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Abstract

While multiple studies have investigated the digital ecosystems in the B2C sectors, empirical research on the upstream of the supply chain is still underexplored. This paper examines the case when a digital platform is incorporated into the century-old auction system. This work offers insights into B2B markets and at the same time, an interesting instance where different pricing mechanisms (online posted price and auctions) co-exist. We investigate how the information of the new digital posted price channel can influence buyers' learning behaviors and consequently, the price dynamics in the auction market. Our empirical analysis reveals that multiple information signals can play a role. While sellers' high price and high-volume sales signals can partially dimmish the existing declining price trend in the sequential auctions where the prices from the earlier auction rounds tend to be higher than from the latter, this information effect does not persist over time. These results highlight the potential benefit of cooperating e-commerce with an auction channel for sellers and the shift in buyers' behaviors in responding to an additional platform in a B2B market.

Keywords: Information Sharing, B2B Multi-channel System, e-Commerce, Learning in Sequential Auctions, Dutch Auctions, Price Dynamics.

1 Introduction

Platforms can be identified as products, services, firms, or institutions that mediate transactions between different two or more parties (Baldwin and Woodard 2009). Platforms are in multiple shapes and forms, operating under largely different rules and policies. With the growth of e-commerce over the past decades, it is not uncommon for firms to utilize multiple platforms at once as part of their multichannel strategy. For instance, in the agriculture sector, the context of this study, supermarkets can purchase their stocks from a platform with posted prices where producers set the price, or they can obtain from auction channels where producers' list prices are not available. Thus, it is more than likely that the information from one channel can spill and influence the activities in another. Firms can exploit this discrepancy in information disclosure policies. A significant body of previous work on multichannel platforms has focused on how different channels in the B2C sector where customers purchase for personal use and in small quantities can influence each other, research on B2B where buyers tend to be more strategic and purchase in large orders, however, is still lagging behind. One of the reasons can be the lack of empirical and individual data (Langer et al. 2012). Another reason can be the long-term nature of the B2B relationship which can be more challenging to handle in an online environment. In this work, we investigate a case where an online posted price channel is introduced to a traditional B2B market where sequential auctions have been the main means of trading. More specifically, we answer the question how the information of the new digital posted price channel can influence buyers' learning behaviors and consequently, the price dynamics in the auction market.

Auctions, where the prices are determined through a competitive process, are not uncommon pricing mechanisms in the procurement process. Buyers in auctions not only make their bids based on their demand, and their experiences but also rely heavily on the information they obtain in the market (Lu et al. 2019). In particular, information sharing play a significant role in sequential auctions where multiple auction rounds take place one after the other and buyers can update their information over time. These information signals influence buyers' behaviors and how prices in the auctions may change from one auction to another (Mezzetti 2011). The introduction of a posted price channel offers a new way for buyers to source their products, but at the same time, it introduces a new set of information which are not previously available in the auctions including the prices set by the sellers and the quantity sold in another channel. Consequently, it is questionable how this new set of signals can affect buyers' learning process and subsequently, the whole price dynamics in the sequential auctions.

We utilize a rich dataset from the multichannel Dutch Flower Auction (DFA) system where buyers and sellers trade through two key channels: (1) a sequential Dutch auction channel (where buyers can bid either online or offline) and (2) an online posted price channel (so-called presales) which was introduced in 2013. We present a stylized model of the DFA in Figure 1. The presales take place first before the auctions. Sellers can decide the price in this channel. Anything that is sold in the presales will be fulfilled together with the auctions and anything that is not sold in the presales will be available in the subsequent auctions.

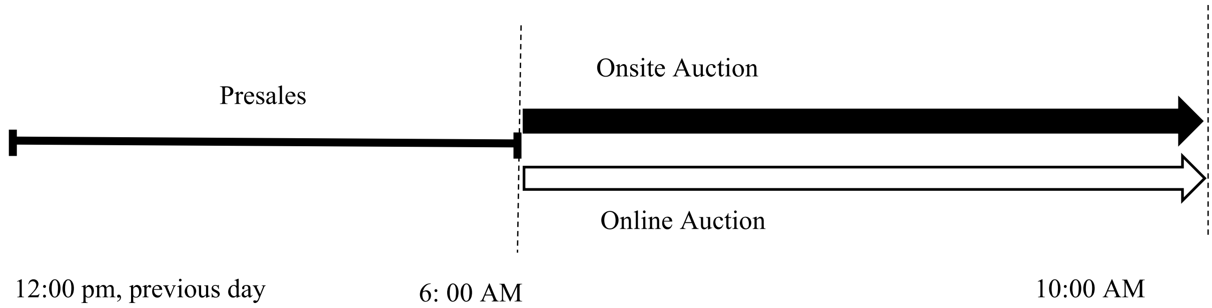

Figure 1. Dutch Flower Auction System

While it is common in Dutch auctions to have a declining price trend (Lu et al. 2019; Van den Berg et al. 2001a) where the prices of the previous rounds are higher than those from the subsequences, our analysis reveals that multiple signals can influence this process. In particular, high posted prices set by the sellers (or manufacturers in this case) and high volume sales can both increase the auction prices and partially dimmish the declining trend. However, the information effects do not persist over time as we see the effect diminishing in later auction rounds. In addition, we find that a low price signal can be harmful to the sellers in the auctions as it can further amplify the declining trend. This result is surprising and interesting as a number of works in information sharing suggested that additional market information can lead to downward pressure and reduce prices (Cui et al. 2021).

We see our work contribute to the area of multichannel B2B markets where it is still underexplored (Lu et al. 2016). This work demonstrates how a digital platform can influence the traditional auction markets and in particular, records a case where multiple pricing mechanisms co-exit. While it is common nowadays for buyers to obtain products via multiple sources, the empirical research landscape on multichannel systems with multiple pricing mechanisms remains largely untouched. We highlight the heterogeneous effects of information signals in the supply chain. We see our findings contributing to a richer understanding of information sharing in the business ecosystem, where there are still several research gaps (Granados et al. 2010). Finally, we add to the area of sequential auction dynamics, extending the body of work beyond the single-channel context and exploring how auction price trends may be altered under different types of information signals.

2 Related Works and Hypothesis Development

2.1 Related Works

Our work is related to the areas of B2B multichannel systems, and sequential auctions.

Multichannel literature considers how different types of channels can affect each other and how they can be incorporated together. There is a vast literature on multi-channel systems, focusing on two key areas: the effect of online on offline posted price channels (e.g., Brynjolfsson et al. 2009; Zhou et al. 2019, Forman et al. 2009; Jing 2018) and online and offline auction channels, especially buyers' channel adoption decisions (e.g., Langer et al. 2012; Overby and Jap 2009; Overby and Ransbotham 2019). The two streams of work posted price and auctions tend to be considered separately in multi-channel literature. Our work bridge the area of auction and posted price channel in multi-channel research. To the best of our knowledge, there have not been any works considering the integration of such mechanisms. In addition, it is noted that the affordmentioned works have largely focused on B2C sector where customers are end-users with small demand. B2B sector where buyers tend to have larger demand and are more strategic in their decisions is less discussed. We shed light on the B2B area in this case and study how quantity signal can play the role.

Our study also draws on sequential auctions literature. In sequential auctions, one auction lot which has multiple units will be auctioned in multiple rounds. The winner of each round obtains a proportion of the lot. The auction round repeats until everything is sold. Each round has fewer stocks available than the previous ones. This strand of literature pays attention to the determinant of sequential auction prices and how the prices will behave from one auction round to another. Milgrom and Weber (1982) under the assumption of symmetric independent private value and single unit demand buyer, find that the equilibrium price path of both English and Dutch auctions is a martingale. Or in other words, there is no trend for auction prices in a sequential system. However, empirical evidence does not support this finding. The declining trend in the price, or the so-called declining price anomaly, has been detected in various contexts such as wine auctions (McAfee and Vincent 1993), art auctions (Beggs and Graddy 1997), and flower Dutch auctions (Lu et al. 2019, Van den Berg et al. 2001). Several theories have been offered to explain the anomaly, but no definite answer has prevailed (Trifunović, 2014). Our study complements this literature by documenting the effects of different types of information signals on auction price trajectories. Moreover, the aforementioned studies focus largely on single-unit demand buyers. We consider the case of multiunit demand buyers which can lead to different results (Trifunović 2014).

In summary, in this work, we address two key areas in the literature which are still underexplored: (1) the corporation of different pricing mechanisms in a business ecosystem and (2) the determinants of price dynamics in sequential auctions. This paper demonstrates how a posted price can affect an auction platform and the role of different types of information in shaping auction prices.

2.2 Hypotheses Development

2.2.1 Information Signal & Price Dynamics

The new online posted price channel can offer additional information to the existing auction channel (Overby and Forman 2015). One of this information includes the posted prices set by the sellers which are not previously available in the auctions. Previous empirical works in marketing and information systems literature have identified two key mechanisms through which additional price information can affect auction prices and buyer's behaviors: (1) *price signaling* and (2) *information sharing*. These explanations, however, offer contrasting effects.

Price signaling research (Bagwell and Riordan 1991; Milgrom and Weber 1982; Wells et al. 2011) draws from signaling theory (Spence 1978). This stream of work argues that when information asymmetry exists or in other words, sellers have information related to products that buyers do not have, high-quality firms can respond by utilizing a high price as a signal of quality. This helps them to differentiate themselves from lower-quality sellers. Inversely, price discounting can send a low-quality signal, harming the seller's revenue (Cao et al. 2018). In retail settings, Knauth (1949) reported a significant positive sales increase when the retail prices were increased from $1 to $1.14. Such evidence of a violation of the downward slopping demand curve was first dismissed in the early days. However, the evidence keeps mounting across different research areas from marketing to economics and information systems over the years, and by the end of the 1980s, based on an integrative review of over 40 empirical works, it has become so apparent that the relationship between price and quality appear to be incontrovertible (Rao 2005). In an auction setting, buy-now-price in English auctions uncovers the value imposed by the sellers. It also reveals the amount at which the sellers are willing to sell and end the auction immediately and hence indirectly offers information on the quality of the product (Li et al. 2009).

Different from price signaling, one stream of empirical auction and information sharing research suggests that high posted prices can work as a *barrier to entry*, preventing buyers from entering the auctions. Ku et al. (2006) found that it is beneficial for sellers to set the starting price in an English auction low to encourage bidders to participate. This increases the competition level and consequently increases the final auction price. Simonsohn and Ariely (2008) demonstrated that bidders herd into low starting price auctions and end up with a lower chance to win, and when they do win, they pay higher final prices. Similarly, Li et al. (2009) found that high posted prices in English auctions can discourage bidders to participate. Cui et al. (2021) suggest that increase in market information sharing can create pressure and reduce the quoted price in the supply chain system.

Overall, the signaling literature suggests that a high price can work as a signal of quality. The high posted price can lead to an increase in auction prices. Empirical auction research, on the other hand, finds evidence that high prices can work as a barrier of entry, reducing competition and as the result, reducing final auction prices.

Auction price dynamics in a sequential auction are commonly measured by the changes of price from round k to its previous round k-1, or $log(p_{jk}/p_{jk-1})$ (Lu et al. 2019; Van den Berg et al. 2001b). This measurement serves as two folds. First, it offers insights into auction price levels and how auction prices will change from one round to another in sequential auctions. The second is a methodological one. As analyzed by Van den Berg (2001), such a first difference measurement control for confounding factors that affect the length of an auction and the prices at different rounds simultaneously, and hence it is widely used in modeling prices in sequential auctions. As mentioned previously in the literature, the price dynamics in sequential descending auctions tend to follow a declining trend where prices of the later rounds tend to be lower than prices of the earlier rounds ($p_{jk} < p_{jk-1}$).

Consequently, in the case posted prices affect the auction prices (p_{jk}) positively, given that sequential auction prices tend to follow a declining trend $p_{jk} < p_{jk-1}$, if p_{jk} and p_{jk-1} increase at a similar rate for lots listed in the posted price channel, the declining rate itself, $log(p_{jk}/p_{jk-1})$, is likely to be reduced.

Conversely, in the case posted prices affect the auction prices (p_{jk}) negatively, given that sequential descending auction prices tend to follow a declining trend $p_{jk} < p_{jk-1}$, if p_{jk} and p_{jk-1} decrease at a similar rate for lots listed in the posted price channel, the declining rate itself, $log(p_{jk}/p_{jk-1})$ in case, is likely to be amplified.

Given this case of a highly perishable goods market where there is a high level of information asymmetry where sellers have information that buyers do not have, buyers are more sensitive to different cues from the sellers (Lu et al. 2019). Thus, the first scenario is more likely to hold. Consequently:

Hypothesis 1: High posted prices will reduce the rate of the declining price for lots with presales in the auctions.

Another information signal that the posted price channel offers is the quantity sold. Cheung and Thadani (2012) proposed that sales volume can operate as word-of-mouth - a marketing tool for the products. Huang and Chen (2006) argued that a large sales volume can work as an indication “to buy”. Goes et al. (2010) posited that in an auction setting, the high volume available for sales can be perceived as a decline in demand and dumping behaviors while a high sales level can be perceived as scarcity which can increase buyers’ willingness to pay. Similar results have been well recorded in several previous studies (Balachander et al. 2009; Cachon et al. 2019). Consequently, similar to the previous line of reasoning, we can expect that high volume sales in the presales can increase the auction prices and consequently diminish the declining trend in auction prices.

Hypothesis 2: High sales in the posted price channel will reduce the rate of the declining price for lots with presales in the auctions.

While there is evidence that these information signals can influence the auction price dynamics, previous research on price anchoring suggests that the effect of the price signal may dimmish over time (Baucells et al. 2011; Baucells and Hwang 2016; Chen and Nasiry 2019; Langer et al. 2012). In other words, recent information may have a higher weight than older information. Consequently, we expect that the effect of the signals from the online posted price channel in the sequential system, as in our case, will reduce as in later rounds of the sequential auction.

Hypothesis 3: The effect of the information signals from the online posted price channel will reduce in the later rounds of the sequential auctions.

3 Research Context and Data

Our research utilizes data from the DFA at Royal FloraHolland, the world's largest B2B floriculture market. Sellers in this market are flower growers from multiple countries and buyers are wholesalers, retailers, supermarkets, and florists worldwide. Sellers send flowers in multiple lots for auctions. In the afternoon the day before the auctions, flowers from around the world arrived at the market. The auction starts at 6 AM every weekday and at the end of the auction day at around 11 AM, flowers are on their way to buyers all around the world.

Each flower lot includes multiple homogenous flower stems. For each flower lot, the auctioneer sets the high price and starts an auction clock which decreases prices over time. Buyers bid by stopping this clock and the one who stops the clock first is the winner. The winner can subsequently decide how much to purchase from the lot. This is considered 1 round of the auction. If there is anything left, the auctioneer resets the clock and the auction can continue through several sequential rounds until everything is sold. By the end of the auction day, normally all the supply is cleared.

In late 2013, an online posted price channel (so-called presales) was introduced. Before the auction starts, from 12 pm on the previous day to 5.55 am on the focal auction day, buyers can purchase a proportion of the lots from the pre-sales channel at the seller's determined price. What is left after the pre-sales will be added to the auctions. All the delivery for sales from the pre-sales is carried out together with the auction. Both sellers and buyers can access the channel without charge. Unlike the presales where prices are controlled by the sellers, the auction is a competitive process that is controlled through auction clocks. The information about market supply is made available a day before the auctions. All the information related to the products, auction lots, and sellers is identical between the presales and the auction market.

As all the information is identical between the two channels, identical lots are auctioned in both channels, identical delivery services are applied and the presales take place before the auctions, this setting allows us to observe the effect of the additional information from the presales which were not available in the auction previously including the price set by the sellers and the quantity sold in the presales channel. In addition, as the information is one-off before the auctions, we can also observe the effect of this dose of information as the auction progresses.

3.1 Data

We obtain a whole year of transactions for large rose products from FloraHolland. The large rose which includes over 100 products of different rose breeds is the largest product group in the market The collected data contains relevant identifications of producers, buyers, products and auction lot, transaction time, quantity sold and availability level, prices, and whether the lots were available in the presales or not. Descriptive statistics are presented in Table 1. On average, presales prices are at 0.405 cents per stem. The average auction price is 0.317 cents (0.358 cents for lots with presales and 0.294 cents for without the presales.

		Total Sample	With Presales	Without Pre-sales
	N	Mean (S.D)	Mean (S.D)	Mean (S.D)
Average Auction Price per transaction, P_{jk}	2,527,376	0.317 (0.203)	0.358 (0.208)	0.294 (0.195)
Lot Size, $Lotsize_{jt}$	480,439	1,848.419 (1,907.134)	1,944.616 (1,857.195)	1,806.982 (1,926.770)
Presales price listed per lot, $PPre_{jt}$	480,439	0.405 (0.587)	0.405 (0.587)	
Market supply per product day, $MSupply_{pt}$	18,486	48,039.190 (77,941.810)		
Presales quantity sold per lot, $QPre_{jt}$	480,439	46.993 (123.688)	46.993 (123.688)	

Table 1. Descriptive Statistics

In Figure 2, we plot the average auction prices for lots with and without presales. The auction round rank is shown on the axis while the price is presented on the y-axis. The average auction prices for lots with presales (with triangle marker) are higher across all rounds than prices of lots without presales (with circle marker). The prices decline in earlier rounds in both cases. It is also noted that 75% of the lots are completed within 8 rounds and half of the lots are completed within 5 rounds. The cases with more than 8 rounds are rarer with larger standard errors. We model this trend in the next section.

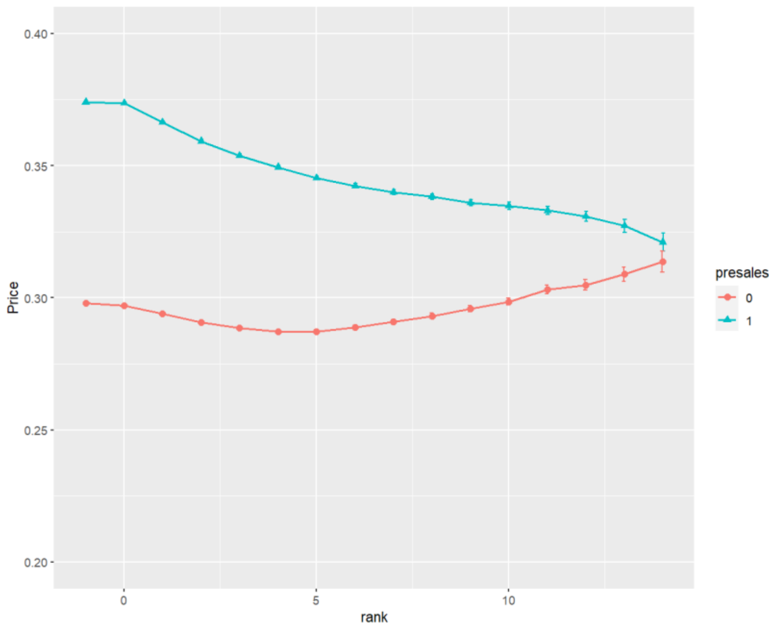

Figure 2. Auction Price Dynamics

4 Models and Results

We model price dynamics using be below equation which is widely used in the area of sequential auctions (example works: Van Den Bergh 2001, Lu et al. 2019).

$$Log\left(\frac{P_{jkt}}{P_{jk-1t}}\right) = \beta_{20} + \beta_{21}Presales_{jt}(Available_{jk-1t} - 2) + \beta_{22}Presales_{jt}(Rank_{jkt} - 2) + \beta_{23}Presales_{jt} + \beta_{24}(Available_{jk-1t} - 2) + \beta_{25}(Rank_{jkt} - 2) + \varepsilon_{jt}$$

The above equation estimates the changes in price from auction *j*, round *k* at time *t* to the previous round *k-1* as the function of whether the lots are available in the presales, $Presales_{jt}$, the quantity available at the beginning of the auction round, $Available_{jk-1t}$, and the rank of the round, $Rank_{jkt}$. As analyzed by Van den Berg (2001), such measurements control for confounding factors that affect the length of an auction and the prices at different rounds simultaneously. Following Van den Berg (2001), the analysis excludes the case of a single unit, single-round auction lot. The baseline for comparison is chosen at a two-unit lot with two auction rounds (i.e., subtracting Availability and Rank by 2). The results offer an overall comparison between the price trends of lots with and without presales. We use R to carry out our analysis.

The result is presented in Table 2. Column 1 models the overall effect of *Presales* (making the lots available in the presales before the auctions) on the auction price trend. Column 2 investigates these effects over the course of the sequential auctions. Column 3 breaks the overall effect down and examines the effect of the presales price and quantity information signals (Hypotheses 1 & 2). Column 4 presents how these effects may change over time (Hypothesis 3).

Dependent variable: *log(p_{jk}/p_{jk-1})*	(1)	(2)	(3)	(4)
Constant	-0.014*** (0.0001)	-0.014*** (0.0001)	-0.014*** (0.0001)	-0.014*** (0.0001)
Presales	0.002*** (0.0001)	0.002*** (0.0001)	-0.008*** (0.0002)	-0.008*** (0.0002)
Available-2	-0.00001*** (0.00001)	-0.00001*** (0.00001)	-0.00001*** (0.00001)	-0.00001*** (0.00001)
Rank-2	0.001*** (0.00002)	0.001*** (0.00002)	0.001*** (0.00002)	0.001*** (0.00002)
Presales:(Rank-2)		-0.0001*** (0.00003)		
Log(PPre)			0.026*** (0.001)	0.029*** (0.001)
Log(QPre)			0.0005*** (0.00003)	0.0005*** (0.0001)
Log(PPre): (Rank-2)				-0.001*** (0.0001)
Log(QPre): (Rank-2)				-0.00001 (0.00001)
N	2,046,937	2,046,937	2,046,937	2,046,937

Note: *$p<0.1$; **$p<0.05$; ***$p<0.01$

Table 2. Auction Price Dynamics

Column 1 compares lots with presales with lots without presales. The *constant* is negative and significant, confirming that auction prices are following a declining trend at the base case. (*Rank-2*) is positive and significant, indicating that the declining trend reduces over time. The coefficient of *Presales* is positive and significant. This offers evidence that presales lots have a significantly lower auction price declining trend than lots that are not in the presales. In column 2, the interaction term *Presales:(Rank-2)* is negative and significant while *Presales* remains positive and significant. This suggests that the positive effect is diminishing as the auctions progress.

In column 3, we examine the effect of different information signals from the presales on the auction price dynamics. Both *PPre* and *Qpre* are positive and significant. High posted prices and high volume sales signals can both influence the auction price dynamics and in particular, reduce its declining rate. Hypotheses 1 & 2 are supported. *Presales* in model 3 which is negative and significant capture the effect when the signals are low. This indicates that a low signal can be harmful to the sellers and amplifier the declining rate of auction prices. How these effects change over the course of the sequential auction is presented in column 4. The interaction term: *PPre: (Rank-2)* is negative and significant while *QPre: (Rank-2)* is insignificant. Consequently, the influence of the price signal reduces as the auction progress, this does not apply to the case of high sales signal. Hypothesis 3 is partially supported.

For robustness check, we investigate an interesting case of no sales in the presales (NSPS). The case is interesting in the sense that NSPS is very similar to not having the presales at all as the whole lot will be available in the auction. All the sales are observed in the auctions. One difference here is that in the case of NSPS, sellers reveal their prices to the buyers. The effect of quantity sold in the presales is controlled and all sales are settled through the auction channel.

	Presales Stage	**Auctions Stage**
Lots Available in the presales	***Re-veal Presales Price***	Full lot Available for Auction
Lots not Available in the presales	***No Presales Price Available***	Full lot Available for Auction

Table 3. No Sales in Presales

We further exact match NSPS lots with lots without any presales based on multiple characteristics including time period, prices in previous days, lot size, product, market supply level, auction time, and the number of auctions on the day. This exact matching process eliminates several selection concerns. We rerun the analysis and the results can be found in table 4. The results are consistent with our main findings. Even in the case of NSPS, high presales price signal can reduce the declining rate of auction prices. The information effect, however, does not persist over time.

Dependent variable: *log(p_{jk}/p_{jk-1})*	(5)	(6)
Constant	-0.013*** (0.0002)	-0.013*** (0.0003)
Presales	-0.008*** (0.001)	-0.008*** (0.001)
Available-2	-0.00001*** (0.00001)	-0.00001*** (0.00001)
Rank-2	0.001*** (0.00004)	0.001*** (0.0001)
Log(PPre)	0.026*** (0.002)	0.027*** (0.002)
Log(PPre): (Rank-2)		-0.001** (0.0003)
N	287,049	287,049

Note: **p<0.1; **p<0.05; ***p<0.01*

Table 4. Auction Price Dynamics with Exact Matching

5 Conclusions

In this paper, we explore how a new online posted price channel can influence the century-old Dutch auctions in a B2B market. Although multi-channel has become the main force in retailing and distribution, few studies have investigated the case where an auction and posted price channels are incorporated. In addition, behaviors of B2B buyers who have high demand and are more strategic are still underexplored. From a theoretical perspective, the study further sheds new light on the mystery of the declining price anomaly phenomenon (Van den Berg et al. 2001). Several studies have empirically recorded evidence deviating from the theoretical prediction that auction prices have a martingale property. Yet, the mechanism behind this anomaly is not fully understood. Previous analytical analysis by Weber and Milgrom (2000) suggests that in the case of affiliated signals, there is an increasing price trend instead of decreasing one. A recent field study by Lu et al. (2019) finds evidence that the declining rate may be reduced when the auction winner's ID is withheld during the auction process.

In this work, our empirical evidence demonstrates a reduction in declining price rates, rather than strictly increasing, for lots when an additional signal is provided, and as the presales price signal increases, the declining rate from one round to another will be reduced. We see our work further contributing to the area of information sharing and B2B multichannel systems. We reveal that B2B buyers can take multiple signals into account. Both high price and high volume signals can influence and reduce the declining price trend in auctions. This result contradicts previous works such as Ku et al. (2006, p. 201) which found that high prices can be harmful to auctions, and Cui et al. (2021) which find that additional market information can reduce the quoted price. This highlights that the effect of information on auction price dynamics is not homogenous, but it can potentially vary depending on the actual message that the signal sends. Further, there is evidence that a low price signal can be harmful, amplifying the auction price declining rate. This effect, however, does not persist across the course of the sequential auction. As the auction progress, we find the price signal effects reduce over time. This is consistent with the theory in the area of price anchoring where it is suggested that buyers tend to put heavier weight on recent information and lower weight on older information.

Practically, this work sheds light on the role of information disclosure in shaping the auction prices in sequential auctions and a B2B multichannel setting. It stresses the value of having a proper information disclosure strategy for suppliers in the market. It is also important for market makers to consider information discrepancies between different channels when designing and developing market policies. Information signals can have an impact and their effects can persist over time. The study further reveals that having a high signal can be beneficial for the supplier, while overly discounting the products on one channel can harm another channel. Revealing good sales results can also be beneficial for suppliers in the market.

This work is limited to two channels with two additional information signals. We expect in many contexts, the system can be far more complicated and hence it can be a fruitful area for future studies. Studies on how different signals can be incorporated are essential for market designers and businesses to develop suitable policies. In this paper, we consider the effect over time. As different signals can be valued differently between different products and buyers' groups, future studies can further explore the moderating effects of these factors.

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