Information Transparency in Multi-Channel B2B Auctions: A Field Experiment

Completed Research Paper

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Abstract

With the large amount of data available via different channels, firms have increasingly viewed information transparency as an important component of their strategy. This paper examines how the disclosure of winners' information affects sellers' revenues in multi-channel, B2B sequential auctions. Using a field experiment, we find that bidders tend to pay higher prices when winners' identities are concealed from public view. At the outset, such finding contradicts the prediction of the well-known linkage principle in auction theory. Our empirical analysis suggests that anonymizing winning bids might discourage tacit collusion and mitigate the declining price trend in these B2B sequential auctions. This paper contributes to the growing literature on information transparency in market design. It also provides valuable insights to practitioners in designing information revelation policies in complex B2B markets.

Keywords: Auction design, B2B markets, Difference-in-Differences, field experiment, information transparency, linkage principle, sequential auctions, tacit collusion.

Introduction

The proliferation of electronic marketplaces has brought tremendous changes to the business world. Compared with the traditional brick-and-mortar markets, these Internet-enabled marketplaces substantially reduce consumer' search costs (Bakos 1997) and thus enable them to better discern products that best fit their needs. Firms, however, are forced to deal with the paradox of the benefits brought by the electronic marketplaces (Granados et al. 2010). On one hand, the increased availability of information allows them to strategically target consumers in various markets. On the other hand, the increased transparency of markets makes it more difficult to capture profits because their competitors and consumers are better informed (Porter 2001). The two sides of the coin of information transparency for firms motivate us to study the strategic revelation of information in Business-to-Business (B2B) environment.

Information transparency which is defined as the level of availability and accessibility of market information to its participants (Zhu 2004) is deemed to be good to the whole supply chain because it helps improve the allocative efficiency (Cachon and Fisher 2000; Lee et al. 2000; Patnayakuni et al. 2006). Yet it affects the two sides of the market, i.e., buyers and sellers, very differently. For example, using a comprehensive analytical model, Zhou and Zhu (2010) show that depending on the competition mode of the downstream industry, one side will always be worse off under the increased transparency enabled by the electronic B2B markets, although the total welfare of market participants are increased regardless of the competition mode.

Given such conflict of interests, a natural question for the B2B market-maker is how to design and implement the information revelation policies for its own benefits[1]. What information should be disclosed? Under what conditions? The answers to these questions depend largely on the real-world context.

In this paper, we focus on information transparency in a complex B2B setting, the Dutch Flower Auctions. The Dutch Flower Auctions are multi-unit, sequential, Dutch auctions. They account for more than 60% of the global flower trade and generate an annual turnover of €4 billion (Kambil and van Heck 1998). The sheer magnitude of transactions in this market makes it important to carefully weigh the trade-offs of different transparency strategies. Using a field experiment, we seek to understand how the disclosure of winners' identities influence the behavior of market participants and the final outcome in these auctions.

Drawing upon the linkage principle (Milgrom and Weber 1982b), which basically states that a seller can expect to increase revenues by providing more information to bidders before and during the auction[2], we expect that disclosing winners' identities would yield higher revenue for the sellers in these auctions. Surprisingly, however, our analysis of the experimental data shows that bidders, on average, pay significantly lower (4.5%) prices when auctioneers disclose the winners' identities rather than withholding such information. Further, in light of the literature on declining price anomaly (Van den Berg et al. 2001), we also look into the informational effects of winners' identities on price dynamics at auction-level. We find that withholding winners' identities tends to mitigate the declining trend in a sequential auction.

Since bidders in these auctions participate in the bidding activities repeatedly over a long period[3], it is likely that the failure of the linkage principle is due to bidders' tacit collusion (Bajari and Yeo 2009; Sherstyuk and Dulatre 2008). In general, collusion is easier to sustain in environments that are more transparent. Therefore, we examine the relationship between bidders' participatory patterns and revelation policies (i.e., whether winners' identities are disclosed or not). Our analysis shows that bidders who restrict their purchases to a few number of sellers (thus more likely to collude), on average, pay lower (9.8%, statistically significant) prices when winner's identities are disclosed. However, when such information is not available, such price-related advantage gets mitigated substantially.

Our paper makes several contributions to the growing body of information systems (IS) literature on the design of transparency strategies in B2B markets. First of all, we present empirical evidence that linkage principle might not hold for B2B sequential Dutch auctions. In other words, sellers might be worse off by revealing more information to bidders. Compared with previous studies, for example, Arora et al. (2007); Greenwald et al. (2010); Zhu (2004)), we study information revelation policies in a complex real-world environment. Additionally, most of the existing studies focus on the revelation of bids in English auctions, we on the other hand examines the revelation of winners' identities in Dutch auctions where only winning bids are revealed and thereby, less transparent by their nature. To the best of our knowledge, no prior work has compared different revelation policies in Dutch auctions using field data. Secondly, our results provide additional insights of the declining price anomaly (Ashenfelter 1989; McAfee and Vincent 1993; Van den Berg et al. 2001). From the managerial perspective, our findings offer a simple and effective way to mitigate the declining trend in multi-unit, sequential Dutch auctions.

The rest of this paper is organized as follows. Section 2 provides a review of related literature. Section 3 introduces the empirical setting. In Section 4, we first present the econometric model and the empirical results, and continue with a discussion of robustness checks and additional analysis. Finally, Section 5 summarizes the findings and discusses the implications.

Related Literature

In this section, we discuss two streams of literature on sequential auctions that are closely related to the current study, namely, information revelation policies and declining price anomaly.

[1]According to Yoo et al. (2007), B2B markets can be classified into three types based on their ownership structure: buyer-owned marketplaces, seller-owned marketplaces, and neutral marketplaces that are owned by independent third parties. The ownership structure has a direct impact on the market-maker's choice of transparency strategies.

[2]The linkage principle was derived under symmetric affiliation (Milgrom and Weber 1982b). In our case, while bidders in the flower auctions typically serve distinct market segments and there is certainly individual-specific, private-value component in their purchases, common-value component surely exists, too. For example, Koppius et al. (2004) have shown that seller's reputation plays a critical role in determining the final transaction prices, suggesting that there is some unknown quality that matters to all potential buyers.

[3]According to the auctioneers, most of the bidders have been participating in the bidding for five or sometimes ten years.

Information Revelation in Auctions

The popularity of online auction platforms has drawn an increasing research interest in the design of information-revelation policies (Arora et al. 2007; Greenwald et al. 2010). While Milgrom and Weber (1982a)'s linkage principle suggests that sellers typically benefit by providing more information to bidders[4], in many real-world applications, the information-revelation problem is more subtle, for example, sellers might not be able to directly release the information, or they might not have full control of bidders' perceived content of the information (Abraham et al. 2013).

When it comes to multi-unit (sequential) auctions, the analysis of different information-revelation policies becomes more difficult and the findings concerning the linkage principle are mixed. Perry and Reny (1999) provide a counter-example where the linkage principle breaks down in multi-unit auctions. On the contrary, Arora et al. (2007) and Greenwald et al. (2010) show that complete information policy (which minimizes the uncertainty on market structure and opponents' cost structure, respectively) generates higher buyer surplus in sequential procurement auctions, suggesting that linkage principle holds for these auctions.

So far, most of the existing research on information-revelation policies in auctions is purely analytical, i.e. the results are derived from equilibrium analysis of different auction models where bidders are assumed to be strictly rational. The few papers that empirically tests the linkage principle using controlled lab experiments (Kagel and Levin 1986; Levin and Smith 1996), the results are again inconclusive. Specifically, researchers find that in experiments involving inexperienced bidders, the winner's curse[5] due to overbidding is more prevalent in sealed-bid auctions (less transparent) than English auctions. This leads to higher revenues in sealed-bid auctions than English ones, contrary to the prediction of linkage principle. However, in experiments involving experienced bidders, the winner's curse is alleviated and sellers' revenues are higher in English auctions, which is consistent with the linkage principle.

Our current study examines the impact of information revelation policy on seller revenue using a large field experiment. Compared with previous work, our empirical setting features a complex, dynamic market where bidders are highly experienced.

Declining Price Anomaly

Within the symmetric independent private value paradigm (IPVP), Weber (1983) shows that in sequential auctions where bidders have single-unit demand, the equilibrium price path under the standard auction formats and pricing rules follows a *martingale*[6]– the expected winning price in the future round and the current round are the same. When bidders have multi-unit demand, Donald et al. (2006) demonstrate that the equilibrium price path follows a super-martingale, i.e., the equilibrium price rises as a sequential auction proceeds. However, such neat theoretical results are not supported by empirical findings. Ashenfelter (1989) and McAfee and Vincent (1993) have found price declines in sequential wine auctions. Similar declining price phenomena are also observed in art auctions (Beggs and Graddy 1997) and flower auctions (Van den Berg et al. 2001).

The contradiction between theory and empirical findings, which has been coined as *declining price anomaly*, has attracted a significant amount of research which attempts to offer plausible explanations. These explanations can be cast into two broad categories. The first category consists of studies that examine bidder heterogeneity (McAfee and Vincent 1993) or product heterogeneity (Engelbrecht-Wiggans 1994). The second category focuses on the informational effect in the sequential auctions. For example, Jeitschko (1998) associates the declining price anomaly with two unique learning effects in sequential auctions–a direct effect where information from the previous rounds is used to form the current bids and an anticipation effect where bidders try to account for the effect of their earlier bids on their opponents' bids.

In this research, we do not attempt to probe into the causal relationships between various endogenous or exogenous factors and the price decline. Instead, we are interested in whether information revelation policy affects the declining trend in fast-paced sequential auctions.

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[4]One can imagine numerous circumstances where the disclosure of information can have negative impact on the auction outcome (for example, if the seller revealed information about the defects of the item under auction), however, the remarkable implication from the linkage principle is that, *ex ante,*, releasing more information can help increase the seller's expected revenue.

[5]For more details about winner's curse, see P. 84 in (Krishna 2002).

[6]In probability theory, a martingale is a model of a fair game where knowledge of past events never helps predict the mean of the future winnings (Williams 1991).

Empirical Setting

In this section, we provide details of the empirical setting and the data collected from the field experiment.

Institutional Details

The empirical data used in this research are obtained from the largest wholesale market of cut flowers and ornamental plants in the world, namely, the Dutch Flower Auctions. The Dutch Flower Auctions play a critical role in maintaining the Netherlands' leadership in the floriculture industry (Kambil and van Heck 1998). They account for more than 60% of the global flower trade. In 2012, the total turnover of the auctioned products (i.e., cut flowers, indoor and outdoor plants) was approximately €4.4 billion.

The Mechanism

The Dutch Flower Auctions use the Dutch auction mechanism. They are implemented using fast-paced auction clocks displayed on a electronic board. Aside from the current asking price, each clock also contains information about the setup of the current auction (for example, monetary unit, minimum purchase units as well as bundling properties). Further, bidders can also see the information of the product under auction (name of the product, identity of the grower, various quality indicators and a representative picture of the product) from the electronic board. Figure 1 provides an illustration of the clock interface.

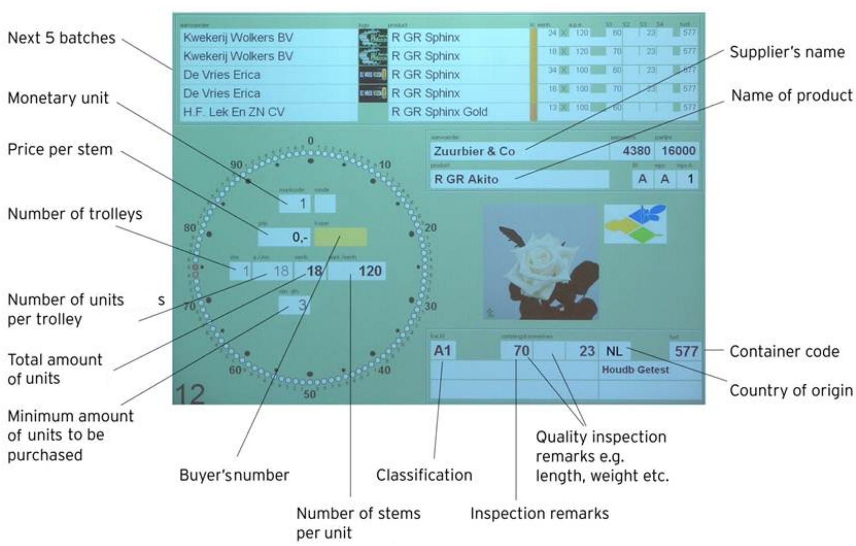

Figure 1. Illustration of the auction screen. The setup of the current auction is shown on the clock whereas the product information and the upcoming schedules are shown on the right and top-left of the screen, respectively.

At the beginning of an auction, the auctioneer decides the starting position of the clock which corresponds to a high price of the product, and sets the clock in motion. As the clock ticks down counterclockwise, each bidder can stop the clock by pressing a button indicating that she is willing to accept the price corresponding to the current clock position. The first bidder who makes a bid wins. The winning bidder, whose identity is shown on the clock screen, can select the portion of the lot being auctioned (which must exceed the minimum required amount). If the winning bidder does not select the entire available amount, the clock ticks backward and restarts at a high position, and the auction continues. This process repeats until the entire lot is sold, or the price falls below the seller's reserve price[7], in which case any unsold goods in that lot are destroyed. Such multi-unit, sequential Dutch auctions operate in a time-efficient manner: on average, each transaction takes 3 to 5 seconds. Therefore, they are well suited to the wholesale market of flowers.

Table 1 gives a stylized example of a sequence of transactions that can be found in our data set. In this example, a lot

[7]Currently, the reserve price is fixed for the entire year, regardless of auction site and flower types.

containing 18 units is sold. Note that the sales prices are not monotonically decreasing or increasing[8]. Also, unlike the existing studies which focus on the situation where only one unit is sold in each round, in our case, the purchase quantity in each round can vary a lot. Because bidders do not know *a priori* whether there will be units left after the current round of auction, they face much higher uncertainty in these auctions.

Table 1. A sample entry in a logbook. The auctioneer's decision variables are italicized.

Transaction Index	Transaction Time	Seller ID	Flower ID	Stem Length	Stems Per Unit	Available Units	*Minimum Purchase Units*	*Starting Price* (cent)	Buyer ID	Purchase Units	Price (cent)
171	08:10:54	5644	103668	70	50	18	1	100	439	2	22
172	08:10:56	5644	103668	70	50	16	3	41	395	5	20
173	08:10:57	5644	103668	70	50	11	4	39	439	7	21
174	08:10:59	5644	103668	70	50	4	4	40	563	4	20

The Auctioneer's Problem

The auctioneers in the Dutch Flower Auctions represent the growers. Therefore, an important goal of their work is to maximize the total revenue. Further, given the perishability of flowers, it is also critical to achieve a quick turnaround in these auctions. In fact, the total time for conducting the auctions has long been a hard constraint for the growth of the market. Auctioneers can influence the dynamics of the sequential multi-unit auctions by controlling the key auction parameters including clock speed, starting prices, minimum purchase quantities and reserve prices. The choices of these parameters often involve tradeoffs between revenue maximization and the total time need to finish the auctions.

Further, auctioneers can also influence the bidding competition by disclosing or withholding extra information about market states (for example, the number of bidders logged into the bidding system) during an auction. The disclosure of certain information have both direct and indirect effects on bidding behavior in sequential rounds. First, bidders are able to use the extra information disclosed in the previous rounds to update their beliefs about their opponents and adjust their bidding strategies. Second, bidders might take into account such direct informational effect and strategically alter their behavior in the previous rounds.

As more and more bidders adopt the remote bidding application and participate in the auctions via the online channel, the design and implementation of information policies, particularly the information revelation policies become increasingly critical to the revenue generation of these auctions (Koppius 2002). For one thing, the online channel allows more bidders to participate in the auctions and significantly increases the market-level uncertainty. For another, it also allows bidders especially the large buyers can better coordinate their bidding activities across different auction sites[9]. Unfortunately, however, due to the limited availability of proprietary data, there is a lack of normative insights that may inform or guide the design of these information policies.

Experimental Design

We conduct a quasi-natural field experiment (Harrison and List 2004) to investigate how the disclosure of winners' information affect the bidding dynamics and outcomes in the complex environment of the Dutch Flower Auctions. The experiment ran from November 19 to December 7, 2012 at a major auction site and we chose a clock which auctioned chrysanthemums, the flowers in season from the whole period of October to December [10]. The experimental treatment was implemented as follows. After the first bidder stopped the clock and made a purchase, all the bidders could see the winning price (indicated by a marker on the clock) and the remaining unit(s), just as in the regular setting of the Dutch Flower Auctions. However, the winner's identity was removed from the clock screen. In other words, none of the bidders, except the winner herself, knew who was the winner in the current round[11].

[8]Van den Berg et al. (2001) show empirical evidence for declining price anomaly in the flower auctions; however, if we look at individual auctions, price trends are inconclusive in these multi-unit sequential auctions.

[9]The auction schedules at different sites are not synchronized and there is indeed potential for arbitrage.

[10]As a matter of fact, chrysanthemums have the second largest transaction amount among all the auctioned products. In 2012, more than 1.1 million units of chrysanthemums were traded.

[11]As the researcher, we always have access to the winners' identities since they were registered in the auctioning system during each transaction.

Aside from the transaction data from the *treatment* site during the experimental period, we also collected data from the same site before the experimental period (from October 29 to November 16), and data from a *control* site[12] where the same type of flower was auctioned before and during the experimental period.

Figure 2 is an overview of the experimental design. Basically, bidders could always observe winners' identities at both the treatment site and control site prior to the experiment period, whereas during the experiment period only bidders at the control site had access to such information. To make sure that bidders were well informed about the change which would be implemented during the experiment period, the auction department of the company held a webinar at the end of October 2012 so that the auctioneers and bidders could exchange their thoughts.

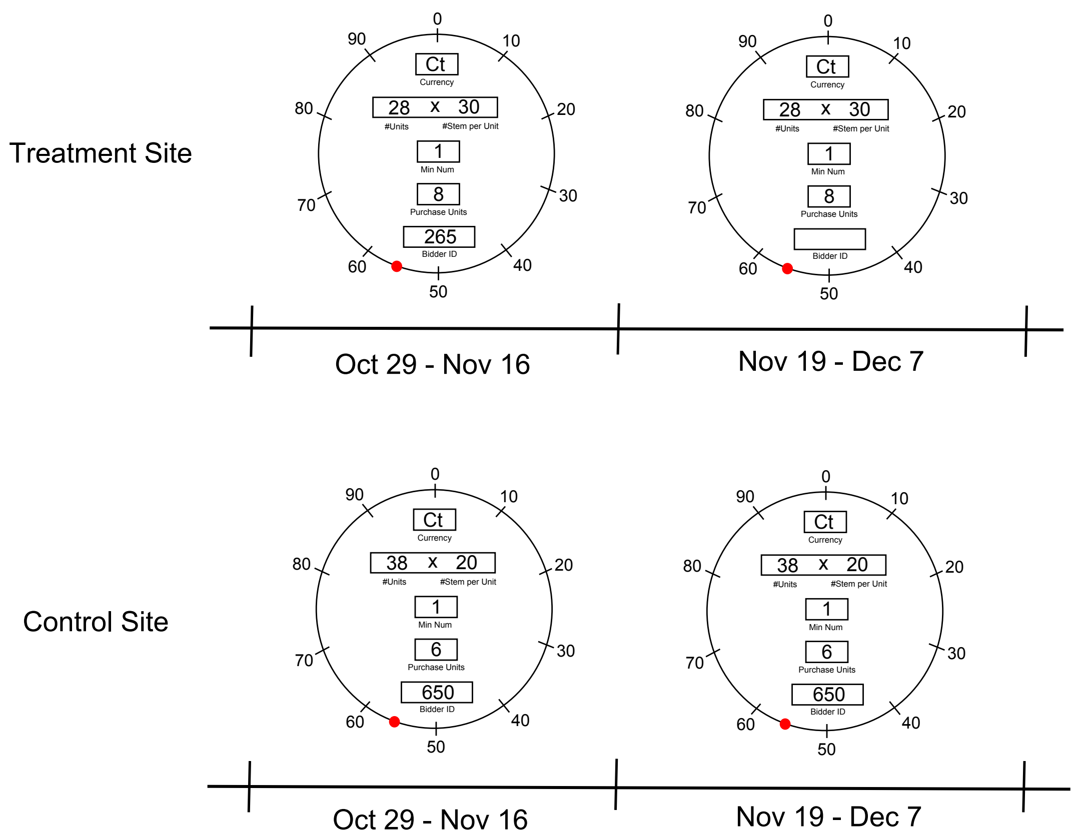

Figure 2. Overview of the experimental design. During the experimental period, bidders at the treatment site could not observe winners' identities.

As opposed to the previous lab experiments that examined information revelation policies (for example, Cason et al. (2011)), the main advantage of this quasi-natural field experiment is that it retains the rich interaction (both explicit and implicit) and dynamics from the real-world B2B auctions and thus allows us to better investigate the nuances of professional bidders' behavior that *naturally* occurs under different revelation policies.

Data and Preliminary Analysis

In order to control for the product heterogeneity, we selected the transactions of *Chrysanthemum spray white/yellow GP*. The total number of transactions at the treatment site during period I (pre-experiment) is 11613 (from 1798 auctions), and the total number of transactions during period II (experiment) is 11899 (from 1855 auctions). Table 2 summarizes the descriptive statistics of the data.

[12]Technically speaking, with the introduction of online channel, bidders can choose to purchase from any one of the six auction sites within the country. There is no *a priori* structural differences in terms of product, auction mechanism and policy between different auction sites. However, bidders usually choose the one closest to their distribution center in order to minimize the logistic cost. This is particular the case for large buyers (e.g., wholesalers). In our case, the treatment site and control are among the top with respect to the annual transaction amount.

We can see that on average, bidders' bidding frequency[13] does not vary from period I to period II. Also, the number of winning bidders in an auction stays the same during the two periods, i.e., on average, there were 6 winners in each auction. However, while bidders' purchase quantity (per transaction) in the experiment period does not differ from the pre-experiment period, the average winning price increased by 14.6% and such increase is statistically significant (P-value < 0.001).

Table 2. Descriptive statistics of the dataset.

Statistics	# of bidders per auction		Bid frequency (auction)		Bid frequency (day)		Price (cent)		Purchase amount	
	I	II	I	II	I	II	I	II	I	II
Mean	6.3	6.2	1.0	1.0	4.3	4.5	26.7	**30.6**	10.5	9.9
Median	6.0	6.0	1.0	1.0	3.0	3.0	25.0	**30.0**	5.0	5.0
Std.	4.1	4.0	0.2	0.2	4.3	4.6	9.6	7.3	16.8	14.9
Skewness	1.1	1.0	6.2	6.3	2.1	2.2	0.4	0.1	6.1	5.6
Minimum	1	1	1	1	1	1	5	5	1	1
Maximum	32	32	3	4	29	34	62	66	347	264

Given that bidders can choose between the online and offline channels in these auctions, we looked into the channel usage patterns before and during the experiment period. Our first finding is that the percentage of online transactions[14] during the two periods does not change, i.e., 90% of the transactions were made via the online channel before the experiment and 91% during the experiment. However, the winning prices from both channels increased significantly during the experiment period (14.8% for online and 15.4% for offline channel), see Figure 3.

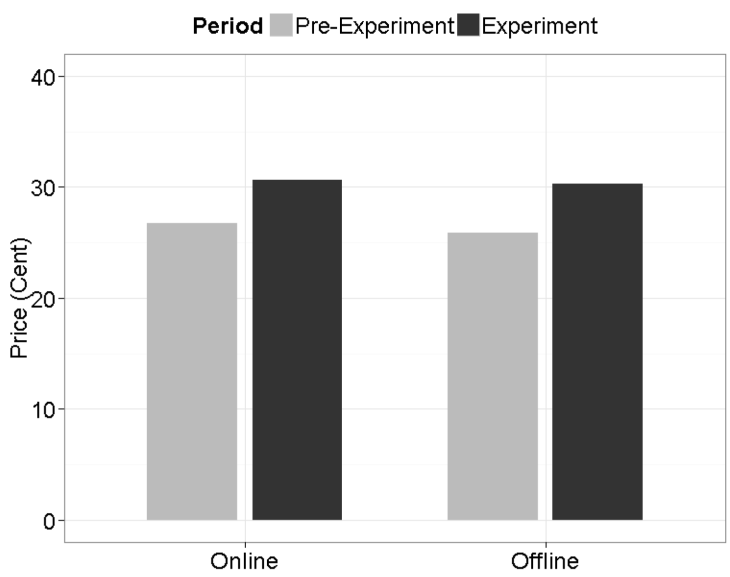

Figure 3. Comparison of average winning prices in pre-experiment and experiment period.

Further, in light of the literature on declining price trend in sequential auctions, we also examined the evolution of transaction prices at auction-level during the pre-experiment and experiment periods, respectively. Given the potential

[13]We use the number of rounds a bidder participated in an auction, i.e., Bid frequency (auction) and the number of auction a bidder participated on a given day, i.e., Bid frequency (day) to characterize bidders' bidding behavior in the two periods.

[14]Here, we refer the "online transactions" as the transactions where the corresponding winning bidders participated in the auctions via the online channel. Similarly, the offline transactions refer to the transactions with the winning bidders bidding offline.

unobserved heterogeneity across lots, we normalized the transaction prices in subsequent rounds with the first round in an given auction. The comparison is depicted in Figure 4, where we have two observations. First, the price exhibits an overall declining trend in both the pre-experiment and experiment periods. Second, the declining trend seems to be alleviated during the experiment period. More specifically, the mean values of normalized prices in the subsequent rounds during the experiment period are higher than those observed during the pre-experiment period, and the variances of the normalized prices also shrink considerably during the experiment period.

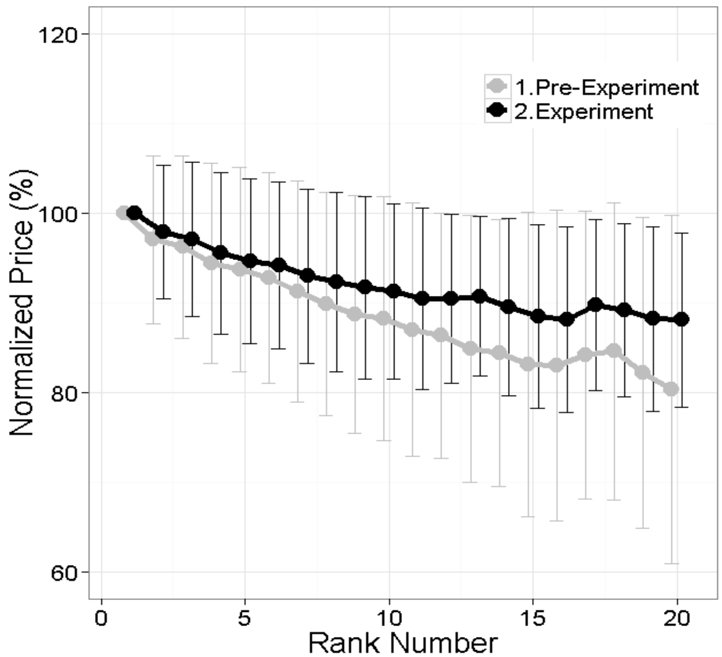

Figure 4. Comparison of price dynamics at auction-level during pre-experiment and experiment periods.The rank number denotes the rank of the current transaction, i.e., if a transaction was made in the 2nd round, the rank number is 2. The vertical bars denote one standard deviations of the normalized prices in each round.

The above aggregate-level results seem to suggest that withholding winners' identities has a positive impact on the transaction prices. However, the main concern about such model-free evidence is that it does not control for any potential systematic changes in market conditions. For example, it is likely that there was a higher demand during the experiment period, or bidders who participated in the auctions during the experiment period are not the same ones participating in the pre-experiment period.

Econometric Model

In order to identify the causal impact of the policy change regarding information transparency on transaction prices of sequential auctions, we apply the so-called difference-in-differences (DID) technique by using a matched sample from the control site. DID is a quasi-experiment technique that models the treatment effect by estimating the difference between outcome measures at two time periods for both the treated subjects and the controls and then comparing the difference between the treated and control groups (Meyer 1995).

If we use $t = 0$ to denote the pre-experiment period and $t = 1$ the experiment period, $\log P_{i,t}$ to denote the log-transformed price for transaction i in period t, the underlying model for DID can be written as follows:

$$\log P_{i,t} = \beta_0 + \beta_1 T_t + \beta_2 G_i + \beta_3 G_i * T_t + \gamma X_{i,t} + \epsilon_{i,t}, \tag{1}$$

where G_i and T_t are both dummy variables, G_i taking the value 1 if transaction i is from the treatment site and 0 if it is from the control site, and $T_t = 1$ if $t = 1$ and 0 otherwise. $X_{i,t}$ is the control variable for the observed covariates, which, in our case, include product characteristics (i.e., stem length, bundling condition, blooming stage) and the transaction-level auction design parameter, minimum purchase quantity. Note that β_1 summarizes the way that both the treatment and control groups are influenced by time. Additionally, all the time-invariant differences between the treatment and control groups are captured by β_2. The DID estimator is just the OLS estimate of β_3, i.e., the coefficient of the interaction term. The model specified in Equation 1 ensures that any variable that remains constant over time (which may not be observable) and not correlated with the outcome variable will not bias the estimated effect.

Results

In this section, we first present the main results and then continue with the robustness check and additional analyses.

Main Results

We applied the DID model to the pooled panel data, i.e., the transactions from the treatment site and control site[15] during the pre-experiment and experiment period. In total, we have 55662 transactions. Fitting the data[16] into the regression model in Equation 1, we can obtain the estimates of the treatment-related effects. Table 3 provides an overview of the estimation results. For the demonstration purpose, we only included the coefficients related to the treatment of the experiment, i.e.,β_1 which captures the overall time-dependent effect, β_2 which captures the time-invariant differences between the two sites, and β_3 for the true treatment effect.

Table 3. Estimation results of the DID model (entire sample).

Variable (Coefficient)	Estimate	Std. error	P-value[17]
Treatment period (β_1)	0.127	0.003	0.000 ***
Treatment site (β_2)	-0.005	0.012	0.674
Treatment period $*$ Treatment site (β_3)	**0.045**	0.005	0.000 ***
Adjusted R^2: 0.187			

Our first observation from Table 3 is that β_1, the time-dependent effect, is positive and significant. This implies that there was a systematic increase in winning prices (which might be driven by some underlying "market trend" or other unobservable factors) from the pre-experiment period to experiment period, regardless of the auction sites. Further, we can see that the true treatment effect is also positive and significant: the winning prices increased by 4.5% at the treatment site during the experiment period. Given the sheer magnitude of these auctions, this means that withholding winners' identities can generate significantly higher revenue.

Further, we would like to know whether the policy change had the same effect on the online and offline channels after controlling for the potential confounding factors (e.g., the potential "market trend"). Therefore, we re-estimated Equation 1 for transactions made via the online and offline channel, separately. Table 4 shows that both online and offline bidders paid more under the treatment condition: on average, online bidders paid 4.1% higher and offline bidders paid 6.5% higher when winners' identities were concealed. Note that previous research by Koppius (2002) argues that offline bidders can acquire more market-state information and thus might have an advantage in the bidding competition[18]. However, the results from Table 4 suggest that the loss of winners' information could not be compensated by other market-state information communicated in the auction room.

Since our preliminary analysis suggests that concealing winners' identities has some mitigation effect on price declining

[15]See Appendix for an overview of the data from the control site.

[16]Before fitting the data to the DID model, we also checked bidders' potential switching behavior, i.e., whether bidders who participated in the auctions at the treatment site during the pre-experiment period switched to auctions at the control site during the experiment period, or the other way around. After cross-checking all the transaction details of the specific flowers during the 6 weeks at the two sites, we did not find any evidence of switching. Thus we can rule out the possibility of selection bias, i.e., only bidders who favored the new revelation policy stayed in the treatment site during the experiment period.

[17]*: P-value $<$0.05; **: P-value $<$0.01; ***: P-value $<$ 0.001.

[18]Unlike early studies about the impact of online channel to an existing market, Koppius (2002) found that the reduced transaction cost and monitoring cost enabled by the online channel do not necessarily result in lower winning prices paid in an auction.

Table 4. Estimation results of the DID model (online and offline sub-samples separately).

	Online transactions			Offline transactions		
Variable (Coefficient)	Estimate	Std. error	P-value	Estimate	Std. error	P-value
Treatment period (β_1)	0.128	0.004	0.000 ***	0.125	0.007	0.000 ***
Treatment site (β_2)	0.005	0.014	0.677	-0.133	0.035	0.000 ***
Treatment period $*$ Treatment site (β_3)	**0.041**	0.006	0.000 ***	**0.065**	0.015	0.000 ***
	Adjusted R^2: 0.185			Adjusted R^2: 0.204		

trend, we also examined the impact of the policy change on price dynamics at lot-level, using the model as follows[19]:

$$\log \frac{P_{t,k,l}}{P_{t,k-1,l}} = \mu_0 + \mu_1 T_t + \mu_2(k-2) + \mu_3(Available-2) + \mu_4 T_t * (k-2) + \mu_5 T_t * (Available-2) + \epsilon_{t,k,l}, \quad (2)$$

In Equation 2, l refers to the lot index, k is the rank number of the transaction, and $Available$ stands for the available units in the current round. Following the suggestions of Van den Berg et al. (2001), we use the difference of the logarithmic prices in consecutive rounds as the dependent variable. The benefits of such practice are two-fold. Firstly, it controls for potential confounding factors that influence the length (the maximum of the rank number) of an auction and the transaction prices simultaneously. Secondly, it addresses the potential correlation of prices within a given lot, as well as the observed or unobserved heterogeneity between different lots, both of which may result in biased estimation.

According to Table 5 that winning prices in sequential rounds did exhibit a clear declining trend, which is consistent with previous studies such as Beggs and Graddy (1997) and Van den Berg et al. (2001). However, we find that concealing winners' identities can mitigate the price declining trend: the main effect (μ_1) is only marginally significant, the interaction effect (μ_5) is highly significant.

Table 5. Impact of policy change on lot-level declining price trend.

Variable (Coefficient)	Estimate	Std. error	P-value
Intercept (μ_0)	-0.0215	0.0012	0.000 ***
Treatment period (μ_1)	0.0028	0.0016	0.0894 ·
Rank number (μ_2)	0.0015	0.0002	0.000 ***
Available units (μ_3)	- 0.00005	0.00001	0.000 ***
Treatment period $*$ Rank number (μ_4)	-0.0002	0.0002	0.2815
Treatment period $*$ Available units (μ_5)	0.00005	0.00002	0.003 **

Robustness Check

Because bidders were informed about the policy change prior to the experiment period, it is likely that the observed differences in transaction prices were due to the novelty effect or *Hawthorne* effect, which is defined as the problem in field experiments that subjects' knowledge that they are in an experiment modifies their behavior from what it would have been without that knowledge (Adair 1984). Therefore, we conducted robustness check to further confirm the findings about the effect of policy change.

Given that the experiment lasted for three weeks, we created three new sub-samples by pooling each of the three weeks' transaction data with the data from pre-experiment period. If the observed treatment effect from Table 3 and Table 4 is due to Hawthorne effect, we would expect the price increase diminish over time (Clark and Sugrue 1988). Thus we re-estimated the model in Equation 1 on the three sub-samples. Table 6 summarizes the estimation results.

Interestingly, we find an overall increasing trend across both the treatment and control sites in Week 1 and Week 2 of the experiment period (i.e., β_1 is positive and significant), whereas in Week 3, there was an declining trend. Similarly, on

[19]Since we are examining the price dynamics in sequential rounds of an auction, we do not need to include the data from control site to account for the potential market trend, or other confounding effects. This is different from previous analyses which make use of the pooled data.

average, prices at the treatment site were significantly lower than the control site in Week 1, while in Week 3, it was the opposite. These observations reinforce our concern about market noise which can bias the results from the aggregated, model-free analysis. Nevertheless, we can see that the treatment effect remains positive and significant over the three weeks: in Week 1, the average price increased by 1.9 % under the treatment condition whereas in Week 2 and 3, price increased by 5.1%, thus providing further assurance that our main results in Table 3 are robust.

Table 6. Results of robustness check on the sub-samples.

	Week 1 (Nov.19-23)		Week 2 (Nov. 26-30)		Week 3 (Dec. 3-7)	
Variable (Coefficient)	Estimate	P-value	Estimate	P-value	Estimate	P-value
Treatment period (β_1)	0.210	0.000 ***	0.200	0.000 ***	-0.026	0.000 ***
Treatment site (β_2)	-0.044	0.011 *	-0.010	0.561	0.042	0.020 *
Treatment period $*$ Treatment site (β_3)	**0.019**	0.015 *	**0.051**	0.000 ***	**0.051**	0.000 ***
	Adjusted R^2: 0.202		Adjusted R^2: 0.210		Adjusted R^2: 0.127	

Additional Analysis

So far, our analysis shows that bidders paid significantly higher prices under the treatment condition, regardless of the market channels they chose. A natural question is why bidders paid more when the winners' identities were concealed.

Given that bidders in this market have been competing in these auctions repeatedly for a long period of time and many of them know each other very well, it is possible that some bidders might engage in tacit collusion, i.e., coordination between several competing players (typically large ones) without overt communication or agreement (Bajari and Yeo 2009; Sherstyuk and Dulatre 2008). There are two essential elements for tacit collusion: 1) a transparent mechanism for coordinating on a collusive outcome; and 2) a plausible amount of mutual understanding among firms (Harrington 2012). For example, if two large bidders always end up in competing for products from the same supplier, they might have the incentive to implicitly coordinate their bids. If this is the case, the public signal of winners' identities would be indispensable to the stability of the cartels – the defect member (bidders who did not follow the collusive strategy) could easily be identified and punished by other members within the cartel. This leads to the following hypothesis:

H1: Bidders with a higher tendency to engage in tacit collusion pay lower prices when winners' identities are disclosed.

In order to test this hypothesis, we first need to quantify bidders' tendency of collusion. We define a bidder's *collusion index* as the inverse of the total number of suppliers from whom he made purchases. The larger a bidder's collusion index is, the higher his tendency of collusion. The underlying rational is that if a bidder always purchases from a few specific suppliers, it is much easier for him to identify the potential collusive partners (especially when winners' identities are publicized) and thus more likely to engage in collusion.

We classify bidders into two types – the ones with high tendency to collusion and those with low tendency to collusion – using the median of the collusion index for all bidders during the pre-experiment period. We then apply a hierarchical linear model (Raudenbush and Bryk 2002) to examine the effect of bidders' tendency of collusion on their winning prices. Compared with ordinary regression models, hierarchical linear models can accommodate non-independence of observations (e.g., in our case, the winning prices of the same bidder might be correlated), and accurately disentangle the effects of between- and within-group variance. The full specification of our model is as follows:

$$Level\ 1: \ \log P_{i,j,t} = \beta_{0,j} + \beta_1 T_t + \beta_2 G_i + \beta_{3,j} G_i * T_t + \gamma X_{i,t} + \epsilon_{i,j,t}, \tag{3a}$$

$$Level\ 2: \ \beta_{0,j} = \alpha_{00} + \alpha_{01} H_j + u_{0,j}, \tag{3b}$$

$$\beta_{3,j} = \alpha_{30} + +\alpha_{31} H_j, \tag{3c}$$

where H_j is a dummy variable, $H_j = 1$ if bidder j is classified as having high tendency of collusion. The estimation results are shown in Table 7.

We can see that overall, bidders with higher tendency of collusion pay significantly lower (9.8%) prices regardless of the change on the information revelation policy. However, such price advantage is mitigated under the treatment condition (α_{31} = 0.035**). Thus H1 is supported.

Table 7. Impact of policy change on potential bidder collusion.

Variable (Coefficient)	Estimate	Std. error	P-value
Collusion tendency (α_{01})	-0.098	0.006	0.000 ***
Treatment period (β_1)	0.127	0.003	0.000 ***
Treatment site (β_2)	-0.002	0.012	0.858
Treatment period $*$ Treatment site (α_{30})	0.042	0.005	0.000 ***
Collusion tendency $*$ Treatment period $*$ Treatment site (α_{31})	**0.035**	0.013	0.009 **
Adjusted R^2: 0.190			

Discussion

Key Findings

Our paper offers several findings with regard to information transparency strategies in sequential auctions. First, we find that overall, bidders tend to pay higher prices when the identities of winners from previous (sub)auctions are not publicly disclosed. Such positive effects hold for both online and offline bidders. This means that the weak signals or the increased market state information available in the auction room cannot compensate for the loss of the information associated with winners' identities. At the outset, this finding contradicts the predictions of linkage principle, which suggests that releasing more information can increase sellers' revenue. Therefore, it calls for finer-grained models to characterize the bidding dynamics in real-world multi-unit sequential auctions.

Further, we provide empirical evidence of declining price anomaly under two revelation policies and show that the less transparent policy can mitigate the price declining trend. Such finding to a large extent confirms the direct-learning effect in sequential auctions (Jeitschko 1998). In other words, bidders base their inferences of the market trend not only on the revealed prices in previous rounds, but also the revealed winners' information. Thus it sheds new lights on the explanations to declining price anomaly (Van den Berg et al. 2001).

We also explore the potential explanations to the observed price increase associated with the policy change by examining bidders' tendency to commit tacit collusion. Our results show that bidders who stick to a small set of trading partners and thereby have higher tendency to collude incur a significant loss of surplus under the less transparent setting. This suggests that winners' identities might be used to enforce the agreement within cartels and deter each other from bidding high.

Contribution

Our findings contribute to the existing literature on information disclosure in auctions. Previous studies on information revelation policies are largely restricted to analytical modeling where bidders are assumed to be fully rational or lab experiments where bidders are typically less experienced. Our research complements them by bringing richness of real-world operation environments while maintaining a high level of control. In addition, despite the growing interest in information revelation policies in online auctions, for example, Arora et al. (2007); Granados et al. (2010); Greenwald et al. (2010), most of the existing research focus on price and product transparency. We provide a different perspective to examine the linkage principle and the current debate between transparency strategies.

The findings from our study also provide important implications to practice. Previous research has shown that sequential auctions are more susceptible to collusion as compared to simultaneous auctions (Sherstyuk and Dulatre 2008). Thus how to effectively detect collusive bidding and deter future collusion is a major issue in the practical design of sequential auctions. In our study, we find that withholding winners' identities in sequential auctions can reduce the potential tacit collusion. In fact, the results from our analysis shows that bidders with higher tendency of collusion is expected to pay significantly higher when winners' identities were not communicated publicly.

As Koppius (2002) points out, information architecture –"what type of information is available to whom, or when and how it becomes available to whom during the market process"– is important for the performance of auctions. With the ongoing trend of moving from place to space (Kuruzovich et al. 2008), choosing appropriate information revelation policy across different market channels becomes even more critical in the design of these multi-channel auctions. Note that although online channels could in principle encourage entry by breaking the physical limitations such as time and space and bringing millions of globally dispersed business entities to the trading activities in auctions, the enhanced communication capabilities resulting from online channels also facilitate collusive behavior. Therefore, market designers must weigh the benefits and threats carefully when disclosing any product- or market-related information.

Limitation and Future Work

The current study bears several limitations. For example, due to practical constraints, we could not extend the experiment period to a longer time and as the result, we were not able to examine whether the increase in transaction prices is persistent, or bidders' behavior might gradually converge after a longer time and the price will fall back to the pre-experiment period (when other factors are controlled). Additionally, we could not infer the complementarity or substitutability of different products from the current dataset and take them into account in the DID model. If there was a demand shock of another product which serves as a complement of the product chosen in our analyses, it would have led to an overestimation of the actual effect of the policy change. However, there is no particular evidence of such demand shock, nor significant change in bidders' bidding patterns (see Table 2). Therefore, this is not a big concern in this paper. Future work can take transaction data from multiple types of products to verify the robustness of our results.

A number of directions are possible as the extension of the current research. Our current analysis only suggests that bidders with higher tendency of collusion pay lower prices under the high-transparent situation (i.e., when winners' identities are disclosed) and incur a substantial loss of surplus under the low-transparent situation. It is interesting to identify and understand the intermediate mechanism by which those bidders acquire and lose the advantage. Further, given that these are B2B auctions, it is also necessary to examine the impact of the policy change to the post-auction trades. For example, it is much more difficult for the customers of a bidder to trace the original purchasing prices in the auction market. This might provide the bidder an opportunity to maximize his profit margin and thus affect his bidding strategies in the auctions. An integrated model which incorporates the post-auction competition can be very helpful in understanding the impact of different revelation policies in the whole supply chain.

Concluding Remark

We study the impact of different information revelation policies in sequential B2B auctions using field experiment. Our analyses document a significantly positive effect on transaction prices associated with the less-transparent policy which conceals winners' identities. This result suggests that higher transparency might, despite all the well-known advantages, facilitate tacit collusion and mitigate competition.

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Appendix: Description of the Data from Control Site

The data we collected from the control site consists of 15789 transactions (from 2425 auctions) during the 3 weeks prior to the experiment and 16361 transactions (from 2378 auctions) during the experiment. 73.5% of the pre-experiment transactions and 76.9% of the in-experiment transactions were through the online channel. Table 8 summarizes the descriptive statistics of the data.

Table 8. Descriptive statistics of the data from control site.

Statistics	# of bidders per auction		Bid frequency (auction)		Bid frequency (day)		Price (cent)		Purchase amount	
	I	II	I	II	I	II	I	II	I	II
Mean	6.3	6.6	1.0	1.0	5.4	5.7	28.4	**31.1**	9.7	9.0
Median	5.0	6.0	1.0	1.0	3.0	3.0	27.0	**31.0**	4.0	4.0
Std.	4.8	5.2	0.2	0.2	6.1	6.5	10.4	7.7	17.5	16.1
Skewness	1.1	1.2	6.9	6.8	2.4	2.4	0.4	0.0	5.6	7.2
Minimum	1	1	1	1	1	1	5	5	1	1
Maximum	33	34	5	6	45	50	70	59	371	390