Understanding B2B Buyer Behavior in Multichannel Markets: How Posted Price Channel Affect Buyers' Strategic Behavior in Auctions

Huong May Truong
Erasmus University, truong@rsm.nl

Alok Gupta
university of minnesota, gupta037@umn.edu

Wolfgang Ketter
Erasmus University, wketter@rsm.nl

Eric van Heck
Erasmus University, evanheck@rsm.nl

Understanding B2B Buyer Behavior in Multichannel Markets: How Posted Price Channel Affect Buyers' Strategic Behavior in Auctions

Completed Research Paper

Huong May Truong
Rotterdam School of Management, Erasmus University
Burgemeester Oudlaan 50, 3062 PA, Rotterdam, The Netherlands
truong@rsm.nl

Alok Gupta
Information and Decision Sciences, Carlson School of Management, University of Minnesota
321 19th Avenue South, Minneapolis, MN 55455 U.S.A.
alok@umn.edu

Wolfgang Ketter
Rotterdam School of Management, Erasmus University
Burgemeester Oudlaan 50, 3062 PA, Rotterdam, The Netherlands
wketter@rsm.nl

Eric van Heck
Rotterdam School of Management, Erasmus University
Burgemeester Oudlaan 50, 3062 PA, Rotterdam, The Netherlands
evanheck@rsm.nl

Abstract

While online and offline posted price channels have been well explored, research in B2B multichannel systems is still lagging behind. In this study, we investigate buyers' strategic behaviors in a unique system where an online posted price channel is introduced to the century-old Dutch auction market in a sequential way. We explore the determinants of buyers' choices and their bidding behaviors. We incorporate learning and experiences and unveil how buyers' behaviors may evolve over time. We further examine the conditions under which buyers may split their demand and utilize multichannel strategy. By analyzing an extensive dataset of over 1 million observations, our results highlight the importance of experiences, buyer's demand and product diversity in shaping key decisions. Further, we provide evidence of an emerging group of buyers that complement both the posted price and the auctions channels.

Keywords: Multichannel strategies, Buyers Behavior, B2B trading system, Dutch Auction, Smart market

Introduction

What drives customers' choices and channel adoption behaviors? How do customers learn? How do their behaviors evolve over time? These key questions in market design and governance have been heavily explored in online and offline posted price channel context (Cavallo 2017; Chen and Hitt 2002; Granados et al. 2012; Neslin and Shankar 2009). Yet, while buyers are increasingly exposed to multiple purchasing mechanisms ranging from offline outlets, online posted price to multiple types of auctions, research on a multichannel system involving both a posted price and an auction channel is still lag behind. Moreover, not much attention has been paid to B2B multichannel markets. One reason for these gaps can be the difficulties in accessing individual-level empirical data(Langer et al. 2012; Lu et al. 2016; Mithas and Jones 2007). Another explanation can be the slower acceptance rate for B2B e-commerce (Krishna and Singh 2018; Langer et al. 2012) as B2B's customer relationship management which is more complex and long-term oriented is not always straightforward to maintain in an online context.

In recent years, some analytical studies have covered the parallel case where an English auction and an online posted price channel are running concurrently (Caldentey and Vulcano 2007; Kuruzovich and Etzion 2017). These aforementioned studies provide evidence that multichannel strategies can increase sellers' revenue. Yet, they rely on several assumptions such as customers are homogenous and are single channel users which are easily broken down in practice. At the same time, a recent study by Einav et al (2018) reports a decline in eBay English auction which is a consequence of customers favor posted price channel for convenience. These seemingly contradicting findings, in addition to the lack of research on B2B buyers' behaviors, raise the essential questions if the posted price will be a threat to auction channels, and especially for B2B cases where auction has been the common means. It further calls in the questions of what we should expect in terms of buyers' respond and who would be the target users of which channels. Such insights are crucial building blocks for not only B2B smart market design research (Bichler et al. 2010) but also for market maker in practice.

In this study, we empirically investigate buyers' behaviors and strategies in a sequential system where an online posted price channel (or so-called pre-sales) is followed by a multiunit sequential Dutch auction system. The century-old Dutch auction mechanism where the price starts from a high level and gradually drops down until a buyer is found facilities clearing speed and has played a significant role in B2B trading, especially for highly perishable goods such as in the agricultural markets. It not only is an essential supply and demand allocation mechanism for growers and wholesales buyers worldwide but also determines the price of numerous of our daily goods ranging from flowers, plants, and fish to our cup of coffee. The growth of e-commerce which facilitates direct trading produce challenges and opportunities for such traditional auction market. Thus, the understanding of how different mechanisms can be managed and integrated are essential.

We analyze a year-worth of flower trading transactions that have been obtained from Royal FloraHolland - the world biggest flower market accounted for around 50% of the global market share (Van Rijswick 2015). A stylized presentation of the studied sequential Dutch Flower Auction (DFA) system is presented in Figure.1. Traditionally, buyers can obtain the products from onsite Dutch auction halls. Since 1996, online auctions have been introduced where buyers can participate in the auctions remotely. In late 2013, an online pre-sales posted price channel was introduced where buyers can obtain the products *before the auction* at the price determined by sellers. A buyer, given their demand, market condition and company's characteristics, will have to first, decide whether to participate in the pre-sales or not, then second, whether to participate in the auction. If the buyers choose to enter the auctions, they will have to select between the online and onsite auction and then, which auction strategies to use.

From the managerial point of view, there are many reasons for FloraHolland to introduce the pre-sales channel. First, it is the reaction for the growth of e-commerce and direct sales and the stall of the traditional auction market. This calls for the re-invention of the traditional auction market and the new pre-sales channel closes the gap between auction and posted price channel. Second, it is part of the effort to link buyers and sellers in a more efficient way. It expands the current trading time frame which restricts between 6 AM to 11 AM and also opens additional sales opportunities worldwide. However, the implementation of such essential strategic move brings about several challenges. First, it was unclear if the new channel would complement or substitute the current channel, what would be the degree of substitution and who would be the users of each channel. In addition, in 2015, the level of sales in pre-sales channel remains at 8% of all the lot. For the channel to be sustainable, further policies are demanded to facilitate the usage of the channel. Hence, the understanding of buyers' behaviors in such channel is key. Furthermore, is the current usage behavior are just simply testing? What can the market maker expect in terms of channels usage as buyers get more familiar with the new pre-sales channel? These are all experimental questions whose answers are not available directly in previous literature.

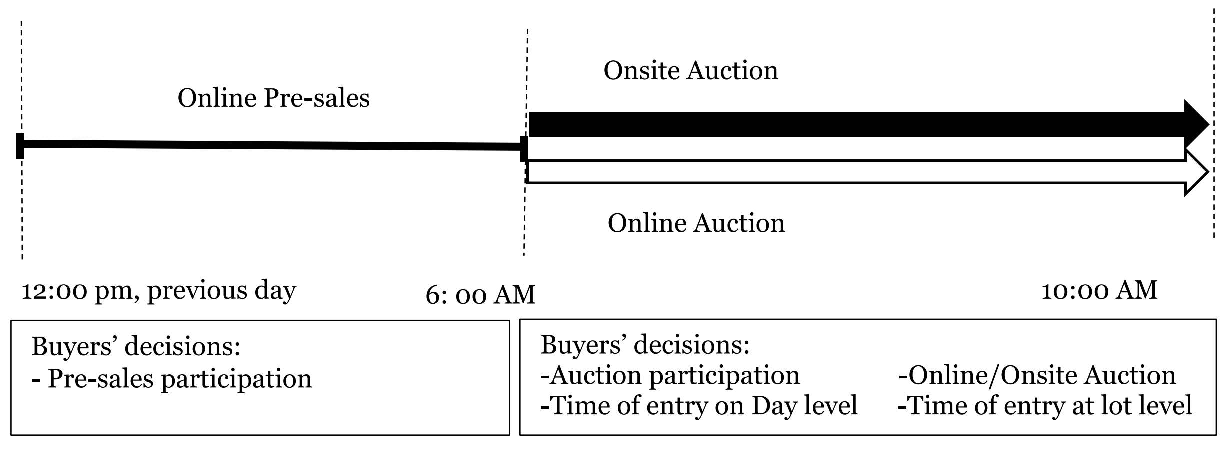

Figure 1: Multichannel Dutch Flower Auction System (Buyers Perspective).

Under the introduction of a new posted price channel, first, we follow buyers' purchasing paths and examine the driving force of different choices. We unveil the conditions when buyers would use the pre-sales while the Dutch auctions have been the default option for decades and what drives them to move to multichannel strategies which have been largely ignored in theoretical models. This facilitates the discussion on how buyers' behaviors may evolve and when the market designer would expect buyers to shift from one decision route to another. Second, we investigate how buyers' experiences influence their decisions, and how the choices of the pre-sales channel may be strategically combined with the strategies in other channels. While learning and strategy adaptation are prevalent in sequential auctions, this area is still rather underexplored (Srinivasan and Wang 2010). In summary, we aim to answer the following questions:

- What drives the pre-sales usage? As buyers get more familiar with the pre-sales, how does this affect their auction and pre-sales usage?
- For the buyers that use both pre-sales and auctions in the sequential system, what are the drivers of their multichannel strategy? How do the pre-sales shape the auction behaviors?

We see our research contribute to information systems, smart market design, and auction research in multiple ways. First, our findings add to the growing research on buyers' behaviors in B2B multichannel system. Insights into customers' behaviors are essential for market designers. The previous study by Langer et al. (2012), has recorded the serious negative effect of reduction in channel growth and participation when such insights on customers demand are ignored by market makers during the design and product allocation process. Second, we explore and provide empirical evidence of buyers strategies in a system that involves both an auction and a posted price channel running in a sequence way. As far as we are aware, while these two trading mechanisms have been increasingly cooperated by businesses (Abele et al. 2003; Kuruzovich and Etzion 2017), such kind of empirical study has not been reported in the literature. Third, we incorporate learning and strategies adaption in our study which as pointed out by Srinivasan and Wang (2010) is underexplored.

Literature Review

Multichannel Auction System

Although customers' behaviors in multichannel systems have been examined heavily over the past decade, the main focus has been on online and offline posted price channel (Granados et al. 2012; Neslin and Shankar 2009; Verhoef et al. 2015). Rarely has any study considered auctions in a multichannel context. One recent branch of literature has partly addressed this gap by investigating "Competing auctions" where the authors focus on how one auction can affect another. This group has its roots in sequential auctions (Ashenfelter 1989; Van den Berg et al. 2001) and more recently has been expanded to "overlapping auction" (Bapna et al. 2009). Another stream has investigated the effect of fixed prices such as Buy-Now-Price, bid increment and reserve price on auction outcomes (Hou 2007; Leszczyc et al. 2009; Pilehvar et al. 2016). Yet, not only consensus has not been achieved, but also almost all have surrounded B2C English auctions. It is important to note that these fixed prices are presented during the auctions, whilst, posted price channel which offers a more complex set of signals such price, quality and supply can take place before, simultaneously or after the auctions. As pointed out by Gallien and Gupta (2007), this different timing and order of the signals can lead to different auction results. Our study aims to widen the knowledge of competing auctions and consider an interesting case where an auction channel is running sequentially with another mechanism: an online posted price channel.

In recent years, a growing body of literature, through analytical models, has evaluated the instance where a posted price channel and an English auction are running concurrently (Caldentey and Vulcano 2007; Kuruzovich and Etzion 2017). The studies stress the value of multichannel strategy as it can offer higher revenue for sellers. In addition, the quality of the posted price channel such as retail location can influence auction outcomes (Kuruzovich and Etzion 2017). Yet, buyers' heterogeneity is rarely discussed. Moreover, buyers demand is normally assumed to be fulfilled by only one channel. This may not hold in practice where buyers can split their demand and use the channels in a complementary manner. Different from previous studies, we study a sequential system. We further, add empirical evidence to both the field of multichannel auction and B2B auction research which is still overlooked (Lu et al. 2016, 2019a; Pinker et al. 2003). Moreover, we focus on buyer behaviors and seek to examine the heterogeneity in their strategies across the channels.

Strategic Behaviors and Experiences in Auctions

This study is also related to the area of strategic behaviors in auctions. Whereas analytical models tend to simplify and assume that bidders are homogenous, empirical studies have long suggested that bidders' strategies are diverse. This diversity can be characterized based on a number of key decisions that bidders need to make: the time that the bidders enter the auction (TOE), the time they exist from the auction (TOX), number of bids during the auctions (NOB) (Bapna et al. 2004, Bapna et al. 2009, Goes et al, 2012, Lu et al, 2016). An early study by (Bapna et al. 2004) using those just-mentioned characteristics records a significant heterogeneity in bidders' strategies and the discrepancy between different strategies' winning likelihood and surplus. In their later work, Bapna et al. (2009) with similar measurement, find 3 stable bidding taxonomies for both overlapping Dutch and English auction. The study finds that overlapping auctions attract a certain group of strategic behavior and create downward pressure on the auction price. Goes et al. (2012) examine ascending uniform price auctions in which winners pay the lowest bid and demonstrate how bidders adapt, change their strategies over time and emphasize the importance of experiences in bidders' choices. A recent paper by Lu et al. (2016) explore the Dutch flower auction context where on a day, there are several auctions with multiple units and each auction can be run in multiple rounds. The paper investigates bidder's TOE at the auction lot level, NOB, bidders' time of entry at day level (TOE-D), bidder's time of exist at day level (TOE-X). Bidders, then, can be specified depending on whether they enter the auction day early or late and whether they tend to enter a particular auction at earlier or later rounds. The study also maps out the diversity in economic outcomes of different strategies. The works so far mainly focus on an isolated auction channel, except for Lu et al (2016) where both an online and onsite auctions are considered. Here, we report the instance where an auction follows an online pre-sales channel and seek to answer how these strategies may be adapted when the additional channel is in place.

It is also interesting to note that, the question of what drives the choice between posted price channel and auctions is still not yet fully understood. As pointed out by Pinker et al. (2003), there is still a lack of research on the choices between auctions and the posted price mechanism. Some early analytical models have been developed (see Pinker et al. 2003). They suggest that the two main determinants of mechanism choice are the sensitivity to transaction cost and the uncertainty about the price of the goods. A recent effort to address this gap by Einav et al. (2018) report a movement of sellers switching from eBay to other posted price channels to meet the change in customer demand. They explain the choice between posted price and online auction in a parallel case by the trade-off between competitive pricing and hassle costs such as the time involved in the English auction. We revisit the choice model for the B2B Dutch auction sequential system. B2B trading normally involves large quantity demanded and several repetition purchases. In addition, Dutch flower auctions are carrying out at a fast pace (3-5 seconds per auction) that is very different from English auction – the focus of previous works. Moreover, we investigate how multichannel buyers may behave and how the decision from one channel may be combined with the strategies in the other. This also expands the research arena which mainly restricts customers' demand to a single channel even in the dual-channel context.

Evidence of how experiences shape auction behaviors has been long reported in a number of early empirical studies (Wilcox 2000), yet, traditionally, auction researches tend to assume that auctions are independent and fail to take into consideration the repeat games (Goes et al. 2012). More recently, this gap has been further highlighted by Srinivasan and Wang (2010) and Goes et al (2012). While the Srinivasan and Wang (2010) show how new bidders can be different from experienced bidders and how winning and losing experiences may lead to different effect, the Goes et al (2012) demonstrate the evolution of strategies in sequential auctions. Both eventually call for further study into the arena. We address this gap by investigating how buyers may adjust their channels usage as their experiences with the new channel increase. Furthermore, we also take into account the heterogeneity in buyers' auction strategies experiences.

Hypotheses Developments

Channel Choices: Presales Channel versus Auction Channels

It is essential to note that presales and auction are fundamentally different. These two mechanisms offer different benefits at different costs. In Dutch Auctions, the price is initially set at a high price and then reduces gradually over time. Bidders who accept the highest price will be the winner. In the case of DFA, these auctions can be accessed both online and offline. This process has several benefits. First, buyers have the opportunity to obtain additional information ranging from the quality of the products to competitors and market's prices. Such kind of information is not available in the online pre-sales channel. Second, this mechanism allows for efficient price discovery at high speed (Kambil and Van Heck 1998). While a transaction in English auction such as the case of eBay can take hours and sometimes days, most of the transactions in DFA can be completed in a matter of seconds. Third, the average auction price can be lower than the price set by sellers in the pre-sales. This can be observed in the case of DFA. One reason for this is that sellers have low incentive to discount their products before the auction. Even if the products are not sold in the pre-sales, they can be added to the auctions. In addition, in our context, it is common for everything to be sold-out through the bidding process which makes it even less likely for sellers to discount their products before the auctions. These overwhelming benefits, however, are achieved at a number of costs. From the lens of transaction cost economies and auction theory, researchers appear to agree that transaction costs are higher for auctions than for posted price mechanism (Pinker et al. 2003). If these costs are waiting time and monitoring cost in English auction (Einav et al. 2018; Pinker et al. 2003), which sunk in Dutch Auction (Katok and Kwasnica 2008), the main costs of Dutch Auction involve the efforts to compete and monitor multiple auctions in a demanding situation. While the same products are auctioned in sequence in DFA, different products can be auctioned in parallel and hence if buyers have a large portfolio, it is likely to increase their transaction costs.

Posted price, on the other hand, allows buyers to secure the products now. This security is offered at the cost of the price set by the sellers which is normally higher than the price obtained in the auction. In addition, pre-sales buyers can potentially face a regret or an opportunity cost if later they find out they have purchased the products at a much higher price or lower quality than what they can obtain from the auction.

Considering the cost and benefits of both channels, we argue that buyers who have a high number of products to be fulfilled are more likely to use the pre-sales. As the number of demanded products increases, it will raise the level of effort that the buyers have to spend in the auctions by increasing the number of auctions they may need to monitor in sequence or in parallel. Hence, to reduce this cost, they may shift some of the demand to the pre-sales. While the diversity of demand may not be a great focus in the B2C context, it is very prevalent in B2B markets where the order list can range up to hundreds of products to be purchased every day. In an extreme case, it may not be possible for bidders to purchase several products at high speed in parallel and thus, the use of pre-sales is an essential move. Hence, we hypothesize that

***H1A**: Buyers are more likely to use the pre-sales as they have a high product diversity demanded*

In addition, we expect that buyers with small quantity demanded for a particular product are more likely to use the pre-sales. This can be explained by a number of reasons. First, for a buyer with a small quantity, the total purchasing cost may be low and the purchasing decision can be rather simple so that participating in the auction may be a hassle. The cost involved with the auction may outweigh the benefit that they can gain from the auction process. The price gap between the two channels may not translate into a significant difference in their total purchasing costs. Consequently, they may opt for the pre-sales. This logic is consistent with auction theory. Pinker et al (2003) suggest that as the product is more complex and the transactions involve higher cost, auction tends to be preferred. A recent paper by Einav et al. (2018) also finds that there is a movement of sellers going from English auction to posted price channel which is driven by the demand for convenience by the B2C customers. Second, another explanation can be that buyers with lower demanded quantity may find it difficult to compete in the auctions. Lu et al. (2016) argue that small buyers who are risk adverse face the competition from larger buyers who have a much higher budget constraint and hence these small buyers may face the risk that bigger buyers would bid aggressively and clear out everything after one round and thus, they- the smaller buyers- fail to obtain their products. The pre-sales help to ease this risk of not obtain anything. Third, as the size of the order increases, the risk involved with the products rises and hence, the buyers might want to confirm the quality of the products and engage in additional search effort for information before finalizing the purchases. Such positive association where uncertainty tends to increase customer information search have been suggested in several previous literatures (Luo et al. 2012). Thus, buyers may bypass the pre-sales and participate in the auctions. In summary, we hypothesize that

***H1B**: Buyers are more likely to use the pre-sales channel when they have low quantity demanded*

As the buyers learn over time, we expect them to recognize the cost and benefits involved with the new presales channel and have a better assessment of their utility. Goes et al. (2012) find evidence that buyers are more likely to move away from disadvantage strategies in the long term. Hence, over time, we would expect a lock-in effect and as the number of participation in the pre-sales channel increases, buyers are more likely to use the pre-sales for their next purchases and even as a substitution for the auction.

***H1C:** As buyers get more experiences with the pre-sales, they are more likely to use it for the next purchase*

***H2**: When buyers already purchase from the pre-sales, they are more likely to opt-out of the auction.*

Multichannel Buyers: Complementing Pre-sales with Auctions.

While analytical research models tend to assume that buyers can only choose one channel and in practice, we may observe a group who will stick to posted price channel only, in DFA, we do observe multichannel buyers. It leads us to question who these buyers are. When do they move from pre-sales usage only to multichannel? If they use the pre-sales, how would they adapt their strategies in the auctions? Here, besides considering the choice between online and onsite auctions, we also follow the previous work in auction strategies and consider two key decisions: (1) TOE, or in other words, for an auction lot which can be carried out in multiple rounds, do they tend to enter at earlier rounds or wait and enter towards the end and (2) TOE-D [1], or in other words, for the day with multiple auction lots, do they tend to enter earlier or later auctions. Adopting similar definitions as Lu et al (2016), we classify buyers who tend to enter early auctions as "*conservative*", while those who tend to enter late auctions as "*forward-looking*". Buyers are classified as "*early bidders*" if they tend to enter auction lots at early rounds and as "*opportunist*" if they tend to enter towards the end of the auction lot.

If buyers already decide to use the pre-sales, they will adopt the multichannel strategies under three scenarios. First, there are some frictions that prevent them from obtaining from the pre-sales. This scenario can be observed in cases such as when they are not yet too experienced with the channel. Second, as analyzed earlier, for buyers with a large portfolio, it may not be possible for them to participate in all of their demanded auctions and hence, they may pass some of their demands to the pre-sales. Third, they may strategically use pre-sales and auctions in a complementary manner. They may use the pre-sales channel which normally has a higher price than the auctions to secure part of the demand and consequently, using the auction channel to hunt for good deals. In other words, we will expect them to exercise forward-looking

[1] Lu et al. (2016) also includes two other measures: NOB and TOX-D for DFA. However, our exploration analysis finds that bidders behave very similarly in terms of NOB while TOX-D is highly correlated with TOE-D and hence these two measures are not considered in this study.

strategy where they enter late auctions or opportunist strategy where they enter toward the end of an auction rather than conservative or early biddings. Buyers may also combine the pre-sales with the onsite auction. This combination allows buyers to gain the benefit from the pre-sales such as stock security and redeem for its drawback of lack of product information with the insights from the onsite auctions. Such strategic behavior of combining purchasing channels is not uncommon, especially with B2B buyers who tend to make decisions more carefully. Verhagen and Van Dolen (2009) find evidence that B2B buyers utilize different channels to gain additional information and economic benefit and business' online image can affect a buyer's offline behavior. We hypothesize that:

***H3A**: Buyers are more likely to move from pre-sales channel only to multichannel strategy when they are not too familiar with the pre-sales channel*

***H3B**: Buyers are more likely to move from pre-sales channel only to multichannel strategy when they have a high product diversity demanded products.*

When buyers already purchase from the pre-sales:

***H3C**: They are more likely to use the onsite auction*

***H3D:** They are more likely to adopt forward-looking strategies*

***H3E**: They are more likely to choose opportunist strategies*

Research Context

Our research takes place under the Sequential Dutch Flower Auction system (DFA). Royal FloraHolland is the world largest B2B floriculture market that attracts over 6000 buyers and sellers trading here yearly. Every day, thousands of lots that include multiple flower stems are traded. From this market, flowers are exported all over the world. In 2015, the market is accounted for around 50% of the global market share (Van Rijswick 2015).

Traditionally, trading is carried out through the Dutch auction mechanism. In late 2013, the market maker introduced an online pre-sales posted price channel. There are many reasons for the pre-sales ranging from opening more opportunities for digital trading worldwide, expanding the trading time frame, linking buyers and sellers in more efficient ways to reacting to the call to reinvent the traditional auction market. Before the auction starts, nowadays, buyers can decide whether to participate in the online pre-sales or not. The pre-sales is an online posted price channel where sellers control the quantity available and the selling price. While the introductory of pre-sales to the traditional auction system is a strategic move for FloraHolland, the lack of guidance from previous literature on how to integrate different mechanism create several challenges. One of those, for example, whether the presales will substitute the auction and if yes, what would be the degree of substitution. Such questions are rather empirical problems. Hence, as a conservative move, the market maker puts a cap on the pre-sales channel which is set arbitrarily as a third of an auction lot in 2015. What is left after the pre-sales will be added to the auctions. Unlike the pre-sales where prices are controlled by the sellers, the auction is a competitive process that is carried out through auction clocks. The auction takes place from 6 AM and normally, everything is cleared by 11 AM. For each flower lot, auctioneer sets the high price and starts the clock which reduces prices over time. Buyers bid by stopping the clock and the one who stops the clock first is the winner. The winner can subsequently decide how much to purchase from the lot. If there is anything left, the auctioneer resets the clock and the auction continues until there is everything is sold or the price goes below the reserve price which is set at a low level at the moment. Buyers can access the auction clock by presenting at the auction halls or remotely using the online system. The information about market supply is made available a day before the auctions. The clock also shows related products information, grower names and a sample picture of the products. The identical information is also available in the pre-sales. It is free for buyers to access the pre-sales channel. As shown in Figure 1, buyers first will decide whether to participate in the pre-sales or not. Then they will decide whether to attend the auction and if yes, whether they should use the online or onsite auction. At the onsite auction, buyers also have the opportunity to check the actual flower lots. The online and onsite buyers compete for the same auction lots. In addition, they will have to decide which auction strategies they should use and what price they will pay accordingly.

Data and Variables Development

We analyze a year of transactions of large-rose products the biggest product group at FloraHolland with over 4 million transactions. The data contains information related to seller and buyer id, lot id, product id, quantity purchased, available quantity and price purchased for each channel, the price set by sellers in the pre-sales and the timing of the transactions. We preprocess the data, reserve products that are traded across all channels and exclude defective lots that were reported by experts at FloraHolland. We generate panel data at the buyer-product-day level and consequently remove buyer-products that are rarely observed (5 observations or less). Greene (2002) points out that if the size of T is small (-the number of observations per unit of analysis) this can lead to bias in the estimation for fixed effects choice model. The generated panel data contains over 100 products traded by nearly 300 buyers across 254 days.

Buyers' Decisions

We capture the strategic decisions of buyers by a series of variables which are defined as below.

Presales and auction participation decisions. $Presales_{ipt}$ is a dummy variable taking the value of 1 if on day *t,* the buyer *i* purchases product *p* from the presales channel and '0' otherwise. Similarly, $Auction_{ipt}$ equals 1 if the buyer *i* purchases product *p* from the auction channels on day *t* and '0' otherwise. On_auc_{ipt} takes the value of 1 if the buyer i participates in the online auction and '0', otherwise.

Auction Strategies. As mentioned in the Hypotheses Development section, we consider two main decisions: TOE and TOE-D. Following similar terminology and approach as Lu et al (2016), we classify bidder's strategy for buyer *i* for product *p* on day *t* as *"Conservative" ($Forw_{ipt} =0$)* if their first win falls within the *first half of the auction day*. Their strategy is classified as *"forward-looking" ($Forw_{ipt} =1$)* if their first win falls within the *second half of the auction day*. For example, if there are 20 auctions for product *p* on day *t* and the buyer's first win is in the 2nd auction, then the buyer's strategy is categorized as "conservative", $Forw_{ipt}=0$. Similarly, we classify bidders' strategies as *"Early Bidding" ($Opp_{ipt}=0$)* if on average, buyers tend to bid within the *first half of an auction lot*. Alternatively, a buyer's strategy is classified as *"Opportunist" ($Opp_{ipt}=1$)* if buyers tend to bid within the *second half* of the auction lot. For example, *i*f one auction is carried out in 10 rounds and the buyer's first win is on round 2, then their strategy is categories as "early bidding", $Opp_{ipt} =0$. Similar to the study of Lu et al (2016), as we only observe winning bid, we do not observe actual entry time. This is also a common challenge in Dutch auction study where the price goes in reverse order. Such use of winning patterns as proxies for bidder's strategic behavior has been shown by Lu et al (2016) to provide valuable insights into buyer's behaviors and the system's economic outcome in the Dutch auction.

Other Variables

We hypothesize that buyers' choices are influenced by their demand and experiences with the channel.

Demand. The demand of the buyers is captured through the *total demanded quantity* for product *p* on day t, Q_{ipt}, and the diversity in their portfolio or the number of products they demand on day t, $Pronum_{it}$. Different from B2C, B2B buyers tend to have a large portfolio. In our data, this ranges up to 900 products. Both variables are log transformed to control for the skewness in our data

Strategies experiences. Following the measurement applied by Goes et al (2012), we capture the experiences of buyers in the pre-sales for product *p* up to day *t*, $Presales\_exp_{ipt}$, as the cumulative number of times the bidders have used the pre-sales. We then control for the total number of times the bidders have participated in DFA and divide $Presales\_exp_{ipt}$ by the cumulative number of times the buyers have used the system up to day t. In other words, the measure captures the proportion of times the buyers choose the pre-sales among all the times they need to choose whether to participate in the channel or not. This measurement is consistent with the *cumulative proportional reinforcement rules* (Laslier et al. 2001) which, as Goes et al (2012) suggest, capture both the behavioral component of learning through experience and the economic construct of utility. Goes et al (2012) suggest that buyers learn from their experiences in repeated games and rely on the cumulative utility to make the decision on the next move. Additionally, as bidders participate more, they learn to evaluate their utilities more accurately and hence as the proportion of experiences surges, the buyers will be more likely to increase the choice of such an option. Using this approach, we also take into account the experiences of buyers across different strategies including online/onsite auction, On_exp_{ipt}, conservative/forward-looking, $Forw\_exp_{ipt}$ and early-bidding/opportunist, Opp_exp_{ipt}.

Other control variables. Following the models by Goes et al (2012), Bapna et al (2009), Lu et al (2016) and Lu et al. (2019), we also control for a number of factors. First, Market supply, $MSupply_{pt}$ is taken into account. The information on supply at the market level is made available to all buyers a day before the auction. Second, we include in our models different information signal from the pre-sales channel including whether there is a pre-sales market or not ($Premarket_{pt}$), the presales average price ($Ppre_{pt}$), proportion of market supply available in the pre-sales ($Avai_{pt}$), and the number of flowers sold in the pre-sales ($MQpre_{pt}$). Third, we also control for buyer's budget constraint which is estimated by their total budget from the previous purchases. Finally, we also include in our models buyer fixed effect, product fixed effect, week fixed effect, day of the week and peak time dummies to account for any unobserved heterogeneity such as seller's reputation and seasonality.

A summary of our variables and descriptive statistics can be presented in Table 1 and Table 2, respectively.

Table 1. Variables summary

Presales	= 1 if the buyer uses the pre-sales channel on day t for product p; = 0 otherwise
Auction	= 1 if the buyer uses the auction channel on day t for product p;= 0 otherwise
On_auc	= 1 if the buyer uses online auction on day t for product p; = 0 otherwise
Forw	= 1 if the buyer adopts forward-looking bidding strategy for product p on day t = 0 if the buyer adopts conservative bidding strategy for product p on day t
Opp	= 1 if the buyer adopts opportunist strategy for product p on day t = 0 if the buyer adopts early bidding strategy for product p on day t
Forw_exp	Cumulative proportion of times the buyer has used forward-looking strategy for product p up to the beginning of day t
Opp_exp	Cumulative proportion of times the buyer has used opportunist strategy for product p up to the beginning of day t
On_exp	Cumulative proportion of times the buyer has used the online auction for product p up to the beginning of day t
Q	The demand for buyer i for product p on day t
Pronum	Number of products demanded by buyer i on day t
Presales_exp	Cumulative proportion of times the buyer has used the pre-sales channel for product p up to the beginning of day t
Msupply	Market supply for product p on day t (measures in 10,000)
Premarket	= 1 if the pre-sales channel is available on day t; = 0 otherwise
Ppre	Average pre-sales price per flower stem set by the sellers
MQpre	Total quantity sold through the pre-sales channel
Avai	The proportion of supply that is made available through the pre-sales channel

Table 2. Descriptive Statistics

Statistic	**N**	**Mean**	**S.D**	**Min**	**Max**
Price (per buyer-product-day)	1,020,025	0.303	0.172	0.050	4.000
Q (per buyer-product-day)	1,020,025	612.367	1,263.363	20	92,990
Pronum (per buyer-day)	53,103	111.993	107.907	1	919
Msupply (per product-day)	26,817	3.694	6.532	0.005	71.404
Avai (per product-day)	26,817	0.142	0.137	0	0.333
Ppre (per product-day)	26,817	0.236	0.255	0	17.000
MQpre (per product-day)	26,817	307.124	797.433	0	19,980

Methodologies and Results

Channel Choices

To test our hypotheses regarding channel choices, we, first, run the below linear probability models (LPM). We include buyer fixed effect, product fixed effect, week fixed effect and day of the week to control for any unobserved heterogeneity such as reputation, peak-time, and seasonality. Error is clustered at the buyer level to control for potential correlated error terms within buyers. With the large dataset as in our case, LPM offers computational ease and the coefficients can be readily interpreted as marginal effects.

$$Presales_{ipt} = \beta_{00} + PS_{pt}\alpha + D_{ipt}\gamma + B_{ipt}\Omega + F_{ipt}\mu + C_{ipt}\eta + \varepsilon_{ipt} \quad (1)$$

$$Auction_{ipt} = \beta_{10} + PS_{pt}\alpha + D_{ipt}\gamma + B_{ipt}\Omega + F_{ipt}\mu + \beta_{11}Presales_{ipt} + C_{ipt}\eta + \varepsilon_{ipt} \ (2)$$

The vector of covariates PS_{pt} includes variables controlling for pre-sales channel' information signal. In particular, we take into account *Premarket*, *Ppre*, *Avai,* and for the *Auction* choice, also, *MQpre*, as this information becomes available before the auction. The vector of covariates D_{ipt} contains variables related to the demand of the buyer including demanded quantity *Q,* and the number of products demanded, *Pronum*. Vector B_{ipt} controls for buyers' experiences including pre-sales experiences and auction strategies experiences. Vector F_{ipt} includes fixed effects such as buyer, product, week fixed effect and day of the week. C_{ipt} contains other control variables including supply level *Msupply and buyer's budget constraint estimation*. *Msupply, Ppre, MQpre, Q, Budget and Pronum* are log transformed.

First, considering the pre-sales choice in model (1), there may be a concern that the choice of channels may influence the buyer's demand. The buyers may spot some unobserved characteristics from the channel and thus alter their total quantity purchased. This leads to the concern of the endogeneity risk of *Q* as part of model (1). Hence, we follow Wooldridge (2010) and estimate a 2SLS. We use demanded quantity for a similar period the year before *Q14* as the instrument variable (IV). While the demand from the similar period last year significantly correlates with the quantity level this year, it is unlikely that it will directly influence the presales choice of day *t*. The Hausman test, however, reveals no evidence for endogeneity. Hence, in this case, the OLS estimation is preferred. Other robustness estimations such as logit specification and 2SLS with alternative IVs are consistent with our main results.

As presented in Table 3 (column 1-2), the coefficient for *Q,* is negative and significant while the coefficient for *Pronum* is positive and significant. It suggests that as total demanded quantity reduces and as the number of products demanded increases, buyers are more likely to choose the pre-sales. H1A and H1B are supported. Both OLS and 2SLS produce consistent results. In addition, we observe that pre-sales experiences are positively correlated with the pre-sales choice. As buyers start to get more experiences with the pre-sales, they are more likely to choose the pre-sales channel for the next purchases. H1C is supported.

Second, considering the auction choice model, as buyers can be self-selected in the pre-sales channel, besides the standard LPM, we also estimate a 2SLS model (Wooldridge,2010). Here, we use *Presales_Growth* and *Presales_activities* and their interactions as IVs. *Presales_Growth* measures the level of membership of the pre-sales channel over time while *Presales activities* take into account the channel's size in terms of cumulative transaction volume. Channel adoption can be influenced by higher transaction volumes, their peers, "word of mouth" and local market penetration rate (Xue et al. 2011). Nevertheless, this growth factor of the pre-sales is unlikely to be a direct determinant of the auction decisions. The F-test and Sargan test support the suitability of our instrumental variables. The OLS and 2SLS of model (2) are presented in Table 3 (column 3-4). Buyers who already chose the pre-sales are more likely to opt-out from the auction. H2 is supported.

Table 3. Channel Choices Result						
		Presales (1)	Presales (2)	Auction (3)	Auction (4)	Auction (5)
		OLS	2SLS	OLS	2SLS	OLS
Pre-sales channel	Avai	0.120*** (0.014)	0.120*** (0.014)	0.0004 (0.002)	-0.0002 (0.003)	0.104*** (0.032)
	Log(Ppre+1)	-0.034*** (0.009)	-0.033*** (0.009)	0.002 (0.002)	-0.002 (0.003)	0.005 (0.019)
	Premarket:1	0.017*** (0.004)	0.017*** (0.004)	-0.002* (0.002)	-0.002** (0.001)	
	Log(MQpre+1)			-0.001** (0.0001)	-0.001** (0.0005)	-0.063*** (0.005)
Demand	**Log(Q)**	**-0.008** *** (0.001)	-0.007** (0.003)	0.016*** (0.002)	0.016*** (0.002)	0.271*** (0.011)
	Log(Pronum)	**0.020***** (0.004)	0.019*** (0.004)	0.006*** (0.001)	0.005*** (0.002)	**0.032***** (0.008)
Experiences	**Presales_exp**	**0.791***** (0.021)	0.791*** (0.021)	-0.154*** (0.027)	0.0170*** (0.045)	**-0.148***** (0.022)
	Forw_exp	-0.032*** (0.004)	-0.032*** (0.004)	0.014*** (0.002)	0.015*** (0.002)	0.620*** (0.073)
	Opp_exp	-0.048*** (0.006)	-0.049*** (0.006)	-0.005** (0.003)	-0.004 (0.004)	-0.050 (0.067)
	On_exp	0.008** (0.004)	0.008** (0.004)	0.007*** (0.003)	0.007*** (0.003)	0.016 (0.016)
Other Control	Log(Msupply)	0.003*** (0.001)	0.002 (0.001)	0.0004 (0.0005)	0.0005 (0.0005)	0.040*** (0.005)
	Log(Budget)	0.002** (0.001)	0.001 (0.001)	0.0003 (0.001)	-0.0002 (0.001)	-0.003 (0.006)
Presales Choice	**Presales**			-0.579*** (0.023)	**-0.559***** (0.057)	
N		1,020,025	1,020,025	1,020,025	1,020,025	49,051
R2		0.349		0.684		0.614
Fixed Effects		Yes	Yes	Yes	Yes	Yes

* p<0.1, ** p<0.05, *** p<0.01

Multichannel Buyers

In H3A & H3B, we hypothesize a number of conditions where pre-sales buyers will switch to multichannel strategies. To test the hypothesis, we re-run the auction choice model for pre-sales buyer only. The analysis results within this particular group can be found in Table 3, column 5. Low pre-sales experiences are associated with using auction in the later stage, while an increase in the number of products demanded is positively associated with the multichannel strategy. These provide evidence to support H3A & H3B.

Table 4 demonstrates the results from our auction decisions models, i.e. online/onsite auction, conservative or forward-looking and early bidding or opportunist. Here, first, we estimate similar OLS to (2). Fixed effects and clustering standard errors at buyer level are utilized to control for unobserved heterogeneity and potential of correlated error term within buyer, respectively. Similar to Lu et al (2016), for the TOE and TOE-D decision, we additionally control online/onsite decision as it has been found that this auction mode decision which needs to be made before the other two can play an important role in TOE and TOE-D decisions. Second, as buyers can be self-selected into the pre-sales channel, again, 2SLS models are estimated. As buyers purchase from the pre-sales, we observe that the likelihood of them choosing the online auction tends to decrease ($\beta_{11} = -0.669, se = 0.354$). Both the OLS and 2SLS models provide a qualitative consistent result. In addition, we find evidence that buyers' likelihood of choosing forward-looking strategy tends to increase when they already use the pre-sales than when they do not ($\beta_{11} = +1.732, se = 0.450$). H3C and H3D are supported. However, we do not find evidence that pre-sales users are also more likely to use the opportunist strategy than when they do not use the pre-sales channel and therefore H3E is not supported.

Table 4. Auction decisions Results

		On_auc (1)	On_auc (2)	For (3)	For (4)	Opp (5)	Opp (6)
		OLS	2SLS	OLS	2SLS	OLS	2SLS
Pre-sales channel	Avai	0.003 (0.004)	0.015** (0.008)	0.038*** (0.009)	0.06 (0.013)	-0.029*** (0.011)	-0.030** (0.013)
	Log(Ppre+1)	0.015*** (0.004)	0.009 (0.006)	-0.004 (0.009)	0.010 (0.012)	0.009 (0.009)	0.009 (0.010)
	Premarket:1	-0.009*** (0.002)	-0.012*** (0.003)	-0.001 (0.004)	0.006 (0.005)	0.001 (0.003)	0.002 (0.004)
	Log(MQpre+1)	0.0001 (0.0002)	0.003** (0.001)	-0.0004 (0.0003)	-0.007*** (0.002)	0.0004 (0.0003)	0.0003 (0.001)
Demand	Log(Q)	0.015*** (0.003)	0.022*** (0.005)	-0.048*** (0.005)	-0.066*** (0.005)	0.125*** (0.005)	0.111*** (0.005)
	Log(Pronum)	-0.014 (0.010)	-0.004 (0.011)	-0.025*** (0.008)	-0.053*** (0.008)	-0.024*** (0.007)	-0.027*** (0.007)
Experiences	Presales_exp	-0.036*** (0.011)	0.235 (0.146)	0.376*** (0.041)	-0.337* (0.197)	0.131*** (0.021)	0.116 (0.136)
	Forw_exp	-0.014*** (0.004)	-0.012*** (0.005)	0.602*** (0.013)	0.597*** (0.013)	-0.020*** (0.006)	-0.020*** (0.006)
	Opp_exp	-0.042*** (0.005)	-0.052*** (0.007)	-0.189*** (0.010)	-0.165*** (0.014)	0.158*** (0.013)	0.159*** (0.014)
	On_exp	0.524*** (0.037)	0.542*** (0.036)	-0.075*** (0.012)	-0.086*** (0.013)	-0.037*** (0.007)	-0.039*** (0.007)
Other Control	Log(Msupply)	-0.002* (0.001)	-0.003** (0.001)	-0.026*** (0.002)	-0.024*** (0.003)	-0.040*** (0.003)	-0.043*** (0.003)
	Log(Budget)	-0.0002 (0.001)	0.001 (0.002)	0.004 (0.002)	0.003 (0.003)	-0.007** (0.003)	-0.006** (0.003)
	On_auc			0.004 (0.016)	0.056*** (0.017)	-0.009 (0.010)	0.010 (0.010)
Presales Choice	**Presales**	-0.015*** (0.004)	**-0.669*** (0.354)	0.010 (0.006)	**1.732***** (0.450)	-0.035*** (0.007)	**-0.002** (0.324)
N		987,994	983,025	987,994	983,025	987,994	983,025
R2		0.774		0.222		0.110	
Fixed Effects		Yes	Yes	Yes	Yes	Yes	Yes

* p<0.1, ** p<0.05, *** p<0.01

As a robustness check, we have also re-estimated the models using Probit. The results which can be found in Appendix A is qualitatively consistent with our main results

A summary of results can be found in Table 5

Table 5. Results Summary

H1A: *Buyers are more likely to use the pre-sales as they have a high product diversity demanded* ***H1B***: *Buyers are more likely to use the pre-sales channel when they have low quantity demanded* ***H1C:*** *As buyers get more experiences with the pre-sales, they are more likely to use it for the next purchase*	H1A is supported H1B is supported H1C is supported
H2: *When buyers already purchase from the pre-sales, they are more likely to opt-out of the auction.*	H2 is supported
H3A: *Buyers are more likely to move from pre-sales channel only to multichannel strategy when they are not too familiar with the pre-sales channel <u>or</u>:* *H3B: Buyers are more likely to move from pre-sales channel only to multichannel strategy when they have a high product diversity demanded products*	H3A is supported H3B is supported

When buyers already purchase from the pre-sales ***H3C**: They are more likely to use the onsite auction* ***H3D:** They are more likely to adopt forward-looking strategies* ***H3E**: They are more likely to choose opportunist strategies*	 H3C is supported H3D is supported H3E is not supported

Conclusions and Future Work

While multichannel systems have been increasingly adopted in several industries, not many studies have focused on B2B multichannel market nor the case where multiple trading mechanisms are incorporated. In this study, we explore buyer's strategic decisions in a unique setting where an online posted price channel is incorporated with a Dutch auction system – a fast reverse mechanism system that has been widely adopted in agricultural markets. The analysis of the large dataset of buyers' transaction records reveals a dynamic picture of the buyer's choices and decisions in a multichannel system context.

First, we identify a number of key determinants of online pre-sales usage including their quantity demand and their portfolio diversity which is less likely to be a focus in B2C study. Second, we incorporate experiences and learning in our work which tends to be ignored in previous research (Goes et al. 2012). We reveal a lock-in effect as users have more experiences with the pre-sales, they tend to stick to the channel in the future and use it as a substation for auction. In addition, there is an emerging group of multi-channel users. While traditional analytical models tend to assume that buyers allocate all of their demands with one channel, splitting the demand is well observed in practice. The empirical analysis unveils a number of conditions when buyers may use both channels such as when they have a large portfolio size, when there is friction in the presales channel or when they strategically complement both channels. There is evidence that as the buyer use the pre-sales for the day, if they join the auctions, they are more likely to opt for offline auction and they also tend to enter later auctions. However, unlike these decisions that can pre-planned at day level, we do not find evidence relating to pre-sales choice with the time of entering the auction lot.

Our study expands the current understanding of B2B buyers' behaviors in a multichannel system where different trading mechanisms are integrated. It sheds light on how buyers in auction market would behave when online posted price channel is introduced. At the same time, our findings stress the importance of experiences in buyers' strategies and multichannel auction markets. These insights are crucial building blocks not only for smart auction market (Bichler et al. 2010) and buyers decision support system design but also for market maker in practice. It further facilitates the discussion of what market maker should expect buyers to behave over time, when they should expect buyers to shift from one channel to another and how to encourage buyers to transfer from one purchasing to another purchasing path. For example, marketing efforts to expose buyers to new products and increase their portfolio diversity may also encourage buyers to move from single to multichannel strategy. While several previous studies have associated multichannel customers with higher profitability and revenue (Neslin and Shankar 2009), such insights on how to encourage buyers from one to another purchasing route can become handy for market maker. Consequently, one direction for future research can focus on the economic performance of multichannel B2B buyers and whether the findings in the B2C area is still held. Lab controlled experiment can also be carried out to further confirm the causality. While the current work focuses mainly on buyers' choices decision, future study can also expand to quantity demand for each channel. Finally, further study on how B2B buyers would adapt their strategies for different product types can also be a fruitful arena for future study.

Appendix A

Appendix A. Robustness Check						
		Presales (1)	Auction[2] (2)	On_auc (3)	For (4)	Opp (5)
		Probit	Probit	Probit	Probit	Probit
Pre-sales channel	Avai	2.084*** (0.068)	0.871*** (0.215)	-0.030 (0.052)	0.108*** (0.026)	-0.082*** (0.025)

[2] While the OLS and 2SLS estimations do not raise any problems with multicollinearity (VIF<4 for all terms), the two terms are dropped for the Probit estimations.

	Log(Ppre+1)	-0.618*** (0.053)	-0.448** (0.150)	0.213*** (0.041)	-0.014 (0.020)	0.016 (0.019)
	Premarket:1	2.111*** (0.076)	2.025 (4.570)	-0.094*** (0.018)	-0.003 (0.009)	0.008 (0.008)
	Log(MQpre+1)		-0.559*** (0.016)	0.001 (0.002)	-0.001 (0.001)	0.001 (0.001)
Demand	Log(Q)	-0.122*** (0.004)	1.471*** (0.017)	-0.082*** (0.003)	-0.153*** (0.002)	0.347*** (0.002)
	Log(Pronum)	0.267*** (0.010)	0.503*** (0.015)	-0.408*** (0.008)	-0.073*** (0.005)	-0.064*** (0.004)
Experiences	Presales_exp	2.118*** (0.021)	-1.196*** (0.039)	-0.129** (0.049)	1.031*** (0.022)	0.361*** (0.022)
	Forw_exp	-1.179*** (0.023)		-0.107*** (0.013)	1.773*** (0.006)	-0.064*** (0.006)
	Opp_exp	-1.707*** (0.046)		-0.187*** (0.014)	-0.630*** (0.007)	0.429*** (0.006)
	On_exp	-0.031 (0.021)	-1.196*** (0.039)	2.341*** (0.012)		
Other Control	Log(Msupply)	0.060*** (0.010)	0.277*** (0.029)	-0.072**** (0.008)	-0.078*** (0.049)	-0.117*** (0.004)
	Log(Budget)	0.011** (0.005)	0.157*** (0.012)	0.024*** (0.005)	0.016*** (0.002)	-0.017** (0.002)
	On_auc				0.238*** (0.006)	0.031*** (0.006)
Presales Choice	Presales		-8.314*** (1.661)	-0.077** (0.024)	0.046*** (0.011)	-0.116*** (0.011)
N		1,020,025	1,020,025	987,994	987,994	987,994
Fixed Effects		Yes	Yes	Yes	Yes	Yes

References

Abele, J. M., Gaesar, W. K., and John, R. H. 2003. "Rechanneling Sales," *McKinsey Quarterly* (3), pp. 64–75.

Ashenfelter, O. 1989. "How Auctions Work for Wine and Art," *Journal of Economic Perspectives* (3:3), pp. 23–36.

Bapna, R., Chang, S. A., Goes, P., and Gupta, A. 2009. "Overlapping Online Auctions: Empirical Characterization of Bidder Strategies and Auction Prices," *MIS Quarterly*, pp. 763–783.

Bapna, R., Goes, P., Gupta, A., and Jin, Y. 2004. "User Heterogeneity and Its Impact on Electronic Auction Market Design: An Empirical Exploration," *Mis Quarterly*, pp. 21–43.

Bichler, M., Gupta, A., and Ketter, W. 2010. "Research Commentary—designing Smart Markets," *Information Systems Research* (21:4), pp. 688–699.

Caldentey, R., and Vulcano, G. 2007. "Online Auction and List Price Revenue Management," *Management Science* (53:5), pp. 795–813.

Cavallo, A. 2017. "Are Online and Offline Prices Similar? Evidence from Large Multi-Channel Retailers," *American Economic Review* (107:1), pp. 283–303.

Chen, P.-Y., and Hitt, L. M. 2002. "Measuring Switching Costs and the Determinants of Customer Retention in Internet-Enabled Businesses: A Study of the Online Brokerage Industry," *Information Systems Research* (13:3), pp. 255–274.

Einav, L., Farronato, C., Levin, J., and Sundaresan, N. 2018. "Auctions versus Posted Prices in Online Markets," *Journal of Political Economy* (126:1), pp. 178–215.

Gallien, J., and Gupta, S. 2007. "Temporary and Permanent Buyout Prices in Online Auctions," *Management Science* (53:5), pp. 814–833.

Goes, P. B., Karuga, G. G., and Tripathi, A. K. 2012. "Bidding Behavior Evolution in Sequential Auctions: Characterization and Analysis," *MIS Quarterly*, pp. 1021–1042.

Granados, N., Gupta, A., and Kauffman, R. J. 2012. "Online and Offline Demand and Price Elasticities: Evidence from the Air Travel Industry," *Information Systems Research* (23:1), pp. 164–181.
Greene, W. H. 2002. *The Behavior of the Fixed Effects Estimator in Nonlinear Models*.
Hou, J. 2007. "Price Determinants in Online Auctions: A Comparative Study of EBay China and US.," *Journal of Electronic Commerce Research* (8:3).
Kambil, A., and Van Heck, E. 1998. "Reengineering the Dutch Flower Auctions: A Framework for Analyzing Exchange Organizations," *Information Systems Research* (9:1), pp. 1–19.
Katok, E., and Kwasnica, A. M. 2008. "Time Is Money: The Effect of Clock Speed on Seller's Revenue in Dutch Auctions," *Experimental Economics* (11:4), pp. 344–357.
Krishna, N., and Singh, J. 2018. "Factors Affecting B2B E-Commerce Adoption Decision: An Analysis of Indian Textile Industry," *Academy of Marketing Studies Journal*.
Kuruzovich, J., and Etzion, H. 2017. "Online Auctions and Multichannel Retailing," *Management Science* (64:6), pp. 2734–2753.
Langer, N., Forman, C., Kekre, S., and Sun, B. 2012. "Ushering Buyers into Electronic Channels: An Empirical Analysis," *Information Systems Research* (23:4), pp. 1212–1231.
Leszczyc, P. T. P., Qiu, C., and He, Y. 2009. "Empirical Testing of the Reference-Price Effect of Buy-Now Prices in Internet Auctions," *Journal of Retailing* (85:2), pp. 211–221.
Lu, Y., Gupta, A., Ketter, W., and Heck, E. van. 2016. "Exploring Bidder Heterogeneity in Multichannel Sequential B2B Auctions," *MIS Quarterly* (40:3), pp. 645–662.
Lu, Y., Gupta, A., Ketter, W., and van Heck, E. 2019a. "Information Transparency in Business-to-Business Auction Markets: The Role of Winner Identity Disclosure," *Management Science*.
Lu, Y., Gupta, A., Ketter, W., and van Heck, E. 2019b. "Dynamic Decision Making in Sequential Business-to-Business Auctions: A Structural Econometric Approach," *Management Science*. (https://doi.org/10.1287/mnsc.2018.3118).
Luo, J., Ba, S., and Zhang, H. 2012. "The Effectiveness of Online Shopping Characteristics and Well-Designed Websites on Satisfaction," *Mis Quarterly*, pp. 1131–1144.
Mithas, S., and Jones, J. L. 2007. "Do Auction Parameters Affect Buyer Surplus in E-Auctions for Procurement?," *Production and Operations Management* (16:4), pp. 455–470.
Neslin, S. A., and Shankar, V. 2009. "Key Issues in Multichannel Customer Management: Current Knowledge and Future Directions," *Journal of Interactive Marketing* (23:1), pp. 70–81.
Pilehvar, A., Elmaghraby, W. J., and Gopal, A. 2016. "Market Information and Bidder Heterogeneity in Secondary Market Online B2B Auctions," *Management Science* (63:5), pp. 1493–1518.
Pinker, E. J., Seidmann, A., and Vakrat, Y. 2003. "Managing Online Auctions: Current Business and Research Issues," *Management Science* (49:11), pp. 1457–1484.
Srinivasan, K., and Wang, X. 2010. "Commentary—Bidders' Experience and Learning in Online Auctions: Issues and Implications," *Marketing Science* (29:6), pp. 988–993.
Van den Berg, G. J., Van Ours, J. C., and Pradhan, M. P. 2001. "The Declining Price Anomaly in Dutch Dutch Rose Auctions," *American Economic Review* (91:4), pp. 1055–1062.
Van Rijswick, C. 2015. "World Floriculture Map 2015," Rabobank Industry Note.
Verhagen, T., and Van Dolen, W. 2009. "Online Purchase Intentions: A Multi-Channel Store Image Perspective," *Information & Management* (46:2), pp. 77–82.
Verhoef, P. C., Kannan, P. K., and Inman, J. J. 2015. "From Multi-Channel Retailing to Omni-Channel Retailing: Introduction to the Special Issue on Multi-Channel Retailing," *Journal of Retailing* (91:2), pp. 174–181.
Wilcox, R. T. 2000. "Experts and Amateurs: The Role of Experience in Internet Auctions," *Marketing Letters* (11:4), pp. 363–374.
Wooldridge, J. M. 2010. *Econometric Analysis of Cross Section and Panel Data*, MIT press.
Xue, M., Hitt, L. M., and Chen, P. 2011. "Determinants and Outcomes of Internet Banking Adoption," *Management Science* (57:2), pp. 291–307.