Buyers' Strategic Behavior in B2B Multichannel Auction Markets: When an Online Posted Price Channel is Incorporated into a Dutch Auction System.

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Abstract

Firms are increasingly adopting different sales channels to reach new potential buyers. Yet, extant research has mainly focused on B2C online and offline posted price channels. B2B multichannel and, especially, systems with multiple pricing mechanisms are largely underexplored. This paper investigates the strategic behaviors of B2B buyers in a unique system where an online posted price channel is incorporated into a Dutch auction market, sequentially. We follow buyers' purchasing paths and examine conditions under which B2B auction buyers will utilize the online posted price channel. We incorporate learning and experience and demonstrate how buyers' behaviors evolve. We investigate an emerging group of buyers who utilize different price mechanisms and their surplus extraction activities. We further explore how the market flow changes when posted prices are incorporated. Our results, using an extensive dataset from the world's largest flower market, highlight the importance of quantity demand, product diversity, and experience in explaining the choice of the new posted price channel. We find a significantly higher average loss of surplus at the product level for multichannel buyers than for single channel buyers and a reduction in the number of small orders in the auction channel. Subsequently, theoretical and managerial implications for B2B multichannel markets and market design are discussed.

Keywords: Multichannel Market, Buyers Strategic Behavior, B2B Trading, Dutch Auctions.

1. Introduction

E-commerce has become increasingly popular in the B2B marketplace. In 2018, the B2B online posted price channel surpassed $1 trillion in sales in the US alone (Don 2019). This digitization trend is widespread across several sectors and it is, especially, gaining momentum in agriculture markets. According to AgFunder's Agri-FoodTech Funding Report, around $800 million was invested in agribusiness marketplaces in 2018 as agribusiness moves quickly to catch up with the e-commerce trends globally (Marketplaces 2020). This investment is creating a more dynamic market with several trading channels and multiple pricing mechanisms. Traditionally, a large proportion of B2B agricultural trading is carried out through Dutch or descending auctions. The century-old Dutch auction mechanism, where the price starts at a high level and gradually drops down until a buyer is found, facilitates a fast clearing speed and has been playing a significant role for highly perishable goods. It is not only an essential supply and demand allocation mechanism for growers and wholesale buyers worldwide but also determines the prices of numerous daily consumption goods ranging from flowers, vegetables, fruits, and fish to tea and coffee. The growth of e-commerce brings opportunities; yet, a natural question is how buyers will behave and navigate in this new marketplace with multiple pricing mechanisms. *We address this question by investigating buyers' strategic behaviors and their surplus when an online posted price channel (so-called pre-sales) is incorporated into a multiunit descending auction market sequentially.* We see our findings generalized to the aforementioned B2B highly perishable goods markets, where such a system can be applied, as well as akin to sequential markets in general.

The extant literature has largely focused on B2C online and offline posted channels (Neslin and Shankar 2009). Studies on B2B multichannel systems and especially those that include different pricing mechanisms remain scarce. One reason for this can be the difficulties in accessing individual-level data (Langer et al. 2012). Recently, some studies have sought to address this research gap through analytical modeling. The initial results suggest that sellers may benefit from integrating B2C English auctions with a posted price channel in a concurrent manner (Kuruzovich and Etzion 2017). These studies rely heavily on highly restrictive assumptions such as homogeneous single-unit demand customers that always use only one of the channels – assumptions that are violated in practice. On the other hand, a recent study by Einav et al. (2018) reports a decline in eBay English auctions because customers favor the posted price channel which offers contradictory results. In general, insights into the buyers' behavior in a B2B multichannel context are underexplored. Such insights are crucial building blocks for B2B smart market design, customer journey personalization research (Bichler et al. 2010), and market makers in practice.

We address this issue by analyzing a rich dataset of over one million flower transactions from Royal FloraHolland, the world's largest flower market with 50% of the global market share (Lu et al. 2016). The market is made up of sellers who are flower growers worldwide, and buyers such as supermarkets, retailers, and wholesalers. Traditionally, buyers could only participate in the auctions physically at the onsite auction halls. In 1996, online auctions were introduced where buyers could participate in the auctions remotely. In late 2013, an online pre-sales posted price channel was introduced where buyers can buy the products before the auctions at a fixed price predetermined by the sellers. The introduction of the pre-sales is FloraHolland's approach to first, capitalize on the growth of e-commerce and direct sales where growers sell their products online using posted prices. The emerging environment called for the reinvention of the traditional auction and the new pre-sales channel closes this gap between the auction and posted price channels. Second, the platform could offer additional insights into buyers' behaviors that have not been previously observed. Third, it is also an effort to link buyers and sellers more efficiently. The pre-sales expand the current trading time which is restricted from 6 to 11 AM and opens additional trade opportunities worldwide.

From the market maker's perspective, the first essential need is to obtain knowledge of customers' behaviors, their target users, segmentation, and responses to this new market design. This further helps to develop important market policy, operation, and marketing strategies. Second, by better segmenting the market, the new channel is expected to extract additional surplus from buyers. Especially, it can attract small buyers which in turn can also lead to better process flow (less small volume transactions) during auctioning. One of the concerns of the market marker is that the pre-sales channel can cause major disruption to the auction market. It can also break down the existing order size structure in the auctions which can increase processing costs. In light of these goals, this study offers insights into buyers' profiles of different channels and evaluates marketing flow and buyers' surplus extraction activities. While the Dutch auction has been the main means of trading for decades, what drives the buyers to utilize this relatively new channel and the potential outcome of this strategy is a fascinating strategic question that has never been previously explored.

We investigate the research framework in Figure 1. First, we examine the drivers of pre-sales usage. Second, we examine whether on average, buyers tend to complement the pre-sales with the auctions. We then compare the loss in surplus between multichannel buyers (i.e., those who utilize both pre-sales and auctions on the day) with single-channel buyers (i.e., those who use the auction only or pre-sales only for the day). Third, we evaluate how buyers' order size in the auctions can change by comparing the number of small order sizes on days of pre-sales and days where there were no pre-sales available. We show that our results are also robust under different model specifications including Linear Probability Model, Probit, 2-Stage Least Squares, and Biprobit. More details are provided in section 3.

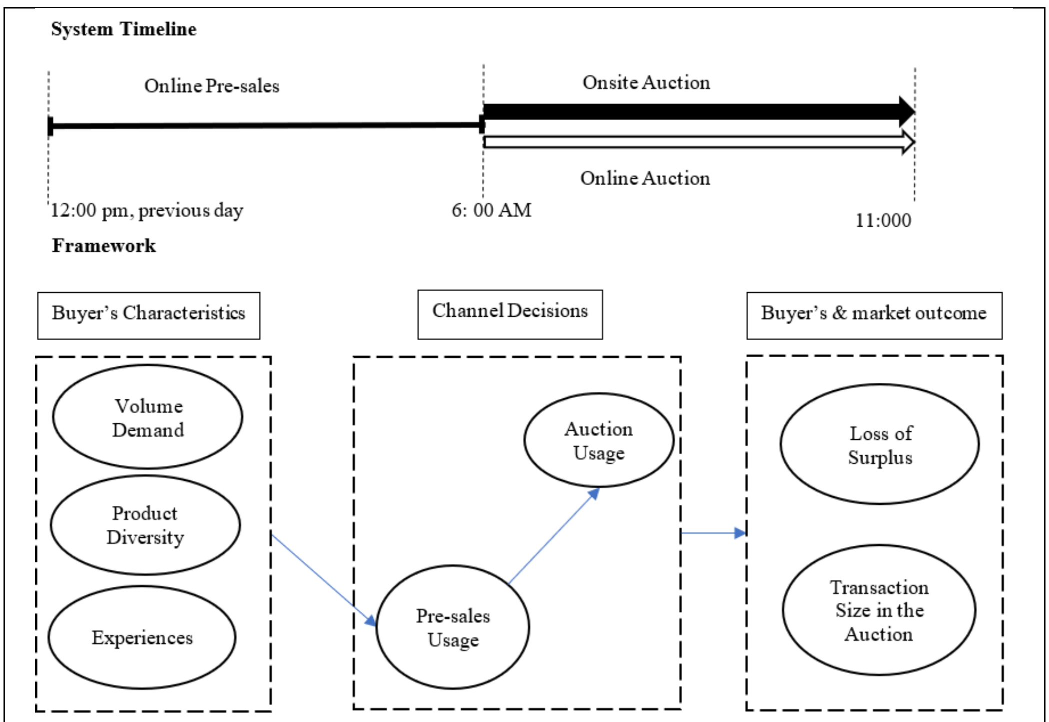

Figure 1. Dutch Flower Auction System and Research Framework

Our study provides several novel results. First, buyers with large demand tend to bypass the pre-sales channel. Pre-sales usage is driven by buyers with comparatively smaller demand or buyers that require large product diversity. Given that most studies focus on the B2C environment where buyers only purchase a limited number of products with small purchasing volume, large demand, and diversity of demand are largely unexplored. Second, we find that buyer experience plays a key role. As buyers get more experience with pre-sales, they tend to stick with the channel for future purchases and buyers tend to substitute one channel for the other. In addition, our results reveal that the pre-sales can extract additional surplus compared to the traditional auction-only buyers. Multichannel buyers are likely to have a higher loss of surplus than single channel buyers and pre-sales-only buyers have a significantly higher loss of surplus than auction-only buyers. Fourth, the incorporation of pre-sales also reduces the number of low-volume transactions in the auctions. We find that both the number of small orders and the proportion of small orders in the auctions are lower for days with pre-sales than for days without pre-sales. Finally, as the pre-sales can extract a higher surplus from buyers compared to auction-only buyers, lots listed in the pre-sales are found to have significantly higher weighted revenue than lots that are not.

Our research contributes to market design and auction research in multiple ways. We offer evidence for B2B buyers' behaviors in the multichannel auction system. The results reveal how small and large demand buyers, as well as small and large product diversity buyers, can behave differently. Insights into customers' behaviors and purchasing trajectories are essential for market designers as it aids several strategic decisions ranging from targeting and personalization to channel features and policy design. Second, we capture empirical evidence when a posted price channel is integrated with an auction channel sequentially. These two trading mechanisms have been increasingly used by businesses (Kuruzovich and Etzion 2017) and as e-commerce gains ground in the traditional auction markets such as in the agriculture sector, it raises uncertainty in terms of the level of disruption and customers response. Yet, not much research has been conducted in this important area. Third, we differentiate our study from previous analytical works by considering the case of multichannel strategies where buyers can consider multiple trading mechanisms and compare economic outcomes between multichannel and single-channel users in the B2B marketplace.

Further, we consider multiunit demand buyers in sequential Dutch auctions which are different from the focus of current literature.

2. Background and Related Literature

Our work is related to the emerging literature of multichannel auction systems, auction market design, and B2B bidders' strategic behaviors. In this section, we review relevant works for our study.

2.1. Multi-mechanism Systems

2.1.1. Multichannel Posted Price System

Multichannel systems are not a new topic in IS and marketing research, however, the vast majority of the attention over the past decade has been paid to B2C online and offline posted price channels where prices and quantity are set by the sellers. A comprehensive literature review can be found in Table 1. The review by Neslin and Shankar (2009) points out that customers behave differently across channels and have a disparate Willingness-to-pay (WTP). They suggested that multichannel buyers are associated with several positive outcomes such as higher sales and engagement. Forman et al. (2009) found that when a discount store was available in the local area, it could reduce the chance of the product entering the top 10 best-selling on Amazon. Brynjolfsson et al. (2009) extended the discussion and suggested that internet channels faced significant competition from offline stores, but were less intense for niche products. A recent study by Zhou et al. (2019) finds that opening a new branch leads to a synergistic increase in online banking transactions. Evidently, both positive and negative effects of the online posted price channel on offline posted price channels have been identified. Thus, the question of whether a new online posted price channel would complement or substitute the traditional auction is not straightforward. Moreover, our study differs from these works by considering B2B buyers' behaviors. Previous B2C researches limit to buyers who have a small demanded quantity for a single product for personal consumption. The difference in motivation and demand characteristics can lead to significantly different results (Bapna et al. 2008, Overby and Ransbotham 2019).

Table 1: Literature Summary

Paper	Key Findings	System studied

(Bapna et al. 2004)	The authors identify a stable taxonomy of bidding strategies in Yankee online auctions. Bidders utilizing different strategies realize different winning likelihoods and surplus.	Online Auction
Bapna et al. (2009)	Overlapping auctions setting has significant negative pressure on auction prices. The negative effect is stronger for information about the following auctions than for information on prior auctions.	Overlapping Auctions
Brynjolfsson et al. (2009)	The paper focuses on cross channel competition. They found that internet channels faced significant competition from offline stores, but less intense for niche products	Online and Offline posted price channels
Caldentey and Vulcano (2007)	The authors developed analytical models for the case of a duo channel context. The results suggest that when sellers 'inventory endowment is large or the discount factor is small or buyers are impatient, a dual-channel strategy is preferred over a single-channel strategy.	Parallel online auction and posted price channel
Einav et al. (2015)	The paper estimates the auction price dispersion, the demand curves, and the effects of multiple fixed prices. Sellers can achieve higher revenue with high BNP.	Online Auction
Forman et al. (2009)	The study explores the trade-off between purchasing from online and offline posted price channels. They found that when a discount store was available in the local area, it could reduce the chance of entering the top 10 best-selling products on Amazon	Online and Offline posted price channels
Ku et al. (2006)	The paper suggests that a low starting price can reduce barriers to entry and encourage higher engagement, and hence increase the final auction price	Online Auction
Kuruzovich and Etzion (2017)	Through analytical models, the paper offers insights into how the demand for the offline posted price channel can affect auctions 'performances. It is suggested that the duo channel can bring higher profits for sellers. The study also suggests that offline characteristics such as retail location can affect auction outcomes.	Parallel online auction and posted price channel
Lu et al. (2016)	The paper explores bidder's strategies in the Dutch auctions. The strategy choices are found to be driven by demand, budget constraints, and transaction costs. The economic performance of different strategies is, then, compared and analyzed.	Online and Offline Auction
Neslin and Shankar (2009)	The study offers a literature review on Multichannel systems. It identifies several challenges such as determining stable customer segmentation, measuring cross channel elasticity, resolving the casual link between multichannel and behavioral outcomes	Online and Offline posted price channels
Overby and Forman (2015)	Buyers utilized e-channel to shift their demand geographically and exploit price differences. This reduced geographic price dispersion. Ecommerce also influenced how sellers distribute supply, but no effect on price dispersion is found.	Online and Offline Auctions
Overby and Jap (2009)	Sellers are more likely to present low quality uncertainty and relatively rare products in the online channel and more likely to present high quality uncertainty and relatively plentiful products in the physical channels	Online and Offline Auctions
Overby and Ransbotham (2019)	The paper reveals different types of adopters of new channels. Channel history is one of the key factors influencing the transition from the incumbent to the new channels.	Online and Offline Auctions
Zhou et al. (2019)	When a branch is open, it leads to a reduction in online banking in the short-term but as customers learn over time, there is a synergistic increase in online banking transaction	Online and Offline posted price channels

2.1.2. Fixed Prices in Auctions

Posted price and auction research tend to be considered separately. As Bapna et al. (2009) pointed out, auction research restricts its analysis to the dynamics within a single auction. Not many studies have considered the case where multiple mechanisms are utilized. A related stream of research has investigated the effect of different price features on auction outcomes. A diverse set of features has been explored such as buyout option or Buy-Now-Price (BNP) in English auctions (Bauner 2015, Grebe et al. 2016), starting price (Einav et al. 2015, Ku et al. 2006), and bid increment (Bapna et al. 2002). Yet, a consensus has not been achieved. Grebe et al. (2016) found that high BNP can lead to a higher auction price as it aids buyers' evaluation. However, Hou (2007) found a negative association between BNP and auction prices. Ku et al. (2006) revealed that lower fixed prices can reduce competition barriers and consequently increase auction prices. Furthermore, these features are presented as part of the auctions, whilst, a new channel such as posted price can be organized before, in parallel, and after the auction. How different information cues are ordered and conveyed can lead to different results (Lu et al. 2019b). Except for (Bapna et al. 2008, 2009), most of these studies on fixed prices concentrate on single unit B2C English auction and when the buyout option is exercised, the auction also terminates. Our study differs in many ways. First, we focus on B2B Dutch auctions rather than English auctions. All the bids (winning and losing) are observed in the English auction while only the winning bid is observed in a Dutch auction. The difference in prior information structure can lead to different results (Lu et al. 2019a). Additionally, B2B buyers whose decisions are more complex and long-term oriented can form different market outcomes compared with B2C buyers. Finally, our research considers multichannel buyers who spread the demand across different pricing mechanisms. This has not been previously explored.

2.1.3. Multichannel Auction Research

One growing stream of studies has been focusing on online and offline auctions. Lu et al. (2016) focused on B2B strategic behaviors in a multichannel online and offline Dutch auction. Overby and Jap (2009) examined the adoption of online and offline auctions in the car wholesale market. The paper finds that the e-channel is utilized for low quality uncertainty and relatively rare products, while the offline channel is utilized for high quality uncertainty and a high level of product availability. In later studies, Overby and Forman (2015) identified that B2B buyers use the online auction channel to exploit price differences. This in turn reduced the price dispersion. Lu et al. (2019a) studied the issue of information transparency in the B2B Dutch auction market. Through a large scale field experiment, they found that concealing the winner's identity can increase the auction prices. Overby and Ransbotham (2019) explored firms' new online channel adoption for the B2B ascending auction. The study further explored different factors that influence the transition from the incumbent to the new channels. Our study builds upon this group of research by considering the combination of a posted price and an auction channel.

Recently, an emerging line of literature has linked the two mechanisms (posted price and auction) together and evaluated the case where a posted price channel and an English auction run concurrently (Caldentey and Vulcano 2007, Kuruzovich and Etzion 2017). These analytical studies find that sellers can benefit from managing a multichannel system. However, they ignore the buyers' heterogeneity. Moreover, since buyers usually have unit demand, it is assumed that their demand is fulfilled by only one channel. This assumption clearly does not hold in practice. Rarely has any empirical evidence been offered from practice regarding the effect of posted price on auctions and vice versa except for the recent study by Einav et al. (2018) on the substitution between eBay and posted price channel. Our study adds to this line of the multi-mechanism system by bringing forward evidence from a case of two trading mechanisms integrated sequentially.

2.1.4. B2B buyers' Strategic Behaviors

This study is also related to the area of strategic behaviors in auctions. Empirical studies have long suggested that bidders' strategies are diverse. This diversity can be characterized based on a number of key decisions of bidders: the time that the bidders enter the auction, the time they exist from the auction, and the number of bids during the auctions (Bapna et al. 2004, 2009, Lu et al. 2016). Bapna et al. (2004, 2009), using the aforementioned characteristics, reported a significant heterogeneity in bidders' strategies and the discrepancy between different strategies' winning likelihood and surplus. Lu et al. (2016) explored the B2B DFA context. They suggested that bidders can be categorized 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. They further revealed that these choices are driven by bidders' demand, budget constraints, and transaction costs.

It is also important to note that the question of what drives the choice between posted price and auctions is still not yet fully understood. Pinker et al. (2003) pointed out a lack of research on the choices between auctions and the posted price mechanisms. They further suggested that the two main determinants of mechanism choice are the sensitivity to transaction cost and the uncertainty about the goods' price. A recent effort to address this gap by Einav et al. (2018) attributes the switch from eBay English auctions to posted price channels to the trade-off between competitive pricing and hassle costs in the English auction. Here, we consider the buyers' choices between a posted price and B2B sequential Dutch auction system.

Another related line of research is the role of experiences in determining buyers' strategic decisions. Lu et al. (2016) suggested that in a Dutch auction, B2B buyers tend to rely on their experience and follow different heuristic strategies. Pilehvar et al. (2016) found that experience plays an essential role in forming B2B bidder's first bid in the English auction. Goes et al. (2012) demonstrated the evolution of strategies in sequential auctions. Despite the growing evidence, most prior research does not explicitly model experience in auction research (Goes et al. 2012). Motivated by this line of research, in this paper we capture the heterogeneity of buyers' auction strategies experience.

3. Theory and Hypotheses Development

As presented in Figure 1, we examine factors driving the posted price channel usage in a B2B sequential system. First, we discuss the role of buyers' characteristics including demanded quantity, product diversity, and experience in posted price channel choice. Second, we explore the economic outcomes of different strategic choices (auction channel usage only, posted price channel usage only, and multichannel channel usage, i.e., both auction and posted price channel usage). Finally, we compare the change in order size in the auctions between days with pre-sales and days without pre-sales.

3.1. Demanded quantity and Product Diversity

B2B buyers are different from B2C buyers in multiple ways. First, they differ in their demand characteristics which can be characterized by two factors: volume or *demanded quantity for a single product*, and *product diversity* **-** the number of different products that buyers have to purchase in a day. While B2C buyers tend to acquire a small number of units of one or a limited number of products for personal use, B2B buyers normally acquire multiple units for several products in a given day to resell these to different retailers (Lu et al. 2016). In multiple-unit sequential auction settings, product diversity is proportional to the number of auctions that buyers will have to participate in as one auction is typically carried out for one single homogeneous product. Keeping everything the same, the higher number of products, the higher number of auctions the buyers have to participate in. This does not always apply to the size of demand. Whether buyers with large demand will have to attend multiple auctions or not depends on a lot's supply volume. The higher the demanded quantity for a single product, however, the higher the financial risk involved and the more time buyers will spend on the purchasing process (Mitra et al. 1999). We explain the choice of the online pre-sales in a sequential system by synthesizing three streams of research and associated theories: auction, information search, and innovation diffusion. We summarize key research on demand volume and product diversity in Table 2.

Table 2: Demand and Channel Choice

Key Paper	**Related Findings**
Einav et al. (2018)	The decline of eBay auctions can be explained by a switch in customers' preferences moving from auctions to posted price channels for convenience
Goes et al. (2010)	The difference in demand leads to differences in strategy and decision space. Buyers with large demand tend to be resellers and hence are more likely to look for bargains and discounts, delaying their participation for additional information.
Kuruzovich et al. (2008)	Buyers with a higher risk on the value of the offer are likely to have higher marketplace search intensity
Langer et al. (2012)	Small volume buyers switch from offline to online auctions due to convenience and flexibility. Online channel is favored by buyers with high product diversity
Lu et al. (2016)	B2B buyers in the Dutch Flower auction are either order-based or speculation-based. Order based buyers are agents. They have large product diversity demand and tend to bid aggressively to fulfill the order. Buyers with large speculation-based demand, are likely to wait a couple of rounds to hunt for bargains.
Mitra et al. (1999)	Perceived risk (such as financial risk associated with a transaction) and information search are positively correlated
Overby and Ransbotham (2019)	Innovation Diffusion Theory posits that the decision of adopting a new channel depends on motivation and awareness, and one factor that can influence buyers' motivation is demand. Firms with high volume demand are less likely to switch heavily to the new channel, but most likely to stay in the main incumbent channel.
Pinker et al. (2003)	Researchers generally agree that transaction costs are higher for auctions than for posted price channels. The larger the financial cost of the transaction, the higher the complexity of the products, the more likely buyers will rely on the negotiation process such as an auction.

First, auction theory proposes that a buyer's choice for auction can be explained by the *financial risk* associated with the demand, the *complex nature of the product,* and the *transaction costs.* Pinker et al. (2003) projected that the larger the financial cost of the transaction and the higher the complexity of the products, the more likely that buyers will rely on a negotiation process or purchase via auction. Conversely, when the value uncertainty of the product is small and the product is common, buyers are likely to prefer a posted price channel. The choice of a trading mechanism can also be driven by the high transaction costs. From the lens of transaction cost economics and auction theory, researchers appear to agree that transaction costs are higher for auctions than for posted price mechanisms (Pinker et al. 2003). These transaction costs include the time and effort spent by the buyers to prepare and collect information for their bids as well as the actual time and effort participating in the actual auctions (Cheema et al. 2005). Kambil and Van Heck (1998) further highlighted the mental challenge involved with the auction environment and especially in a case such as the Dutch Flower auction where a high-speed clock is used. These higher transaction costs generally reduce auction usage (Cheema et al. 2005). Einav et al. (2018) further pointed out that the benefit of the auction is competitive pricing while the posted price channel offers low transaction costs. They find evidence that B2C buyers, who normally have small demand, moved away from the eBay English auction channel for higher convenience. Langer et al. (2012) found that convenience, flexibility, and lower transaction costs drive small demand and higher product diversity buyers to switch from offline to online channels, that is, from a higher transaction cost to a lower transaction cost option. Consequently, from the auction research's perspective, we expect that, ceteris paribus, buyers with high product diversity (which directly increases transaction costs) are likely to prefer posed price channel over auction channels; a higher demand, that increases the scale of the transaction and financial risk, is likely to drive buyers to auction based trading while small demand buyers are likely to choose the pre-sales for convenience.

Second, researches on buyer search models suggest that buyers continue their information search until the cost of additional search exceeds the benefit (Overby and Kannan 2015). Hence, higher demand, which relates to higher transaction financial value, can lead to longer search and decision time. Studies in the information search area also posit that higher financial risk and uncertainty can encourage buyers to engage in additional search activities (Kuruzovich et al. 2008, Mitra et al. 1999). Consequently, this implies that higher demand can lead to additional searches; hence, buyers can delay the purchasing time and bypass the first stage (i.e., the pre-sales) in the sequential system.

The choices between the posted price and an auction in a sequential system can also be explained through the Innovation Diffusion Theory. The theory posits the decision of adopting a new channel depends on motivation and awareness and demand does influence buyers' motivation (Overby and Ransbotham 2019). Goes et al. (2010) considered the case of a single unit and multiple unit demand buyers. They suggest that differences in demand lead to differences in strategy and decision space. Buyers with large demand tend to be resellers and, hence, are more likely to look for bargains and discounts, delaying their participation for additional information. Overby and Ransbotham (2019) found that volume purchases play a key role in channel adoption strategies for firms. Particularly, firms with higher quantity purchases are less likely to switch to the new online channel, but most likely to stay in the incumbent channel. Lu et al. (2016) examined B2B Dutch flower auction system and suggested that buyers in this market are either *order-based* or *speculation-based.* While the earlier typically buys on order, the latter purchase when they foresee a hot market for a particular product. Order based buyers are normally agents. They have a large diversity in product demand and receive commission fees based on the purchase price and, hence, can bid aggressively to fulfill the order. Buyers with large speculation-based demand, on the other hand, are likely to wait for a few auction rounds to hunt for a bargain. The study also suggests that buyers with small demand are likely to have more restricted budget constraints and, consequently, face the risk that bigger buyers would bid aggressively to clear out the market rapidly. Therefore, buyers with small demand are more likely to purchase early to guarantee the product fulfillment. Consequently, pre-sales channel which takes place before the auction and offers acquisition security is likely to be utilized by buyers with high product diversity (likely to be order based) and buyers with small demand.

In sum, we propose that pre-sales are used by buyers with low demand or high product diversity. One direct implication is that as small quantity buyers move to the pre-sales, on average, auction transaction size on the days with pre-sales will be higher than on the days without pre-sales.

Hypothesis 1A. As the demand volume increases, buyers are less likely to purchase from the pre-sales.

Hypothesis 1B As the product diversity increases, buyers are more likely to purchase from the pre-sales

Hypothesis 1C Average transaction size in the auction will be higher on the days with pre-sales than on the days without pre-sales.

3.2. Buyers' Experiences

As buyers learn over time, we propose that experience with the additional channel can play a key role in determining their strategic choices. Previous literature on *buyers' learning* largely agrees that experience is positively associated with channel usage and buyers with high experience also tend to be locked-in in the channel. Several explanations have been attributed to this effect. Xue et al. (2011) suggested that as buyers' experience increases, there will be a rise in the degree of channel *"lock-in"* due to channel familiarity and ease of use. In addition, buyers' loyalty to the new channel gets reinforced because of the additional effort required to learn about the channel. Overby and Ransbotham (2019) attributed the effect to channel habit and channel understanding. They found that firms with a long history with the incumbent channel still largely stay with the incumbent channel while those with short channel history are likely to replace it with the new channel. Goes et al. (2012) offered another explanation. They suggested that in an auction, bidders learn about their own utility over time and decide to continue with the existing strategy or not based on the cumulative utility, where bidders tend to move away from less rewarding strategies in the long term. Hence, a high level of experience is likely to imply a positive utility cumulated over time and increases the likelihood of bidders choosing it again in the future. Based on these previous findings, we hypothesize that as buyers gain more experience with the pre-sales, they are more likely to use it in the next purchases and they are also more likely to be locked in and stay with the channel. In addition, given that pre-sales users can have different motives (different demand requirements) and transit towards more beneficial options (Goes et al. 2012, Overby and Kannan 2015), we propose that on average, buyers are more likely to substitute pre-sales for auctions instead of using it as a complementary channel.

Hypothesis 2A: As buyers' experiences with the pre-sales channel increase, they are more likely to use it for the next purchase.

Hypothesis 2B: Once buyers purchase from the pre-sales, they are more likely to opt-out from the auction

3.3. Channel Choices Outcome

Buyers can be divided into auction-only buyers who only use the auctions to fulfill their demand for a day, pre-sales-only buyers who only utilize the posted price channel, and multichannel buyers who use both channels for their purchases. We examine the economic outcomes of different strategic choices. We note that in Dutch auctions, buyer's true value is not observed; bidder's surplus is commonly operationalized through "loss of surplus" (Lu et al. 2016) which is the difference between buyers' winning price and the lowest winning price within the same lot. It is a measure of the maximum possible surplus other buyers could have derived. It compares the difference in buyer's surplus magnitude and is relevant in this case as it allows us to contrast different groups of buyers including the emerging pre-sales channel buyers, the multichannel buyers, and the traditional auction buyers – the default profile over the past decades.

3.3.1. Auction Only and Pre-sales Only Buyers

Sequential Auction researches suggest that bidders can learn the market dynamics and update their WTP over time to maximize their payoff. Those who are more patient and wait longer can gain more information and thus, minimize their loss of surplus (Goes et al. 2010, Lu et al. 2016). However, buyers run the risk of failing to obtain the product over time, and hence it is the trade-off between minimizing the risk for fulfillment and maximizing their payoff. This indicates that auction buyers in the multichannel sequential system are more likely to have a lower loss of surplus than pre-sales buyers.

In addition, pre-sales, as discussed in Section 3.1, can attract buyers with large product diversity and small demand. This group is likely to be *order based* buyers (Lu et al. 2016). They are agents who focus on order fulfillment to earn commission fees rather than minimize the loss of surplus from their purchases. They also tend to bid aggressively early to obtain the products and are more willing to pay a premium for their products (Lu et al. 2016). Conversely, auctions attract buyers with large demand and smaller product diversity. This group tends to look for a bargain (Bapna et al. 2009, Goes et al. 2010), they are more likely to search for additional information to optimize their payoff. Consequently, we hypothesize that:

Hypothesis 3A: Pre-sales Only Buyers have a significantly higher loss of surplus than Auction Only Buyers.

3.3.2. Multichannel Buyers

We consider the case of multichannel buyers who utilize both the pre-sales and auctions to fulfill their demand for the day. Previous literature offers two main explanations for this behavior where buyers split their demand. On one hand, *Auction Theory* suggests that bidders in sequential auctions can exhibit *modified demand reductions behavior* (Goes et al. 2012, Lu et al. 2016) where bidders spread their demand across different auctions over time. This strategy helps them to gain knowledge about other buyers and the market trend and consequently, *maximize their payoffs* (Bapna et al. 2009). In addition, Goes et al. (2012) added that multiunit demand buyers who utilize this strategy are also likely to combine an early bid with a late bid to obtain necessary market information and discount. They tend to be big buyers that are looking for a bargain and are more likely to extract a higher surplus (Goes et al. 2012).

On the other hand, The *B2B sourcing policy* and *multichannel* literature suggest that firms can split their purchases when there is diversification or synergy benefit from both sources of suppliers (Burke et al. 2007). The online posted price channel can offer product security, but it creates challenges for buyers to access the quality of the products (Forman et al. 2009). Consequently, buyers can utilize the offline channel (in this case the auction) to obtain this information (Overby and Jap 2009). This group of buyers does not prioritize payoff maximization. Instead, they are willing to pay higher prices than single-channel buyers due to the increase in benefits, channel engagement, satisfaction, and buyers' sorting (Montaguti et al. 2015, Neslin and Shankar 2009).

In the sequential system which involves multiple channel types as in our case, buyers face two main types of risks. First, as time goes on, buyers run the risk of not obtaining anything (we label it "fulfillment" risk). Second is the risk of purchasing incorrect products which do not meet their expected quality from the online channel where the products' physical cue is missing (we label it product risk).

Considering the auctions and the pre-sales, the pre-sales which take place before the auction, allow the bidders to guarantee their demand and reduce the risk of not obtaining anything at the end of the auction. However, as for an online channel, the pre-sales lack physical product information. The auctions, especially offline auctions, on the other hand, offer this physical products information as well as other market trends. However, as the auctions take place after the pre-sales, the longer the bidders wait, the higher the chance they can obtain some discount but at the same time, the higher the risk they do not obtain anything. In other words, the pre-sales channel lowers fulfillment risk, but product risk remains high. Whilst, auctions can reduce product risk, buyers face higher fulfillment risks.

Consequently, a multichannel strategy can offer buyers benefits from both channels. Buyers can use the posted price channel for product security to reduce their fulfillment risk and overcome the channel's drawback by obtaining physical information from the auction. The diversification benefits manifest as reducing both types of risk by spreading the purchases across two channels with different risk profiles.

These two viewpoints based on different motivations, which we label as *payoff maximization* and *risk-aversion*, offer different outcomes. If *payoff maximization* is dominant, we are likely to observe multichannel buyers extracting higher surplus and they are more likely to enter late during the bidding process. If *risk-aversion* is dominant, previous literature predicts that multichannel buyers by diversifying and reducing their risks are likely to extract a lower surplus in return and they are more likely to use the offline auction rather than the online auction. In our case, the online posted price channel is unlikely to offer additional market trends as in the auction. Hence, bidders are unlikely to use it as part of their modified demand reduction strategy. The payoff maximization explanation is less likely to hold. Overall, we propose that a multichannel buyer in the DFA is more likely to fit the *risk-aversion* explanation. In other words, based on previous sourcing and e-commerce theory, we hypothesize that:

Hypothesis 3B: Multichannel buyers have a significantly higher loss of surplus than single-channel buyers.

Hypothesis 3C: Multichannel buyers are more likely to use onsite auctions than online auctions.

More specifically, we expect that multichannel buyers who reduce their fulfillment risk by participating early in the pre-sales are more willing to lower their surplus compared to auction-only buyers who have high fulfillment risk but have more chances to seek additional discounts. We hypothesize that

Hypothesis 3B.1: Multichannel buyers have a significantly higher loss of surplus than auction-only buyers.

Similarly, we expect that risk aversions buyers, minimizing their fulfillment and product risks by spreading the purchases across both channels, are more willing to extract a lower surplus in return compared to pre-sales only buyers who may face higher product risks. Risk-averse buyers benefit from offline auctions by obtaining additional product information and are more willing to raise their bids in the auctions to secure products that meet their required standards, lowering their product risk.

Hypothesis 3B.2: Multichannel buyers have a significantly higher loss of surplus than pre-sales-only buyers.

4. Research Context

We collect the data from the Dutch Flower Auction system (DFA) at Royal FloraHolland. Royal FloraHolland is the world's largest B2B floriculture market. In 2018, its annual turnover was around EUR 4.6 billion. Over 100,000 transactions are taken place every day.

The Dutch auction has been the primary trading mechanism in the floriculture market for decades. In Dutch or descending auction, one auction is carried out for one *auction lot* that includes multiple flower stems of typically, one homogenous product[1] from one single seller. For each auction lot that has multiple flower stems, first, the auctioneer set the price at a very high level; then, it is gradually dropped down until a buyer is found. The buyer who accepts the highest price is the winner. In DFA, this process is operationalized through digital clocks. The clock indicates the price. For an auction lot, the auctioneer sets a high price and starts the clock, the clock ticks counterclockwise and indicates a decrease in price over time. Bidders express their desired price by stopping this clock. The bidder who stops the clock first (and accepts the current price indicated by the clock) is the winner and the winner then decides the portion of the lot s/he would like to acquire. This completes one auction *round*. If there is anything left, the clock is reset. The auction continues for further *rounds* until the whole lot is cleared or the price goes below the reserve price. Normally, everything is sold at the end of the day and anything that is left (which is very rare) is destroyed. Auctions take place from 6-11 AM every workday. Nowadays, bidders can access the clocks remotely using an online auction or by arriving at the auction halls where they can also examine different lots.

In late 2013, FloraHolland introduced the online pre-sales posted price channel (or pre-sales). The pre-sales channel takes place every day before the auction and sellers do control both the available quantity and the selling price. While the introduction of pre-sales is a strategic move for FloraHolland, the lack of guidance from previous literature on how to integrate different mechanisms creates several challenges and concerns. For example, one key question is whether the pre-sales will substitute the auction and, if yes, what would be the degree of substitution. Hence, as a conservative move, the market maker put a cap on how much of a given lot can sellers make available on the pre-sales channel; currently, this is set as a third of an auction

[1] DFA has a large product varieties. Each product is one flower breed. For example: Athena rose, Grace Kelly rose, Vendela rose etc.

lot. Sellers can decide the quantity available in the pre-sales, however, almost all just follow this market cap. What is left after the pre-sales is still sold via the traditional DFA auctions. Anything that is sold in the pre-sales is also fulfilled together with the auction. Unlike the auctions where prices are determined through a competitive process, the prices in the pre-sales are determined by the sellers. The information about market supply is made available a day before the auctions. Identical information is provided across all channels. It is free for buyers to access the pre-sales channel. As shown in Figure 1, buyers first decide whether to participate in the pre-sales or not. Then, after the pre-sales with the newly collected information, they decide whether to participate in the auction and, if yes, whether they should use the online or onsite auction. There is a high level of information asymmetry in the DFA where sellers normally have more information about the lots than the buyers such as the freshness, conditions, and other quality of the lot. At the onsite auction, buyers also have the opportunity to examine the actual flower lots before the auctions.

5. Data and Key Variables

We analyze a year's worth of transactions of large-rose products - the largest product group at Royal FloraHolland for 2015. For each transaction, the data records purchase quantity, the available quantity of the whole lot (or lot size), purchase price, sales channel, and the timing of the transactions. For each lot, the data also contains information on whether the lot is available in the pre-sales or not, the pre-sales price, and the pre-sales available quantity that is set by the sellers. Additionally, we also have information on buyers, sellers, and product characteristics such as country of origin, the total number of products purchased, the total number of products available, and product details. We preprocess the data and reserve products that are traded across all channels. We exclude defective lots reported by experts at Royal FloraHolland. Eventually, we generate a panel data at buyer-product-day level. We exclude infrequently traded products and buyer-products that are rarely traded (five observations or less). Greene (2002) pointed out that if the number of observations per unit of analysis is small, it can lead to bias in the Fixed Effects choice model. The generated data contains over 100 products traded by 294 buyers across 254 days.

5.1. Key Variables

We consider buyers' channel choices, their surplus extraction, and market transaction size.

Presales is a dummy variable taking the value of 1 if on day *t*, the buyer *i* purchases product *p* from the pre-sales channel and '0' otherwise. Similarly, *Auction* equals 1 if the buyer *i* purchases product *p* from the auction channels on day *t* and '0' otherwise. *Auctions_Mode* takes the value of 1 if the buyer *i* participates in the online auction and '0', otherwise. Given the buyer's decisions on the day, they are separated into *Auction_Only* buyers who only use the auction to fulfill the demand *Presales_Only* buyers who only use the pre-sales and *Multi* who utilize both pre-sales and auctions.

We use normalized *loss-of-surplus* (Lu et al. 2016) which is the difference between the buyer's winning price and the lowest winning price divided by the highest winning price minus the lowest winning price in one lot *j*: $(P_j - P_{j,min})/(P_{j,max} - P_{j,min})$. The loss of surplus is then averaged for each buyer across their auctions to obtain their average performance, *Loss_Surplus,* for product *p* on day *t*.

Transaction_Size indicates the average number of flower stems per auction transaction for *p on* day *t*.

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

The demand of the buyers is captured through the total demanded quantity for product *p* on day *t*, *Q*, and product diversity they demand on day *t*, *Diversity*.

Following Goes et al. (2012)'s approach, we capture the experiences of buyers in the pre-sales for product p up to day *t*, *Pre-sales_Exp*, 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 *Pre-sales_Exp* 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, as Goes et al. (2012) suggest, is consistent with the cumulative proportional reinforcement rules which capture both the behavioral component of learning through experience and the economic construct of utility. Goes et al. (2012) posit that buyers learn from their experiences in repeated games and rely on the cumulative utility to decide on the next move.

5.2. Other Control Variables

We construct control variables based on previous models in auction research such as Bapna et al. (2009), Goes et al. (2012), and Lu et al. (2016, 2019). Bapna et al. (2009) suggested that auction prices are driven by auction type, market and product characteristics, and bidder behavior. Goes et al. (2012) conceptualized that bidders' strategy depends on bidders' experiences and demand, and supply factors. Lu et al. (2016) posit that buyers' strategic choice is driven by budget constraint, demand, and auction channel mode. Lu et al. (2019) suggested that auction prices are affected by information, supply and product characteristics, day of the week (DOTW), and week fixed effects. Following these works, we construct the following variables:

Market supply, *Supply*. This factor can influence auction prices and bidders' behaviors (Goes et al. 2012) - the supply information is available to all buyers a day before the auction.

We control for *market information* available through the pre-sales channel. These include whether there is a pre-sales market or not (*Presales_market*), the pre-sales average price (*Presales_Price*), the proportion of market supply that was available in the pre-sales (*Presales_Avai*), the number of products that were available in pre-sales (*Presales_Product*), and the quantity sold in the pre-sales (*Presales_Q*). The buyers can observe all of this information before the auctions.

Our model considers the buyer's *budget constraint*, *Budget*, which is estimated by their total budget from the previous purchases. Lu et al. (2016) found that *Budget* can affect buyers' strategic choices.

Buyers can use *historical prices* to form their bids (Pilehvar et al. 2016); hence, we control for average market price, *Market_Price*, for product *p* from the previous day *t-1*.

Auction Strategies experiences. As pointed out by Goes et al. (2012) and Overby and Ransbotham (2019), auction prices and channel choices can be influenced by buyers' *channel experiences* and buyers' *experiences with different bidding strategies*. Consequently, similar to the case of *Pre-sales_Exp,* we implement Goes et al. (2012)'s approach to construct buyers' *channel experiences* and *bidding strategies experiences*. *Channel experiences* include pre-sales experiences, *Pre-sales_Exp*, and online/onsite auction channel experiences, *AuctionMode_Exp.* For bidding strategies, Lu et al. (2016) found that bidders' strategies are different based on the time they bid at day level (i.e., they enter early or late auctions) and the time they bid at auction lot level (i.e., they enter early or late auction rounds). Hence, first, we classify bidders' bidding strategies based on the *time they enter the auction lots*, *TOE_Lot,* and the *time they enter the auction day*, *TOE_Day. TOE_Lot* takes the values of "0" if, on the auction day *t*, buyers tend to bid aggressively at the beginning of the auctions and "1" if they tend to wait till the end of the auction lot. *TOE_Day* takes the value of "0" if on the auction day, the buyers participate in early auctions and "1" if they wait till the end of the day and enter later auctions. Then, we apply Goes et al. (2012)'s approach and construct buyers' experiences with early/late bidding strategies for the auction lots, *TOE_Lot_Exp,* and for the auction day, *TOE_Day_Exp*. In sum, we consider auction channel mode experiences *AuctionMode_Exp* and bidding experiences, *TOE_Lot_Exp,* and *TOE_Day_Exp*.

We also include buyer and product fixed effects, week, and day of the week (DOTW) to account for any unobserved heterogeneity such as seller's reputation and seasonality.

There is evidence that the growth of the overall platform can be a signal influencing channel usage (Xue et al. 2011). Consequently, we construct the pre-sales channel's membership growth from the previous day, $Growth_{t-1}$ A large growth rate can be an indication for buyers to join the pre-sales. FloraHolland can also update buyers with this information through different news and social platforms. However, the growth rate of the *overall platform* from *yesterday* is unlikely to *directly* influence the buyer's decisions for *a particular single product in the auction today*. This gives a case to use *Growth* as an instrument for *Presales* in our auction decisions. To further strengthen the case, we adopt the Hausman style instrument approach (Fisher et al. 2017, Hausman 1996) and consider the *Growth* of the overall platform, excluding the focal product. We present the detailed arguments and diagnostic tests along with the models in the next section.

A summary of variables and descriptive statistics can be found in Table 3 and Table 4.

Table 3. Descriptive Statistics

Statistic	N	Mean	S.D	Min	Max
$Average\_PricePaid_{ipt}$	1,020,025	0.303	0.172	0.050	4.000
$Loss\_Surplus_{ipt}$	1,020,025	0.452	0.352	0.000	1.000
$Transaction\_Size_{pt}$	26,817	309.400	160.539	40.000	1920.000
Q_{ipt}	1,020,025	612.367	1,263.363	20.000	92,990.000
$Diversity_{it}$	53,103	111.993	107.907	1.000	919.000
$Log(Supply_{pt})$	26,817	3.694	6.532	0.005	71.404
$Presales\_Price_{pt}$	18,487	0.342	0.242	0.070	17.000
$Presales\_Avai_{pt}$	26,817	0.142	0.137	0	0.333
$Total\_Presales\_QSold_{pt}$	26,817	307.124	797.433	0	19,980.000

Table 4. 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

Auction_Mode	= 1 if the buyer uses online auction on day *t* for product *p*; = 0 otherwise
Auction_Only	= 1 if buyers only use the auction on day *t* for product *p*; = 0 otherwise
Presales_Only	= 1 if buyers only use the pre-sales on day *t* for product *p*; = 0 otherwise
Multi	= 1 if buyers use both the auction and the pre-sales on day *t* for product *p*; = 0 otherwise
Loss_Surplus	Buyer's average loss-of-surplus for product *p* on day t
Transaction_Size	Average auction's transaction size (number of flower stems) of product *p* on day *t*
Q	The demand for buyer *i* for product *p* on day *t*. The variable is log-transformed
Diversity	The number of products demanded by buyer *i* on day *t*. The variable is log-transformed
Presales_Exp	Cumulative proportion of times the buyer has used the pre-sales channel for product *p* up to day *t*
Supply	Market supply for product p on day t (measures in 10,000). The variable is log-transformed
Premarket	= 1 if the pre-sales channel is available on day t; = 0 otherwise
Presales_Price	Average pre-sales price per flower stem set by the sellers. The variable is log-transformed
Presales_Avai	The proportion of supply that is made available through the pre-sales channel
Presales_Q	Total quantity sold through the pre-sales channel. The variable is log-transformed
Presales_Product	Number of products available through the pre-sales. The variable is log-transformed
Budget	Buyer's budget for product *p* on day *t*. The variable is log-transformed
Market_Price	The average price of product *p* on day *t-1*. The variable is log-transformed
AuctionMode_Exp	Cumulative proportion of times the buyer has used the online auction for product *p* up to day *t*
TOE_Lot_Exp	Cumulative proportion of times the buyer has used late bidding strategy at lot level for product *p* up to day *t*
TOE_Day_Exp	Cumulative proportion of times the buyer has used late bidding strategy at day level for product *p* up to day *t*
Average_PricePaid	Average price paid by buyer *i* for a single flower stem of product *p* on day *t* overall (across all channels)
Total_Presales_QSold	Total quantity sold in the pre-sales for product *p* on day *t*
Growth	pre-sales channel's membership log growth for product $\bar{p}$ on the previous day *t-1*

6. Methodologies and Results

In this section, we present our empirical strategies and results. First, we examine buyers' pre-sales and auction usage (H11A, H1B & H2). Next, we consider buyers' loss-of-surplus and multichannel buyers' behaviors (H3). Finally, we study transaction size at the market level (H1C).

6.1. Channel Choice: Pre-sales and Auctions Usage (H1A, H1B, H2)

Presales choice of buyer *i*, for product *p* on day *t* can be modeled through the following equation:

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

The vector of covariates D_{ipt} contains variables related to the demand of the buyer including quantity demanded, *Q*, and product diversity, *Diversity*. Vector B_{ipt} controls for buyers' experiences including pre-sales experiences, buyers' auction mode experiences, and bidding experiences (i.e., *Presales_Exp, AuctionMode_Exp, TOE_Lot_Exp, TOE_Day_Exp)*. Vector F_{ipt} includes Fixed Effects such as buyer and product Fixed Effects, week, and DOTW. This extensive set of Fixed Effects captures unobserved time-invariant buyer-specific, product-specific, and unobserved temporal dynamics that can affect the pre-sales choice adaption decision. C_{ipt} contains other control variables including supply level (S*upply)*, market information available at the beginning of the pre-sales (*Presales_Price, Presales_Avai, Presales_Product*), buyer's budget constraint (*Budget)*, historical price (*Market_Price)*, and pre-sales channel *Growth*.

We opt for Linear Probability Models (LPM) as an estimation method for several reasons. First, the nonlinear fixed-effects model suffers several shortcomings in terms of both estimation and methodology which can raise questions about the statistical properties of the estimators (Greene 2002). LPM allows us to utilize Fixed Effects and control for heteroscedasticity, and autocorrelations in the error terms. The error is clustered at the buyer level to control for potential correlated error terms within buyers. Alternative error clustering methods have been tested and we opt for the most conservative estimation to prevent bias and overstatement of our results. In addition, the demanded quantity is potentially endogenous, hence as suggested by Hong and Pavlou (2017), two-stage least squares (2SLS) can offer a more consistent estimator. Finally, with the large dataset, LPM offers computational ease and the coefficients can be readily interpreted as marginal effects. We also consider the Probit model which shows consistent results.

We estimate model (1) using LPM. The results with and without control variables are shown in Table 5 columns 1 and 2. Although the Fixed Effects wipe out several sources of unobserved heterogeneity, fixed effects are not able to control for unobserved factors that change over time. The choice of channels may influence the buyer's demanded quantity *Q*. Buyers may spot some unobserved characteristics from the channel or obtain private information on the lots that are not observed by the researchers and thus alter their total purchase quantity. Such concern cannot be addressed by the Fixed Effects implementation alone. Hence, we follow Wooldridge (2010) and estimate a two-stage least squares model (2SLS). We employ demanded quantity for a similar period the year before, *Q14,* as the instrument variable (IV). The notion of using a lagged variable as an instrumental variable as described in this study is widely used in practice and previous research (Burtch et al. 2016). To implement the IV, it needs to meet two key conditions: first, the IV should be relevant and correlated with the endogenous variable, *Q;* second, it should not directly affect the pre-sales choice and cannot be correlated with the idiosyncratic error term (Wooldridge 2010). As pointed out by Burtch et al. (2016), historical behavior can be conceptually and theoretically valid if we assume that there is a certain level of stickiness in buyers' behavior. This is likely to hold in the case of the

B2B agriculture market. Buyers here tend to have a certain group of loyal customers who follow cyclical purchasing patterns. We further test for this relevance condition using a series of weak instrument tests.

Table 5. Presales Decisions (H1A, H1B, H2A)

	Presales		Presales		Presales		Q	
	(1) LPM+FE		(2) LPM+FE		(3) 2SLS + FE		(4) First Stage	
Q	**-0.011*****	**(0.002)**	**-0.011*****	**(0.002)**	**-0.018*****	**(0.004)**		
Diversity	**0.025*****	**(0.005)**	**0.024*****	**(0.005)**	**0.026*****	**(0.005)**	0.284***	(0.019)
Presales_Exp	**0.831*****	**(0.023)**	**0.778*****	**(0.021)**	**0.775*****	**(0.021)**	-0.319***	(0.067)
Supply			0.002	(0.001)	0.004*	(0.002)	0.265***	(0.013)
Presales_Avai			0.080***	(0.011)	0.081***	(0.011)	0.187***	(0.023)
Presales_Price			-0.026***	(0.006)	-0.026***	(0.006)	-0.064***	(0.016)
TOE_Lot_Exp			-0.048***	(0.005)	-0.048***	(0.005)	-0.086***	(0.026)
TOE_Day_Exp			-0.073***	(0.008)	-0.073***	(0.008)	0.062	(0.045)
AuctionMode_Exp			-0.001	(0.005)	0.001	(0.005)	0.247***	(0.042)
Budget			0.001	(0.001)	0.003*	(0.002)	0.329***	(0.015)
Market_Price			-0.006**	(0.003)	-0.008**	(0.003)	-0.160***	(0.011)
Presales_Product			0.017***	(0.006)	0.017***	(0.006)	0.057***	(0.021)
Growth			0.032***	(0.004)	0.032***	(0.004)	-0.015***	(0.003)
Q14							0.071***	(0.004)
Buyer, Product FE	No		Yes		Yes		Yes	
Week & Day of the Week (DOTW)	No		Yes		Yes		Yes	
N	802,973		800,874		800,874		800,874	
R2	0.346		0.355				0.456	

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

The first stage result is presented in Table 5. While *Q14* is likely correlated to *Q*, *Q14* will be suitable for the model under the condition that this past decision is further back enough to be uncorrelated with the decision today or the unobserved lot information. This is likely to be the case, as flowers are highly perishable goods and the demand from last year is unlikely to influence the decision of today. Note that, while *Q14* is not exogenous of the system, they are observed and *predetermined* with respect to the current pre-sales decision. Regressors that are predetermined can be treated as if they are exogenous at least asymptotically, in the sense that consistent estimators can be derived (Greene 2011).

We carry out several diagnostic tests to examine the validity of the IV and our 2SLS estimation. The first-stage result is presented in Table 5 Column 4. The IV is significantly correlated with *Q* (p <0.001). Cragg–Donald F statistics (83.586) and Kleibergen–Paap F (72.502) statistics are well above Stock and Yogo (2005) critical value of 16.38 and hence eliminate the weak instrument concern. The coefficients are similar between the LPM estimation and the 2SLS estimation. The Hausman test fails to reject the Null hypothesis ($\chi^2 =$ 4.411, p=0.986) which suggests that endogeneity might not be a serious concern, and hence LPM, which is more efficient, is preferred. It is important to note that, in the B2B market, it is unlikely that the total number of products purchased for the day is decided endogenously within the pre-sales decision model. For B2B buyers including agents and wholesales, their product decisions are typically planned carefully or driven by their own clients. Hence, the endogeneity of *Diversity* is unlikely to be a concern. Regardless, we carry out a robust check where, similarly, we instrument *Diversity* with the total number of products purchased from a similar period in 2014. The results are consistent and presented in the appendix.

As presented in Table 5, the coefficient for Q is negative and significant *(β=-0.011, se=0.002)*. As the quantity demanded increases by 10% the chance the buyers use the pre-sales is reduced by 0.11% point and vice versa, as the quantity demanded reduces, buyers are more likely to use the pre-sales channel. The coefficient for *Diversity* is positive and significant *(β=0.024, se=0.005)*. As product diversity increases, buyers are more likely to choose the pre-sales channel. H1A and H1B are supported. Both the LPM and 2SLS produce consistent results. The effect size of the demand characteristics suggests that buyers with small Q or large *Diversity* are more likely to use the pre-sales and there is a certain level of consistency in buyer's choices. They are likely to switch when there is a decent level of fluctuation in the demand (which happens often given the large standard deviation in our data). In addition, we observe that pre-sales experiences are positively correlated with the pre-sales choice. H2A is supported. We run different robustness checks for this model which include Probit, Heckman with 2SLS, and under-sampling. We present the detail in Section 7. The results are qualitatively consistent.

Next, we model the substitution/complementary effect of pre-sales on auction choice. Auction choice of buyer *i*, for product *p* on day *t* can be modeled through the following equation:

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

Similar to the case of *Presale,* we control for demand covariates, D_{ipt} , buyers' experiences, B_{ipt}, and vector F_{ipt} *which* includes buyer and product Fixed Effects, and week and DOTW. C_{ipt} contains other control variables including, pre-sales information signal, supply level, buyer's budget, and market historical price. We opt for LPM with the error term clustered at the buyer level. Fixed Effects address several sources of unobserved heterogeneity, controlling for time-invariant product-specific and buyer-specific characteristics as well as unobserved temporal dynamics. As buyers may obtain lot quality information which is unobserved to the researchers, besides the standard LPM, we also estimate a 2SLS model (Wooldridge 2010). We search for an IV that is correlated to the pre-sales decision but does not directly influence the auction decision nor is correlated with the unobserved lot quality. As pointed out in section 5, the growth of the platform can encourage buyers to join the channel (Xue et al. 2011). This performance on the overall platform is also presented to the buyers through different news and social platform. Hence, the growth rate of the overall platform from the previous day, $Growth_{t-1}$, can be positively associated with the *Presales.* This is further backed up by our empirical results in Table 6. The coefficient of *Growth* is positive and significant *(p <0.001).*

Table 6. Auction Decision (H2B)

	Auction (5) LPM+FE		Auction (6) LPM+FE		Auction (7) 2SLS + FE		Presales (8) First Stage	
Presales	**-0.613*****	**(0.023)**	**-0.578*****	**(0.023)**	**-0.682*****	**(0.033)**		
Q			0.016***	(0.002)	0.015***	(0.002)	-0.009***	(0.001)
Diversity			0.006***	(0.001)	0.008***	(0.001)	0.020***	(0.001)
Presales_Exp			-0.149***	(0.027)	-0.066*	(0.032)	0.801***	(0.021)
Supply			0.001	(0.001)	0.001	(0.001)	-0.002**	(0.001)
Presales_Avai			0.001	(0.002)	0.005**	(0.002)	0.033***	(0.006)
Presales_Price			-0.001	(0.001)	-0.003	(0.002)	-0.016**	(0.006)
Presales_Q			-0.001***	(0.0001)	0.001	(0.001)	0.007***	(0.001)
TOE_Lot_Exp			0.011***	(0.002)	0.007***	(0.002)	-0.038***	(0.004)
TOE_Day_Exp			0.013***	(0.003)	0.007**	(0.003)	-0.055***	(0.006)
AuctionMode_Exp			0.006*	(0.003)	0.007**	(0.003)	0.004	(0.004)
Premarket			-0.001	(0.001)	-0.002**	(0.001)	-0.004*	(0.002)
Budget			-0.001	(0.001)	-0.001	(0.001)	0.0003	(0.001)
Market_Price			0.003***	(0.001)	0.002***	(0.001)	-0.004*	(0.002)
Presales_Product			-0.001	(0.002)	0.001	(0.002)	0.008	(0.005)
Growth							0.019***	(0.002)
Buyer, Product FE	No		Yes		Yes		Yes	
Week & DOTW	No		Yes		Yes		Yes	
N	1,020,025		1,015,040		1,015,040		1,015,040	
R2	0.672		0.684				0.354	

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

We further carry out weak instrument tests and both Cragg–Donald F statistics (998.54) and Kleibergen–Paap F statistics (631.88) are well above Stock and Yogo (2005) critical value. It suggests that weak instrument is not a major concern. Second, this IV should be uncorrelated with the error terms. It is such a case under the condition that yesterday's pre-sales channel growth does not affect today's product's quality. This is likely to hold. Given that we control for buyers and product-specific fixed effects, the auction decision is independent across buyers and products and is only allowed to be correlated within buyers and within products. As the growth of the pre-sales excludes the focal product market and is from the previous day, it is unlikely that it is correlated with the error terms of the auction decision function of the focal product today. This strategy of utilizing different markets is motivated by the idea of the widely used Hausman style instrument (Fisher et al. 2017, Hausman 1996).

We find a substitution effect between the two channels. When buyers purchase from the pre-sales, they are more likely to opt out from the auction channel. The coefficient is negative, significant, and consistent across the LPM and the 2SLS estimations. The results indicate that as buyers purchase from the pre-sales, they are 57 percent point less likely to enter the subsequent auctions. H2B is supported. We also estimate the model using Probit and Biprobit. The results (Section 7) are qualitatively consistent.

6.2. Multichannel buyers and Surplus Extraction (H3)

In H3, we hypothesize that auction only buyers are more likely to extract a higher level of surplus than pre-sales only buyers and multichannel buyers are like to spread the demand across channels for risk reduction, and consequently, multichannel buyers will have a higher loss of surplus than single channel buyers and they are more likely to utilize the onsite channel. We test these hypotheses in this section.

First, we estimate Fixed Effects models that control for buyers and products unobserved heterogeneity. Errors are clustered at the buyer level. We set the reference level at *Auction_only* initially (columns 9 & 11 in Table 7) then we also change the reference level to *Presales_only* (columns 10 & 12 in Table 7). This provides a statistical comparison between single-channel usage and *Multichannel* usage.

Next, we also estimate a 2SLS model that addresses the potential endogeneity risk of Multichannel strategy choice. *Growth* at day t-1 in other markets has been utilized as the IV for the model. As discussed earlier, while the growth level of pre-sales channel in other markets can be correlated with pre-sales decision and hence, multichannel strategies choice, in the Fixed Effects model where the *Loss_Surplus* is only allowed to be correlated within buyers within product market, it is very unlikely that the error terms will be correlated with IV that is constructed in other markets from the previous day. As the channel strategies is a categorical variable, we follow the procedure by Wooldridge (2010) in which first, we estimate a multinomial logit for channel strategies using all the control variables and our IV; then we obtain the fitted probability for different category levels and these predicted fitted are used as the instruments for the 2SLS model. The first stage is provided in the Appendix. The IV is significantly associated with different channel strategies. Both the Fixed Effects and the 2SLS provide consistent results. The results of the model are presented in Table 7. Pre-sales only buyers have a significantly higher loss-of-surplus than Auctions only buyers while Multichannel buyers have a significantly higher loss of surplus than both auction only and pre-sales only buyers. H3A and H3B (H3B.1 & H3B.2) are supported.

Table 7. Surplus Extraction (H3A, H3B)

	Loss_Surplus (9) FE		*Loss_Surplus* (10) FE		*Loss_Surplus* (11) 2SLS + FE		*Loss_Surplus* (12) 2SLS + FE	
Auction_Only			**-0.088*****	**(0.010)**			**-0.103*****	**(0.016)**
Presales_Only	**0.088*****	**(0.010)**			**0.103*****	**(0.016)**		
Multi	**0.108*****	**(0.006)**	**0.020****	**(0.008)**	**0.183*****	**(0.031)**	**0.080*****	**(0.016)**
Q	-0.095***	(0.008)	-0.095***	(0.002)	-0.096***	(0.002)	-0.096***	(0.002)
Diversity	0.046***	(0.003)	0.046***	(0.003)	0.045***	(0.003)	0.045***	(0.003)
Presales_Exp	-0.039***	(0.009)	-0.039***	(0.009)	-0.063***	(0.012)	-0.063***	(0.012)
Supply	0.019***	(0.001)	0.019***	(0.001)	0.019***	(0.001)	0.019***	(0.001)
Presales_Avai	-0.035***	(0.008)	-0.035***	(0.008)	-0.036***	(0.008)	-0.036***	(0.008)
Presales_Price	0.001	(0.005)	0.001	(0.005)	0.002	(0.005)	0.002	(0.005)
Presales_Q	-0.001***	(0.0003)	-0.001***	(0.0003)	-0.002***	(0.0003)	-0.002***	(0.0003)
TOE_Lot_Exp	-0.003	(0.003)	-0.003	(0.003)	-0.002	(0.003)	-0.002	(0.003)
TOE_Day_Exp	-0.074***	(0.007)	-0.074***	(0.007)	-0.072***	(0.007)	-0.072***	(0.007)
AuctionMode_Exp	0.012**	(0.006)	0.012**	(0.006)	0.011**	(0.006)	0.011**	(0.006)
Premarket	0.004*	(0.002)	0.004*	(0.002)	0.004*	(0.002)	0.004*	(0.002)
Budget	0.002*	(0.001)	0.002*	(0.001)	0.002*	(0.001)	0.002*	(0.001)
Market_Price	-0.001	(0.003)	-0.001	(0.003)	-0.001	(0.003)	-0.001	(0.003)
Presales_Product	0.012**	(0.005)	0.012**	(0.005)	0.012**	(0.005)	0.012**	(0.005)
Buyer, Product FE	Yes		Yes		Yes		Yes	
Week & DOTW	Yes		Yes		Yes		Yes	
N	1,015,040		1,015,040		1,015,040		1,015,040	
R2	0.122		0.122					

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

We model the Multichannel buyers' auction mode decision in Table 8.

Table 8. Auction Mode Decision (H3C)

	Auction_Mode (13) LPM+FE		*Auction_Mode* (14) FE+2SLS	
Presales	**-0.014*****	**(0.003)**	**-0.052*****	**(0.026)**
Q	0.014***	(0.003)	0.014***	(0.003)
Diversity	-0.014	(0.010)	-0.013	(0.010)
Presales_Exp	-0.014	(0.001)	0.003	(0.015)
Supply	-0.001	(0.001)	-0.001	(0.001)
Presales_Avai	0.005	(0.004)	0.006	(0.004)
Presales_Price	0.010***	(0.004)	0.010***	(0.004)
Presales_Q	0.001	(0.001)	0.0003*	(0.0002)
TOE_Lot_Exp	-0.020***	(0.004)	-0.020***	(0.004)
TOE_Day_Exp	-0.039***	(0.007)	-0.039***	(0.007)
AuctionMode_Exp	0.538***	(0.037)	0.538***	(0.037)
Premarket	-0.008***	(0.002)	-0.008***	(0.002)
Budget	-0.001	(0.001)	-0.001	(0.001)
Market_Price	0.004*	(0.002)	0.004*	(0.002)
Presales_Product	0.003	(0.006)	0.003	(0.006)
Buyer, Product FE	Yes		Yes	
Week & DOTW	Yes		Yes	
N	983,025		983,025	
R2	0.775			

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

Multichannel buyers are 5.2% more likely to participate in the offline auction than when they only participate in the auction. H3C is supported.

Overall, we find that multichannel have a significantly higher loss of surplus than single-channel buyers and they are also more likely to participate in the offline auction. The results support the *risk-aversion* explanation where buyers split their demand to reduce their risks. As a robustness check (further details in Section 7), we also rerun the model using Probit and Biprobit. The results are qualitatively consistent. In addition, we examine the demand reduction prediction and model buyers' time of entry in the auctions. Again, we don't find evidence that multichannel buyers are more likely to participate in the auction late. This further provides support for the *risk-aversion* mechanism.

6.3. Market Level Analysis (H1C)

One of the concerns from the market maker is that the pre-sales can break the transactions even smaller which raises the logistic cost. In this section, we examine this issue. We expect that as smaller buyers move to the pre-sales, the transaction size in the auction will be bigger for days with pre-sales than for days without pre-sales. If the buyers overly break their demand due to the pre-sales, we will observe the opposite result. We aggregate the data to the market level. Then we match days with pre-sales with similar days without pre-sales based on product, time, market supply level, the number of products available, average customer's demanded quantity, average customer's budget, and market price from the previous day. We employ different matching techniques. The results are shown in Table 9.

Table 9. Matching Estimation (H1C)

	N	Average transaction size Diff (S.E)
PSM	14,378	11.141***(2.541)
Exact Matching (caliper = 0.5)	24,089	9.267***(0.881)
Exact Matching (caliper = 0.25)	8,016	13.400***(1.251)
Exact Matching (caliper = 0.1)	598	22.342 ***(4.128)

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

We find that the average transaction size in the auction is significantly larger for days with pre-sales than for days without pre-sales (by 10-20 units). We don't find evidence that the transactions in the auction are overly broken down in the day with pre-sales.. H1C is supported.

6.4. Additional Analysis: Sellers' Revenue and Experiences Moderation Effect

We analyze the effect of the pre-sales channel on the seller's revenue in this section. As we observe that multichannel and pre-sales only buyers extract significantly less surplus than auction only buyers, we can expect auction lots that were available in the pre-sales to perform better than lots that were not. We match lots with pre-sales with similar lots without the pre-sales using different matching methods. The lots are matched based on product, seller, time period, market supply level, the number of products available, auctioning time, and market price from the previous day. Lots with pre-sales have significantly higher weighted revenue than lots without. The effect size is estimated between 5.6% -12%.

Table 10. Matching Estimation on Sellers' Revenue

	N	Average transaction size Diff (S.E)
PSM	305,038	0.056***(0.002)
Exact Matching (caliper = 0.5)	142,908	0.092***(0.002)
Exact Matching (caliper = 0.25)	66,342	0.098***(0.003)
Exact Matching (caliper = 0.1)	36,652	0.120***(0.004)

In section 6.1, we find that the pre-sales channel attracts small buyers while large buyers tend to prefer the auction channel. We further examine how experiences may moderate this effect. The interaction model is presented in Appendix I. The coefficient of *Q* is negative and significant *(β=-0.022,se=0.004),* while the interaction term *Q:Presales_Exp* is positive and significant *(β=0.087,se=0.025),* This result suggests that whilst large quantity buyers may prefer auction channel, they become more flexible over channel choices as they are increasingly exposed to the pre-sales channel.

7. Robustness Tests

We carry out several robustness checks for our analyses.

First, one may concern about the linearity assumption of LPM and 2SLS that might not fit well with the binary dependent variable. Hence, we re-estimate our *Presales* decision model (1), *Auction* decision model (2), and *Auction_mode* decision model using Probit and Biprobit estimations. All the results (Appendix C) are consistent with our LPM and 2SLS analyses.

Second, pre-sales usage makes up around 5% of the observations. Hence it is unbalanced and one may concern that this can underestimate our coefficients. However, the problem with rare events lies with a finite sample where researchers do not have enough data to observe and detect the patterns.. This bias will vanish when the sample is large (King and Zeng 2001). We have a sufficiently large sample of pre-sales usage so this may not be a concern. Nevertheless, for robustness check, we carry out under-sampling and rerun our *Presales* model. The results (Appendix E) are consistent with our main analysis.

Third, buyers can be self-selected into days with and without pre-sales. In other words, *Premarket* can be endogenous. It is noted that this variable works mainly as our control variables and the results with and without control variables are consistent across all of our models, so even *Premarket* is endogenous, it may not be a major concern. For the robustness check, we address the endogeneity of *Premarket* directly. As *Presales* is truncated, to address the endogeneity of *Premaket* in model (1), we follow Wooldridge's (2010) approach where we combine Heckman with 2SLS models. We use *Disruption* which records the dates where there is technical disruption. These exogenous incidences prevent the pre-sales market to take place. The results (Appendix D) are consistent with our main analyses.

Fourth, one may argue that the buyers make the pre-sales and auction choices simultaneously. However, as there is a large time gap between the pre-sales and auction, buyers can obtain additional information and update their decision over time. By modeling the decision stage by stage, it allows to dive deeper into each decision and reflect on this kind of learning behavior. For the robustness check, we examine the simultaneous scenario, also the first stage of the loss surplus model (Appendix F). Consistently, pre-sales usage is driven by small volume demand and large product diversity.

Fifth, in H3, we expect that buyers will split their demand for diversification benefits. We find evidence that multichannel buyers have a significantly higher loss in surplus and they are more likely to use the offline auction. To further test *payoff maximization* viewpoints, we model buyers' time of entry to the auctions (Appendix G). Again, we don't find evidence that buyers are more likely to enter the auction late.

Finally, for the market level analysis, we retest the results using the proportion of small transactions between the two cases. An increase in the number of small transactions can be masked by an increase in the number of large transactions and this is not reflected through the average measurement. We use ex-post data and define transactions that belong to the bottom 10% in terms of size for a product as small transactions. We re-estimate the Matching analysis. The results (Appendix H) support our main findings.

8. Conclusion and Discussion

This study investigates how B2B buyers behave in a novel multi-mechanism system that includes a posted price and an auction channel. We build upon the line of multichannel auction systems (Bapna et al. 2009, Lu et al. 2016, 2019b, Overby and Kannan 2015, Overby and Ransbotham 2019) and contribute to the emerging line of research on multi-mechanism markets (Einav et al. 2018, Kuruzovich and Etzion 2017). We explore the determinants of buyers' strategic choices in the new system, conditions under which buyers will use the new pre-sales channel, and the interrelation between the two channels over time. We investigate a new group of buyers who combine both the posted price and the auction channels. We compare surplus extraction activities between the emerging buyer groups, i.e, pre-sales only and multichannel buyers with the traditional auction only buyers. Finally, we study market outcome in terms of transaction size and seller's revenue. The findings summary can be found in Table 11.

Table 11. Results Summary

H1A. As the demanded quantity increases, buyers are less likely to purchase from the pre-sales.	H1A is supported
H1B As the product diversity increase, buyers are more likely to purchase from the pre-sales	H1B is supported
H1C Average transaction size in the auction is higher on the days with pre-sales than on the days without pre-sales.	H1C is supported
H2A: As buyers' experiences with the pre-sales channel increase, they are more likely to use it for the next purchase.	H2A is supported
H2B: Once buyers purchase from the pre-sales, they are more likely to opt-out from the auction	H2B is supported
H3A: Pre-sales Only Buyers have a significantly higher loss of surplus than Auction Only Buyers.	H3A is supported
H3B: Multichannel Buyers have a significantly higher loss of surplus than single-channel buyers	H3B is supported
H3C: Multichannel Buyers are more likely to use onsite auctions than online auctions.	H3C is supported

First, different from B2C research which focuses on buyers with a single unit and single product demand, we examine a B2B environment with substantial demand heterogeneity. The results suggest that online pre-sales attract small demanded quantity buyers and buyers with large product diversity. As the demanded quantity gets significantly large, buyers are more likely to prefer the auction system. This is consistent with some findings in the B2C sector such as Einav et al. (2018) which find that B2C buyers (with a small quantity demanded for a single product) move from eBay to posted price channels for convenience. We expand the literature further to the case of B2B buyers with large demanded quantities and especially to the case of heterogeneous demand diversity. Experiences with the channel play an important role. Over time, ceteris paribus, buyers tend to be locked in the new system with their increase in exposure to the new channel. We next consider multichannel buyers who split demand across different pricing mechanisms that were rarely explored. We don't observe modified demand reduction behavior for multichannel buyers who spread their demand to optimize the expected payoff (Goes et al. 2012). Instead, we find evidence of buyers utilizing both channels for their diversification benefits. We further examine the buyers' surplus extraction activities. Multichannel and pre-sales only buyers lower their surplus compared to the traditional auction-only buyers. Consequently, we find that sellers can benefit from this channel and lots listed in the pre-sales have significantly higher revenue than lots that are not. Finally, we study the transaction size. We do not find evidence that the pre-sales break the auction order into smaller transactions.

From the practitioners' point of view, this study evaluates buyers' behaviors in the new market design, market flow, and sellers' revenue. The new design is promising. We find an improvement in revenue for sellers without major interruption. The multichannel system offers additional choices, flexibility, and security for the buyers and the online system can also provide additional insights into buyers purchasing patterns and behaviors which have not previously been captured. Thus, it can potentially benefit other similar B2B Dutch auction markets such as the flower auction markets in Japan, Brazil, or the European fish markets that are facing a similar digitization trend. We characterize customer segments for each channel and identify conditions for different channel choices and we also map the accordant buyers' economic outcomes. Such information can play an important role in customer targeting, marketing, and operations strategies as well as future personalization and smart market designs (Bichler et al. 2010). For example, policies targeted at increasing buyers' product diversity and facilitating the experiences in the pre-sales may help to increase pre-sales and multichannel usage. Similarly, the lack of product diversity in the market, high minimum purchase quantity, technological difficulties, and inability to access product quality information are some factors that may create friction and inhibit buyers from entering the posted price channel.

Future studies through field or lab experiments can causally test these counterfactual policies. We have only addressed one form of multi-mechanism system, a large swath of space exists for additional exploration into this exciting area of multi-mechanism market design. Tantalizing evidence exists from analytical models that even different timing of the posted price channel can offer different results (Caldentey and Vulcano 2007). This work focuses on the heterogeneity in buyers' strategic decisions and we have also not addressed the supply side of the market as well as the impact of product heterogeneity that is offered through such market design. A structural investigation might prove important. Different product markets with different supply and demand structures with different risks profile may lead to different behaviors. This can also be a fruitful topic for future research.

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Appendix A. Descriptive Statistics

Statistic	N	Mean	S.D	Min	Max
$Average\_PricePaid_{ipt}$	1,020,025	0.303	0.172	0.050	4.000
$Average\_AuctionPricePaid_{ipt}$	987,944	0.301	0.171	0.050	4.000
$Average\_PresalesPricePaid_{ipt}$	49,051	0.358	0.191	0.050	2.500
$Loss\_Surplus_{ipt}$	1,020,025	0.452	0.352	0.000	1.000
$Transaction\_Size_{pt}$	26,817	309.400	160.539	40.000	1920.000
Q_{ipt}	1,020,025	612.367	1,263.363	20.000	92,990.000
$Diversity_{it}$	53,103	111.993	107.907	1.000	919.000
$Presales\_Exp_{ipt-1}$	1,015,040	0.037	0.121	0.000	1.000
$Supply_{pt}$	26,817	3.694	6.532	0.005	71.404
$Presales\_Price_{pt}$	18,487	0.342	0.242	0.070	17.000
$Presales\_Avai_{pt}$	26,817	0.142	0.137	0	0.333
$Presales\_Q_{pt}$	26,817	307.124	797.433	0	19,980.000
$Presales\_Product_{t}$	254	72.780	12.751	22.000	90.000
$Budget_{ipw-1}$	493,262	361.600	991.568	2.000	309,857.900
$Market\_Price_{pt-1}$	26,710	0.2811	0.149	0.050	1.762
$AuctionMode\_Exp_{ipt-1}$	1,015,040	0.764	0.389	0.000	1.000
$TOE\_Lot\_Exp_{ipt-1}$	1,015,040	0.349	0.312	0.000	1.000
$TOE\_Day\_Exp_{ipt-1}$	1,015,040	0.155	0.158	0.000	1.000
$Growth_{pt-1}$	26,710	0.001	0.447	-1.497	1.677

Appendix B. Correlation Table

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	**Loss_Surplus**	1.00																
2	**Transaction_Size**	-0.03	1.00															
3*	**Q**	-0.26	0.35	1.00														
4*	**Diversity**	0.01	-0.07	0.19	1.00													
5	**Presales_Exp**	0.06	-0.02	-0.10	-0.10	1.00												
6*	**Supply**	-0.02	0.64	0.43	-0.12	0.02	1.00											
7*	**Presales_Price**	0.01	-0.11	0.02	-0.04	0.13	0.17	1.00										
8	**Presales_Avai**	0.01	-0.15	-0.09	0.02	0.18	-0.18	0.49	1.00									
9*	**Presales_Q**	0.01	0.13	0.16	-0.08	0.18	0.46	0.56	0.53	1.00								
10*	**Presales_Product**	0.01	0.01	0.01	0.08	0.06	0.05	0.13	0.22	0.24	1.00							
11*	**Budget**	-0.06	0.28	0.45	0.06	-0.01	0.56	0.29	-0.04	0.32	-0.04	1.00						
12*	**Market_Price**	0.02	-0.38	-0.10	0.01	0.06	-0.12	0.52	0.16	0.11	-0.05	0.30	1.00					
13	**AuctionMode_Exp**	-0.04	0.01	0.15	0.30	-0.06	-0.05	0.01	0.02	-0.02	0.04	0.07	0.03	1.00				
14	**TOE_Lot_Exp**	-0.03	-0.04	-0.05	-0.04	-0.31	-0.14	-0.11	-0.08	-0.17	-0.03	-0.18	-0.05	0.04	1.00			
15	**TOE_Day_Exp**	-0.08	-0.03	0.02	-0.05	-0.27	-0.09	-0.06	0.02	-0.08	-0.03	-0.05	-0.01	-0.04	0.30	1.00		
16	**Growth**	0.01	0.01	0.04	0.15	0.00	0.11	0.04	0.05	0.08	0.23	-0.03	-0.01	-0.01	0.01	0.00	1.00	
17	**Q14**	-0.07	0.24	0.39	0.22	-0.12	0.16	0.04	-0.07	0.14	0.01	0.18	-0.06	0.15	-0.04	-0.02	-0.02	1.00

Appendix C. Probit and Biprobit estimations

	Presales (15) Probit		*Auction* (16) Probit		Auction_Mode (17) Probit		*Auction* (18) Biprobit		*Auction_Mode* (19) Biprobit	
Presales			-11.900***	(3.049)	-0.014***	(0.003)	-2.902***	(0.080)	-0.429***	(0.052)
Q	-0.120***	(0.004)	1.720***	(0.018)	0.014***	(0.003)	0.872***	(0.013)	0.194***	(0.003)
Diversity	0.265***	(0.010)	0.404***	(0.031)	-0.014	(0.010)	0.174***	(0.009)	-0.021***	(0.003)
Presales_Exp	2.127***	(0.022)	-1.162***	(0.059)	-0.014	(0.010)	-3.550***	(0.027)	0.222***	(0.045)
Supply	0.016	(0.010)	0.268***	(0.029)	-0.001	(0.001)	0.192***	(0.007)	-0.136***	(0.003)
Presales_Avai	1.553***	(0.070)	0.651***	(0.227)	0.005	(0.004)	0.680***	(0.063)	0.214***	(0.031)
Presales_Price	-0.384***	(0.062)	-0.188	(0.188)	0.010***	(0.004)	-0.003	(0.007)	0.227***	(0.037)
Presales_Q			-0.539***	(0.017)	0.001	(0.001)	-0.397***	(0.007)	0.001	(0.001)
TOE_Lot_Exp	-1.188***	(0.023)			-0.020***	(0.004)			-0.230***	(0.009)
TOE_Day_Exp	-1.729***	(0.046)			-0.039***	(0.007)			-0.633***	(0.018)
AuctionMode_Exp	-0.047*	(0.022)	0.470***	(0.076)	0.538***	(0.037)	-0.057***	(0.014)	3.844***	(0.007)
Premarket			2.197	(5.708)	-0.008***	(0.002)			-0.156***	(0.014)
Budget	0.014***	(0.005)	0.037**	(0.017)	-0.001	(0.001)	0.033***	(0.007)	0.031***	(0.003)
Market_Price	-0.099***	(0.021)	0.006	(0.150)	0.004*	(0.002)	0.353***	(0.021)	-0.013	(0.009)
Presales_Product	0.355***	(0.054)	0.006	(0.150)	0.003	(0.006)	-0.006	(0.039)	-0.905***	(0.017)
Growth	0.422***	(0.007)								
N		800,874		1,015,040		983,025		1,015,040		983,025

Appendix D. Premarket Endogeneity

	(22) *Presales*		(23) *Auction*		(24) Loss_Surplus		*(25) Auction_Mode*	
Presales			-0.682***	(0.033)			-0.052**	(0.026)
Presales_Only					0.103***	(0.016)		
Multi					0.183***	(0.031)		
Q	-0.018***	(0.004)	0.015***	(0.002)	-0.096***	(0.002)	0.014***	(0.003)
Diversity	0.026***	(0.005)	0.008***	(0.001)	0.045***	(0.003)	-0.013	(0.010)
Presales_Exp	0.775***	(0.022)	-0.066**	(0.032)	-0.063***	(0.012)	0.003	(0.015)
Supply	0.004**	(0.002)	0.001	(0.001)	0.019***	(0.001)	-0.001	(0.001)
Presales_Avai	0.081***	(0.011)	0.005**	(0.002)	-0.036***	(0.008)	0.006	(0.004)
Presales_Price	-0.026***	(0.006)	-0.003	(0.002)	0.002	(0.005)	0.010***	(0.004)
Presales_Q			0.001	(0.001)	-0.002***	(0.0003)	0.001	(0.0002)
TOE_Lot_Exp	-0.048***	(0.005)	0.007***	(0.002)	-0.002	(0.003)	-0.020***	(0.004)
TOE_Day_Exp	-0.073***	(0.008)	0.007**	(0.003)	-0.072***	(0.007)	-0.039***	(0.007)
AuctionMode_Exp	0.001	(0.005)	0.007**	(0.003)	0.011**	(0.006)	0.538***	(0.037)
Premarket			-0.002**	(0.001)	0.004*	(0.002)	-0.008***	(0.002)
Budget	0.003*	(0.002)	-0.001	(0.001)	0.002*	(0.001)	-0.001	(0.001)
Market_Price	-0.008***	(0.003)	0.002***	(0.001)	-0.001	(0.003)	0.004*	(0.002)
Presales_Product	0.021***	(0.006)	0.001	(0.002)	0.012**	(0.005)	0.003	(0.006)
Growth	0.034***	(0.004)						
IMR	0.009***	(0.002)						
N		800,874		1,015,040		1,015,040		983,025

Appendix E. Undersampling Estimation

	Presales		*Presales*	
	(20) LPM+FE		(21) Probit+FE	
Q	-0.022***	(0.004)	-0.085***	(0.007)
Diversity	0.042***	(0.011)	0.240***	(0.019)
Presales_Exp	0.301***	(0.022)	2.104***	(0.055)
Supply	0.009**	(0.045)	0.035	(0.021)
Presales_Avai	0.333***	(0.029)	1.893***	(0.140)
Presales_Price	-0.066***	(0.022)	-0.380***	(0.107)
TOE_Lot_Exp	-0.362***	(0.036)	-1.479***	(0.039)
TOE_Day_Exp	-0.540***	(0.046)	-2.081***	(0.078)
AuctionMode_Exp	0.028**	(0.012)	-0.100**	(0.048)
Budget	-0.001	(0.004)	0.016	(0.011)
Market_Price	-0.008	(0.010)	-0.057	(0.040)
Presales_Product	0.079***	(0.024)	0.512***	(0.104)
Growth	0.076***	(0.005)	0.463***	(0.015)
N		86,927		86,927

Appendix F. Loss_Surplus First Stage

	(26) Presales_Only		*(27) Multi*	
Q	-1.475***	(0.013)	0.587***	(0.011)
Diversity	0.185***	(0.023)	1.180***	(0.036)
Presales_Exp	3.407***	(0.048)	3.103***	(0.063)
Supply	-0.464***	(0.027)	-0.202***	(0.033)
Presales_Avai	-0.423**	(0.195)	0.362*	(0.214)
Presales_Q	0.823***	(0.012)	0.591***	(0.013)
Presales_Price	-0.331**	(0.155)	-0.393**	(0.156)
TOE_Lot_Exp	-38.315***	(4.770)	-1.151***	(0.061)
TOE_Day_Exp	-64.615***	(0.512)	-1.499***	(0.119)
AuctionMode_Exp	0.056	(0.049)	0.554***	(0.081)
Premarket	7.492***	(1.256)	5.941***	(1.805)
Budget	-0.041***	(0.015)	-0.094***	(0.015)
Market_Price	-0.185***	(0.053)	0.037	(0.057)
Presales_Product	0.260*	(0.147)	0.228	(0.150)
Growth	0.194***	(0.019)	0.255***	(0.022)
N		1,015,040		1,015,040

Appendix I. Presales decision –additional analysis

	Robust check: Instrument Diversity		Moderation analysis	
Q	**-0.019*** **	**(0.005)**	**-0.022*** **	**(0.004)**
Diversity	**0.131*** **	**(0.006)**	**0.026*** **	**(0.005)**
Presales_Exp	**0.776*** **	**(0.021)**	**0.333*** **	**(0.127)**
Q: Presales_Exp			**0.087*** **	**(0.025)**
Supply	0.004	(0.003)	0.003*	(0.002)
Presales_Avai	0.082***	(0.011)	0.080***	(0.011)
Presales_Price	-0.026***	(0.006)	-0.026***	(0.006)
TOE_Lot_Exp	-0.048***	(0.005)	-0.049***	(0.005)
TOE_Day_Exp	-0.073***	(0.008)	-0.072***	(0.008)
AuctionMode_Exp	-0.001*	(0.002)	-0.002	(0.005)
Budget	0.001	(0.001)	0.003*	(0.002)
Market_Price	-0.007*	(0.004)	-0.008***	(0.003)
Presales_Product	0.018***	(0.007)	0.017***	(0.006)
Growth	0.032***	(0.004)	0.032***	(0.004)
Buyer, Product FE	Yes		Yes	
Week & (DOTW)	Yes		Yes	
N	800,874		800,874	

Appendix H. Matching Estimation Small Transaction Proportion

	N	Small Transaction Proportion Diff (S.E)
PSM	14,378	-0.019***(0.001)
Exact Matching (caliper = 0.5)	24,089	-0.016***(0.001)
Exact Matching (caliper = 0.25)	8,016	-0.017***(0.002)
Exact Matching (caliper = 0.1)	598	-0.028***(0.001)

Appendix G. Time of Entry in Auction

	(28) 2SLS+FE	
Presales	-0.200***	(0.036)
Q	-0.053***	(0.003)
Diversity	-0.018***	(0.005)
Presales_Exp	0.561***	(0.043)
Supply	-0.022***	(0.002)
Presales_Avai	0.048***	(0.001)
Presales_Price	0.004	(0.008)
TOE_Lot_Exp	0.582***	(0.015)
TOE_Day_Exp	-0.196***	(0.010)
AuctionMode_Exp	-0.101***	(0.012)
Presales_Q	0.001	(0.001)
Premarket	-0.006*	(0.004)
Budget	-0.001	(0.003)
Market_Price	0.001	(0.004)
Presales_Product	0.001	(0.007)
Auction_mode	0.050***	(0.016)
N		983,025