipping cost (log)		-0.746***		-0.677***		-0.701***		-0.826***		-0.729***		-0.788***
		(0.146)		(0.151)		(0.150)		(0.159)		(0.161)		(0.154)
Scheduled time (hours)		0.002		-0.001		-0.001		-0.001		-0.003		0.000
		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)
Constant	7.328***	-5.826***	7.279***	-6.118***	7.275***	-6.136***	7.260***	-5.007***	7.260***	-5.155***	7.331***	-5.291***
	(0.135)	(1.138)	(0.144)	(1.177)	(0.144)	(1.171)	(0.147)	(1.157)	(0.146)	(1.169)	(0.132)	(1.140)
Obs	1,245	1,245	1,091	1,091	1,103	1,103	1,150	1,150	1,088	1,088	1,241	1,241
R-squared	0.002	0.232	0.003	0.241	0.003	0.247	0.003	0.239	0.003	0.246	0.002	0.237

NOTES: Coefficients from OLS regressions on the number of other bidders; standard errors in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$, + $p<0.1$

Table E3
The effect of jump bidding on the number of bids.

Control group	P						N					
Analysis	ITT		PP		AT		ITT		PP		AT	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment effect	0.946+	1.107**	1.149*	1.245**	1.061*	1.202**	0.562	1.117**	0.468	1.197**	-0.053	1.048*
	(0.506)	(0.412)	(0.531)	(0.433)	(0.529)	(0.430)	(0.530)	(0.426)	(0.540)	(0.432)	(0.515)	(0.415)
Avg estimated value (log)		6.903***		7.019***		7.040***		6.842***		6.909***		6.842***
		(0.296)		(0.318)		(0.314)		(0.293)		(0.299)		(0.283)
Uncertainty (log)		0.644		0.675		0.676		0.249		0.274		0.232
		(0.493)		(0.487)		(0.486)		(0.506)		(0.502)		(0.510)
Avg shipping cost (log)		-1.126**		-0.948*		-1.006**		-1.523***		-1.296**		-1.424***
		(0.360)		(0.376)		(0.373)		(0.389)		(0.393)		(0.375)
Scheduled time (hours)		0.004		-0.006		-0.006		-0.007		-0.013*		-0.002
		(0.006)		(0.006)		(0.006)		(0.006)		(0.006)		(0.006)
Constant	17.745***	-30.010***	17.447***	-29.759***	17.429***	-29.665***	18.129***	-25.436***	18.129***	-25.750***	18.544***	-26.647***
	(0.360)	(2.814)	(0.383)	(2.929)	(0.383)	(2.908)	(0.392)	(2.826)	(0.390)	(2.860)	(0.352)	(2.787)
Obs	1,245	1,245	1,091	1,091	1,103	1,103	1,150	1,150	1,088	1,088	1,241	1,241
R-squared	0.003	0.343	0.004	0.342	0.004	0.346	0.001	0.360	0.001	0.366	0.000	0.360

NOTES: Coefficients from OLS regressions on the number of bids by other bidders; standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table E4
The effect of jump bidding on the number of jump bids.

Control group	P						N					
Analysis	ITT		PP		AT		ITT		PP		AT	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment effect	0.110	0.131	0.084	0.086	0.070	0.078	0.072	0.152	0.020	0.132	-0.070	0.105
	(0.103)	(0.091)	(0.107)	(0.095)	(0.107)	(0.095)	(0.114)	(0.101)	(0.115)	(0.102)	(0.110)	(0.097)
Avg estimated value (log)		1.102***		1.092***		1.093***		1.154***		1.134***		1.136***
		(0.066)		(0.070)		(0.069)		(0.069)		(0.071)		(0.067)
Uncertainty (log)		0.115		0.095		0.100		0.086		0.089		0.113
		(0.109)		(0.107)		(0.107)		(0.120)		(0.119)		(0.120)
Avg shipping cost (log)		0.113		0.088		0.089		0.027		0.041		0.074
		(0.080)		(0.083)		(0.082)		(0.092)		(0.093)		(0.088)
Scheduled time (hours)		-0.001		0.001		0.001		-0.000		0.000		-0.002
		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)
Constant	2.033***	-6.384***	2.008***	-6.466***	2.008***	-6.502***	2.071***	-6.573***	2.071***	-6.544***	2.148***	-6.392***
	(0.073)	(0.624)	(0.077)	(0.646)	(0.077)	(0.641)	(0.084)	(0.667)	(0.083)	(0.676)	(0.075)	(0.654)
Obs	1,245	1,245	1,091	1,091	1,103	1,103	1,150	1,150	1,088	1,088	1,241	1,241
R-squared	0.001	0.218	0.001	0.213	0.000	0.215	0.000	0.226	0.000	0.220	0.000	0.223

NOTES: Coefficients from OLS regressions on the number of jump bids by other bidders; standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table E5
The effect of jump bidding on average size of jumps.

Control group	P						N					
Analysis	ITT		PP		AT		ITT		PP		AT	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment effect	-0.058*	-0.057*	-0.087***	-0.090***	-0.086***	-0.089***	-0.070*	-0.065*	-0.105***	-0.096***	-0.130***	-0.114***
	(0.028)	(0.027)	(0.026)	(0.026)	(0.026)	(0.026)	(0.030)	(0.029)	(0.027)	(0.026)	(0.028)	(0.028)
Avg estimated value (log)		0.119***		0.095***		0.095***		0.126***		0.109***		0.121***
		(0.020)		(0.019)		(0.019)		(0.020)		(0.018)		(0.019)
Uncertainty (log)		0.044		0.042		0.043		0.018		0.018		0.023
		(0.032)		(0.029)		(0.029)		(0.034)		(0.031)		(0.034)
Avg shipping cost (log)		0.089***		0.060**		0.063**		0.081**		0.066**		0.094***
		(0.024)		(0.022)		(0.022)		(0.026)		(0.024)		(0.025)
Scheduled time (hours)		-0.001*		0.000		0.000		-0.000		0.000		-0.001*
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Constant	0.446***	-0.665***	0.440***	-0.611***	0.441***	-0.627***	0.458***	-0.717***	0.458***	-0.692***	0.484***	-0.628***
	(0.020)	(0.185)	(0.019)	(0.174)	(0.019)	(0.173)	(0.022)	(0.191)	(0.019)	(0.174)	(0.019)	(0.186)
Obs	1,245	1,245	1,091	1,091	1,103	1,103	1,150	1,150	1,088	1,088	1,241	1,241
R-squared	0.003	0.051	0.010	0.047	0.010	0.049	0.005	0.057	0.014	0.065	0.017	0.072

NOTES: Coefficients from OLS regressions on the log-transformed average size of jump bids by other bidders; standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

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