MIS Quarterly

RESEARCH ARTICLE

The Effect of Posted Prices on Auction Prices: An Empirical Investigation of a Multichannel B2B Market[1]

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Although multichannel sales strategies have become common due to the use of advanced information technologies, how one trading mechanism can influence the outcome of another, especially in the B2B market, remains largely underexplored. This paper investigates the effect of price and quantity information from an online posted-price presales channel on the performance of the century-old sequential Dutch auction system. Sellers can control the price paid and make a proportion of their stock available in auction presales. Anything left after presales is sold via auctions. Our analysis of nearly 1.5 million flower lots reveals a positive effect with higher auction prices and total revenue for lots listed in presales than for lots that are not. The result holds even for lots with no actual sales in the presales, indicating that buyers pay close attention to the additional information from the posted-price presales channel. By teasing out the information effect of presales prices and presales quantity on auction prices, we evaluate a number of pricing strategies. The results suggest that selling at a high price in presales is still more beneficial than selling more by discounting prices.

Keywords: Auctions, E-commerce, information signal, multichannel, sequential B2B auctions, information revelation, posted price

Introduction

The internet has had a profound impact on how trading systems such as auctions are operated. Traditionally, sellers offered their products offline, in auction halls; today, however, products can be sold simultaneously in not only online and offline auctions but also online and offline posted-price channels. These complex multichannel systems provide businesses with a number of opportunities and challenges (Bapna et al., 2000; Bichler et al., 2010; Ghose & Yao, 2011; Kambil & van Heck, 1998; Koppius et al., 2004). A significant amount of research has explored these

[1] Siva Viswanathan was the accepting senior editor for this paper. Ni Huang served as the associate editor.

individual trading channels and the substantial differences between online and offline systems (Adomavicius et al., 2012; Bapna et al., 2000; Granados et al., 2012; Ketter et al., 2012; Lu et al., 2016), yet relatively little has focused on how one channel can affect the outcomes of other channels or how a seller can strategize in a multitrading mechanisms environment. *In this study, we address these gaps by empirically investigating the effect of an online posted-price channel on the performance of a B2B Dutch auction system*.

The Dutch auction, or descending auction, is a common mechanism in B2B agricultural markets worldwide. More than 40% of the world's trade in cut flowers circulates through this mechanism (Bloomberg, 2020). It also shapes the supply chain of many daily goods ranging from flowers, plants, and fish to tea and coffee. Some notable examples of Dutch auction markets include Royal FloraHolland—the world's largest B2B floriculture market, Ota—Japan's largest vegetable and flower market, and Pefa—a B2B fish trading system for the European market. The popularity of this mechanism lies in its ability to facilitate a fast clearing speed that is essential for highly perishable goods (Kambil & van Heck, 1998). While this auction system has been the main means of trading for decades, over the past several years, online posted-price channels have expanded their foothold in this sector. In 2019, agribusinesses invested over $780 million in online agri-marketplaces to catch up with global e-commerce trends (Marketplaces, 2020). The rise of online posted-price channels raises the question of how this new channel will affect the traditional B2B auction market.

The answer to this question is crucial yet remains unclear. Traditional auction research still largely uses a single auction as its unit of analysis and excludes the potential effect of information spillovers among different channels (Bapna et al. 2009).

Auctions and posted-price channels are fundamentally different. Auction prices are determined by competition among bidders, whereas posted prices are controlled by sellers. Moreover, these different mechanisms can have different information structures. There is abundant evidence on the crucial role that information can play in the auction price formation process (Arora et al., 2007). Hence, one could conjecture that a posted-price channel, when added to an auction, could reveal additional insights and increase sellers' transparency, consequently influencing the auction's prices. The assessment of the impact of such additional information on the current system is valuable, given the lack of a coherent body of literature on information revelation strategies in auctions (Granados et al., 2010).

We add to the previous cohort of studies on multichannel auctions, auction design, and information disclosure in sequential auctions. We empirically examine an interesting case of a B2B multichannel system that contains an online posted-price channel and an auction system running sequentially. More specifically, we study the Dutch flower auctions (DFA) system in which sellers and bidders trade through (1) an offline B2B multi-unit sequential-auction channel where bidders are physically present at the auction (on-site auction), (2) an online auction channel where bidders bid remotely, and (3) an online posted-price presales channel (i.e., "presales") that takes place before the auctions. Figure 1 provides a presentation of the DFA system. Sellers can decide whether to offer presales or not, how much to offer, and at what price.

In summary, we aim to answer: What is the effect of an online posted-price channel on auction prices in a sequential multichannel auction system? We tested the *overall effect of presales listings on auction prices*. We then examined *why presales listings matter*. Given that the information related to the products, sellers, and supply is identical across the two channels, we thus posit that bidders can use the additional information from the presales channel, including (1) the price set by the sellers and (2) the quantity sold prior to the auctions, to form their valuations.

Theoretically, high prices have been well-established as a *signal of quality* (Bagwell & Riordan, 1991; Mehta et al., 2003; Milgrom & Roberts, 1986; Wolinsky, 1983; Zhao, 2000). High presales prices can work as a credible quality signal for buyers; hence, presales prices have a positive association with auction prices. Likewise, bidders may perceive the quantity sold in presales as an indication of market scarcity and "word-of-mouth" popularity (Cheung & Thadani, 2012; Goes et al., 2010; Ketter et al., 2009; Yu et al., 2014). This information can serve as a strong indication to buy and can consequently boost auction prices.

To test these possibilities, we utilized a large data set of more than 1 million flower lots traded over an entire year at the world's largest floriculture market. First, we uncovered an overall positive effect of the presales channel on auction outcomes. Second, we found that lots in the presales, even those without any sales, still had significantly higher auction prices than lots that were not included in the presales. Third, we followed the signaling framework (Spence, 1978) to further guide our empirical analysis, finding evidence to support that the presales price can work as a signal for bidders. Furthermore, we revealed a significant positive effect of presales quantity sold on auction prices.

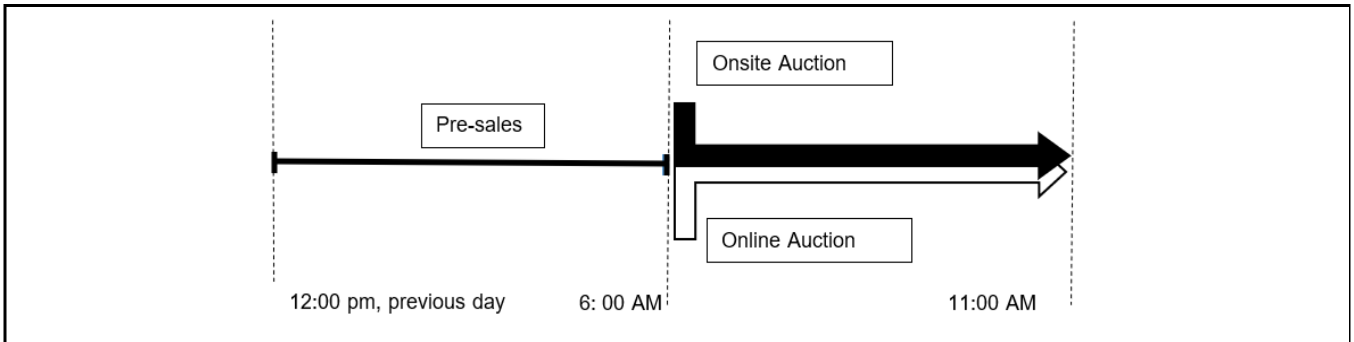

Figure 1. Multichannel Dutch Auction System Representation

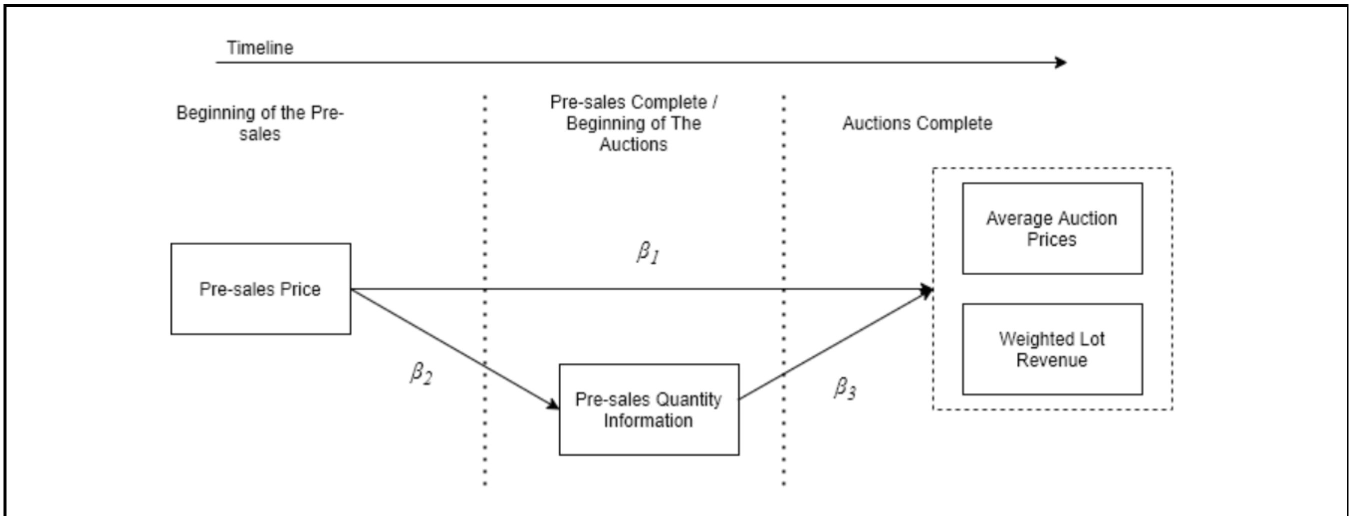

Figure 2. Mediation Model

While we show the *direct positive effect* of both the presales price and the presales quantity sold on auction outcomes, in practice, it is not straightforward to achieve high levels of both at the same time. An increase in presales prices can reduce the quantity sold and, in order to sell higher quantities, sellers generally need to discount their prices. Estimating the *total effect* of *presales prices* on auction prices—or the combination of the *direct effect* of presales prices on auction prices and the *indirect effect* of presales prices on auction prices via the influence of the presales quantity sold—can answer an intriguing question: Is it better to set higher prices in presales even if this results in fewer sales (selling high) or is it preferable to sell more in presales by discounting prices (selling more)? The conceptual model representing both the *direct* (β_1) and *indirect effects* of presales prices (roughly, $\beta_2 \times \beta_3$) is shown in Figure 2, with a detailed explanation in the next section. Through mediation analysis, we identify *a significant total positive effect* of presales prices, finding that selling high is more beneficial than selling more by discounting.

The main econometric challenge of this study is the risk of endogeneity, which may be inherited in price-quantity models. To address the issue, we used a large set of fixed effects to control for time-invariant unobserved heterogeneity. We examined related methodological approaches (such as Hausman instruments and cost shifters) as well as theoretical frameworks from the information systems literature to construct suitable instrumental variables (IVs). The results are also robust under different model specifications.

Our findings contribute to information systems and auction research in several ways. First, we demonstrate how an online presales channel contributes to and affects auction prices and weighted total revenue. We expand the current research on competing auctions, shedding light on the potential impact of integrating different pricing mechanisms, such as posted-price channels, with auction channels in a sequential way. Second, we investigate the effects of additional information disclosure and price signaling on sellers' outcomes. Our results contribute to a richer understanding of information transparency and firm performance. Third, in contrast to previous analytical studies, our work offers empirical evidence from the field. Finally, while much of the previous research has considered single-unit B2C English auctions, the current study focuses on multi-unit B2B Dutch auctions, which are systematically different (Lu et al., 2016).

Literature Review and Motivations

Our research is closely related to the areas of multichannel auctions, auction design, and information disclosure in auctions. Below we highlight the state of knowledge and our key contributions to this literature.

Traditional auction research tends to focus on within-auction dynamics (Bapna et al. 2009). A number of recent papers have attempted to address this issue. Bapna et al. (2009) examined the case of overlapping auctions, advocating that information from other overlapping auctions can influence prices in the focal auction. Goes et al. (2012) proposed that the number of overlapping auctions can influence bidders' strategies. Although this stream of studies considers the role of information in the auction process, the assumption that an auction is an isolated channel may be inappropriate for modern multichannel environments. Our paper represents one of the first efforts to broaden the current state of knowledge beyond the individual channel by considering how the information of a posted-price channel can influence the outcomes of an auction-based channel.

Several studies have explored the differences between posted-price and auction channels, generally concluding that sellers will favor auctions when bidders are heterogeneous and sellers can benefit from price discrimination (Pinker et al., 2003; Wang, 1993). More recently, Kuruzovich and Etzion (2017) found that when online auction and offline posted-price channels run simultaneously, the quality of the offline offer (in terms of price) has a positive impact on the online auction price. Most of this research has employed analytical models of English auctions. These models are set in single-unit auction contexts with homogeneous buyers with single-unit demands. Here, we are the first to consider multi-unit auctions where a proportion of the lot can be presold. Second, we empirically explore a sequential system that has, to the best of our knowledge, not yet been studied.

This study is also related to the area of auction feature design. A variety of auction features have been previously examined. This includes the minimum bid, bid increment, reserve price, and buy-now-price (BNP) in English auctions. The research results have thus far been rather mixed. Hou (2007) found that a high minimum bid can aid in evaluation and increase the auction price. Whereas Ku et al. (2006) posited that lowering the minimum bid can increase competition and the auction price. Bapna et al. (2000, 2002, 2003) illustrated that bid increment has an impact on revenue in multiple unit auctions. Leszczyc et al. (2009) demonstrated that bidders exposed to BNP may have higher valuations than those who are not. Interestingly, in a study of eBay China and America (Hou, 2007), this positive association between BNP and auction price was rejected. Our study deviates from this stream of research in several ways. First, all forms of fixed prices (reserve price, bid increment, minimum bid, and BNP) are visible during an auction. Posted prices can take place at any time, in contrast to a focal auction. As Gallien and Gupta (2007) explained, differences in the timing, available strategic options, and the disparity in competition assessment as a result of different prior information can lead to different evaluations, decisions, and outcomes. In addition, we consider auction lots with multi-units that can be split across different channels. In a single-unit auction, the sales process is completed when a buyer successfully purchases the product, whereas in a multi-unit auction, bidders can observe the quantities already sold, which can influence their evaluation.

Finally, we contribute to the area of information disclosure in auctions. It is well-established that information can contribute significantly to bidding outcomes (Y. Lu et al., 2019; Pilehvar et al., 2016; Wells et al., 2011) and proper information feedback can increase auction efficiency (Adomavicius et al. 2012). Yet, as Arora et al. (2007) indicated, there is still a lack of guidance and direction on information revelation policy for auction sellers. Granados et al. (2010) proposed several research gaps in the field of strategic information transparency concerning, for example, the joint effects of different information elements and the effect of information disclosure and distortion on buyers. We address these gaps and investigate the impact of information in a posted-price channel on an auction channel.

Multichannel Auction System

The Influence of Posted Prices on Auction Prices in a Sequential System

Previous literature suggests that online posted prices can affect auction prices in two key ways: (1) they can act as a *quality signal* or (2) they can work as a *barrier to entry* for bidders.

In online marketplaces, especially for highly perishable goods, it is common to have a high level of *information asymmetry* (Ghose & Yao, 2011). In other words, sellers may have information about the products that buyers do not have. As Gebhardt (2014) documented, in the flower market, buyers traditionally face challenges in assessing the quality of perishable goods, market tastes, the level of supply and demand, and the price and production costs for flowers that are globally sourced and can vary over time. Moreover, as B2B buyers are increasingly switching to online channels for transportation and monitoring cost reductions (Lu et al., 2016), online systems that remove multiple physical product cues can widen the information asymmetry gap, making it even harder for buyers to assess product qualities.

Signaling theory (Connelly et al., 2011; Spence, 1978) suggests that information asymmetries can lead to market inefficiencies when companies who cannot communicate the quality advantage of their products fail to differentiate and receive adequate compensation and thus withdraw from the market (Lin et al., 2013b). Spence (1978) posited that parties with private information can overcome the aforementioned *adverse selection problem* by sending signals about quality to other parties. The paper modeled a labor market in which high-quality job seekers sent an information signal of high quality, i.e., educational level, to potential employers. The signal, which is *costly* for lower-quality job seekers to imitate, allows high-quality job seekers to differentiate themselves from lower-quality job seekers. Consequently, a job seeker sending a signal of high quality is also more likely to get the job offer and receive a higher salary.

In business contexts, previous studies have suggested that high posted retail prices can be used as a credible signal for product quality (Bagwell & Riordan, 1991; Milgrom & Roberts, 1986; Wells et al., 2011). Bagwell and Riordan (1991) and Wells et al. (2011) posit that high-quality sellers can use high posted prices to communicate high quality and differentiate themselves from lower-quality sellers. Lower-quality sellers tend to avoid this high-price strategy because they face several signaling costs, including a high level of investment, potential costs related to replacement and repairs, and the threat of losing future customers, referrals, and sales volume. Similarly, these types of signaling costs can also be observed in DFA, where failing to meet buyers' expectations can also lead to complaints and returns that are costly to resolve in terms of both the time and money needed to respond to the complaints, process the returns, and resell the products. This is particularly challenging in markets like DFA that sell highly perishable goods. Selling a lower-quality lot at a high price may also be considered deceptive, and since repeated sales are common in the B2B marketplace, this can damage sellers' reputations and future sales. In summary, this stream of work on price and signaling theory suggests that online posted prices can work as a quality signal for auction bidders.

Signaling theory offers two main predictions (Lin et al., 2013b) that are used as common tests to establish signaling. Ex ante, signal senders can communicate their quality and are thus more likely to achieve better outcomes. For example, more highly educated job seekers, ex ante, are more likely to obtain higher-quality jobs and receive higher salaries (Spence, 1978). In addition, the theory makes an ex post prediction that the signal is credible—in other words, the signal sender indeed offers higher quality. For the job market, Spence revealed that more highly educated job seekers also tend to be more productive (Connelly et al., 2011; Spence, 1978).

Hence, if this is the dominant explanation, ex ante, we can expect to observe a positive association between presales prices and auction outcomes. Ex post, lots with high presales prices are more likely to be of higher quality; hence, it is reasonable to expect that they are less likely to be returned.

An alternative explanation from the literature suggests that high prices can act as a *barrier to entry*, driving buyers away from auction lots and reducing auction prices. Ku et al. (2006) found that low starting prices entice buyers to increase their time and effort (sunk costs) and eventually escalate their commitment. Lower prices can also increase the number of bidders participating in the auction, as buyers with high budget constraints may see a chance of winning; consequently, this increase in competition makes higher auction prices more likely (Bapna et al., 2009; Ku et al., 2006). We tested these alternative explanations to see which explanation is dominant in this case.

Sales Quantity in the Presales

Different from the single-unit auction, in DFA, growers can sell a proportion of their lots before the auction, and buyers can observe such information. Cheung and Thadani (2012) proposed that sales volume can operate as word-of-mouth advertising. Huang and Chen (2006) argued that a large sales volume can function as an indication to buy. Buyers may believe that other buyers can have access to better information than they do and hence follow others' choices. Goes et al. (2010) posited that in an auction setting, the high sales volumes may be perceived as a dumping behavior precipitated by a decline in demand, whereas high sales levels may be perceived as scarcity and increase buyers' willingness to pay. Motivated by these results, we expect that high sales volumes in the auction presales may serve as an indication of scarcity and provide a cue to bidders to buy, which can raise subsequent auction prices. The conceptual model is presented in Figure 2.

Research Context

The DFA system is managed by Royal FloraHolland, the world's largest B2B floriculture market maker with more than 50% of the global market share (Kambil & van Heck, 1998; van Rijswick, 2015). The system serves over 4,000 growers and nearly 2,500 buyers (Royal FloraHolland, 2017). On average, over 100,000 transactions are processed every day. In 2017, this system generated over 4.6 billion euros in turnover (Royal FloraHolland, 2017).

Dutch Auction Mechanism

At Royal FloraHolland, flowers and plants are traded using sequential multi-unit Dutch auctions operated by digital auction clocks. Flowers are traded in lots. One auction for a single auction lot includes multiple flower stems of homogeneous products from the same seller. The clock indicates the prices and provides information on the current flower lot, including quantity available for purchase (or lot size), monetary unit, product ID, product photos, product quality, grower ID, logos, and the next lots to be auctioned. For each lot, the auctioneer sets the high price (significantly higher than the final auction prices) and starts the clock—the price decreases over time. This covers all auction price ranges and provides time for the buyers to bid. Buyers bid by stopping the clock, indicating they are willing to accept the price at the current clock position. The buyer who stops the clock first is the winner and then decides how much of the lot to purchase. If any units remain, the auctioneer resets the clock and the asking price. An illustration of the auction screen is presented in Figure 3.

The same products are auctioned together in sequence. The order of products in the auction is fixed and provided to all buyers and sellers. Within the product, however, the order of growers is randomized to counter the potential issue of the declining price anomaly phenomenon (van den Berg et al., 2001). The day before the auctions take place, information on the supply is made available to bidders. Traditionally, auctions required bidders to be present at the auction hall (referred to as an on-site auction), where bidders could examine the actual products. In 1996, FloraHolland introduced online auctions, allowing bidders to carry out bidding remotely. The online auction channel has become popular in recent years; by the end of 2015, the number of transactions made via online auctions had overtaken the number made via on-site auctions.

Posted-Price Presales Channel

In 2013, FloraHolland introduced an online posted-price presales channel where sellers can set prices and sell a portion of their stock to bidders online. FloraHolland introduced the presales for a variety of reasons. First, it was a strategic move on the part of FloraHolland, whose auction market was facing a potential threat from the growth of e-commerce. The emerging trend called for the renovation of the auction clock, and presales narrowed the gap between direct sales and the auction channel. Second, presales increase the trading time, which was previously restricted to 4-5 hours a day, allowing FloraHolland to connect buyers and sellers more efficiently (Royal FloraHolland, 2016). The only difference from traditional e-commerce is that the presales take place prior to the auctions, from 12 p.m. the previous day until 5:55 a.m. on the focal auction day. *A maximum of a third of an auction lot* can be made available through the presales channel (Royal FloraHolland, 2017b). After presales conclude, the remaining quantity (between around 67% and 100%) is auctioned. Hence, if there are no sales in the presales, the whole lot will be available in the auction. Anything sold during presales is fulfilled together with the auction sales. It is free for sellers and buyers to participate via the presales channel, and the presales channel provides the same information (same grower information, photos, and product information) as the auction clock. An illustration of the presales screen is shown in Figure 4.

Data and Variables

We obtained two data sets from Royal FloraHolland. The first set includes transaction data on cut flowers for the entirety of 2015 and contains auction prices, presales prices, quantity sold in the auctions and presales, sales channels and other related products, and growers' information. The second data set tracks presales lots, including whether the lot is listed in the presales, the price listed in the presales, and the quantity made available via the presales channel. We aggregated the two data sets to the flower *lot level*—the main unit of analysis for this study. We excluded mixed auction lots, where multiple types of cut flowers are sold together; defective lots, which are noted by the experts at the auction upon the arrival of the lot; and products that contribute insignificantly to turnover and are traded infrequently (12 observations or less). As shown by Greene (2002), the estimation of models such as nonlinear fixed effects models (which we used) can be biased when the number of observations per group is relatively small. We also filtered out lots sold during high-demand periods, including Valentine's Day, Mother's Day, and Christmas, when pricing behaviors differ significantly from the rest of the year (Lu et al., 2016). The aggregated data included 1,481,314 lots of 495 products from 1,895 sellers. A simplified example of the data is presented in Table 1.

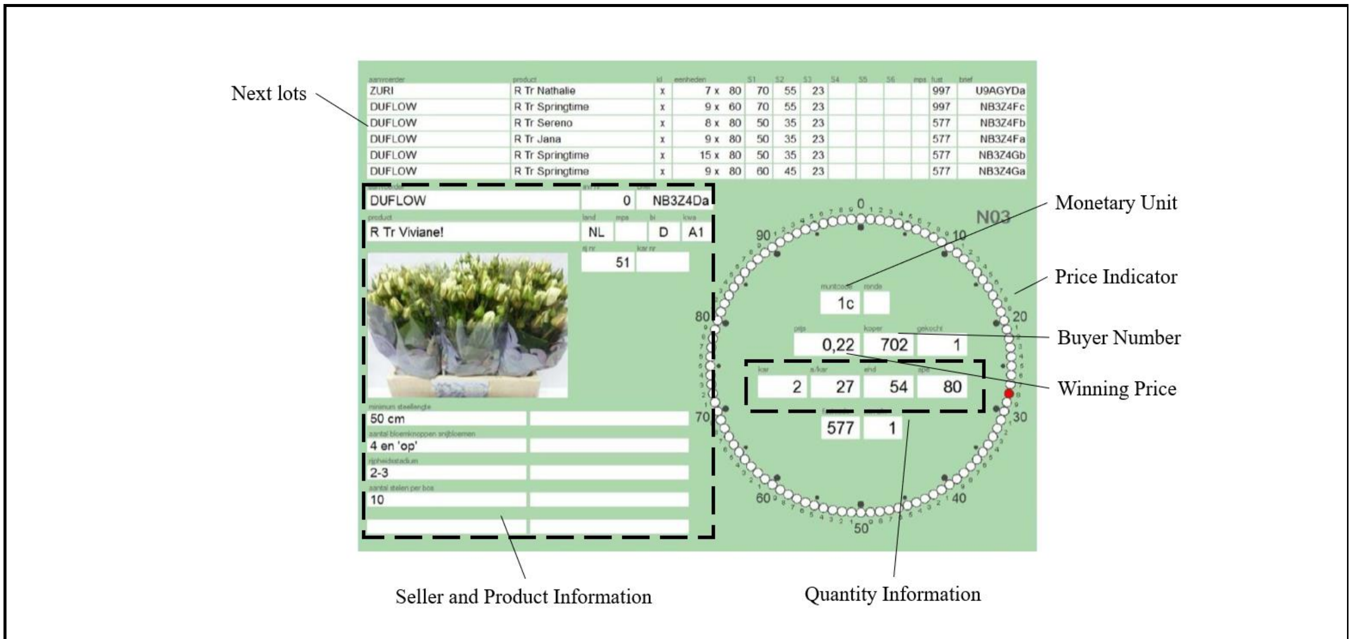

Figure 3. Illustration of the Auction Screen (Royal FloraHolland, 2015)

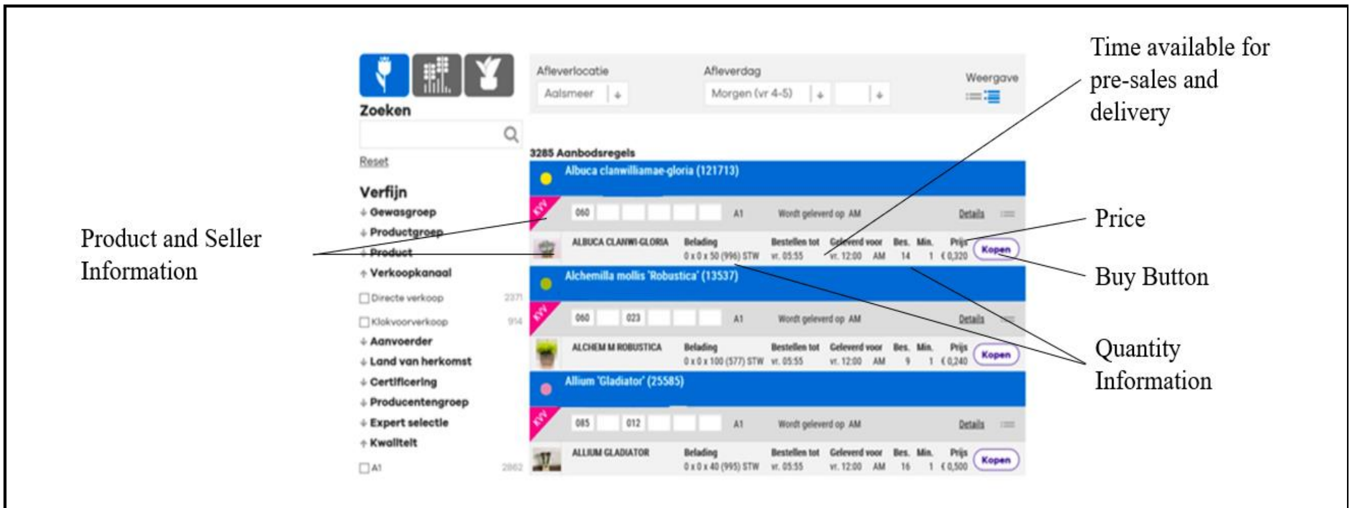

Figure 4. Illustration of the Presales Screen (Royal FloraHolland, 2018)

Table 1. Data Example

Lot ID	Grower ID	Date	Auction quantity	Product code	Average auction price	Lot size	Presales availability	Presales price	Auction channel	Presales quantity
1235	1234	2/1/2015	300	27157	0.68	300	0	-	1.0	-
2234	1234	2/1/2015	200	27157	0.58	300	1	0.70	1.0	100
3378	1234	2/1/2015	100	27157	0.59	120	1	0.65	0.0	20
2135	4569	2/1/2015	150	27157	0.44	150	1	0.75	0.7	0

Besides this combined data set, we collected other data from exogenous sources, including presales for plant products, data from the Food and Agriculture Organization of the United Nations (FAO), and Twitter posts from sellers, to supplement our models. This data is presented along with our models and analysis.

Variables Development

Dependent variables: We adopted a common measurement for auction channel performance and examined the effect of presales on *PAUC*—the average auction price per flower stem sold. In addition, we checked our results against the overall outcome of the auction lot, i.e., lot-weighted revenue (*FPR*), which is measured by the total revenue from all channels *c* weighted by the total lot size—*LOTSIZE*: $FPR_i = log(TOTALREVENUE_i / LOTSIZE_{i,})$. Cut flowers that are not sold by the end of the day are destroyed (although this outcome is rare in our data); thus, to reveal the growers' "true revenue," it is reasonable to weigh the revenue by lot size rather than by the total quantity sold. We took the natural logarithm on all of our continuous variables to control for the skewness in the data set (Ghose & Yao, 2011).

Presales use: *PRESALES* is a binary variable, taking the value of 1 if the lot is included in the presales for day *t* and 0 otherwise.

Presales price: *PPRE* indicates the presales price per flower stem, which is set by the seller.

Presales quantity: *QPRE* reflects the total quantity sold in the presales for lot *i* on day *t.* According to the market maker's rules, a seller can only offer a maximum of a third of the lot in the presales channel. For example, if the lot has a lot size of 90 flower stems, a seller can offer a maximum of 30 stems in presales. Hence, *QPRE* is censored in nature, which is addressed in our models.

We followed models from previous empirical studies (Kuruzovich & Etzion, 2017; Y. Lu et al., 2019; Pilehvar et al., 2016) and used the information observable by bidders to construct control variables. Y. Lu et al. (2019) specified that auction lot prices can be influenced by the information in the market, lot size or supply level, product characteristics, and weekly patterns. The model also includes week and grower fixed effects. Kuruzovich and Etzion (2017) modeled the lot auction prices in an English auction for car products based on the simultaneous posted-price channel's quality, product characteristics, special occasion (weekend), level of supply in the market, and other information that the bidders observe in the auction (such as feedback messages from eBay, length of auction, and number of bids). Pilehvar et al. (2016) predicted the final price in an English auction using past price histories, level of supply in the market, number of open auctions of the same product, supplier characteristics, timing of auctions, and time and fixed effects. Consequently, we controlled for the following variables:

Lot size: *LOTSIZE* denotes the total flower stems available for each lot *i*. FloraHolland makes this information available to all the bidders a day before the auction. In addition, it is presented on the auction clock. The variable has been found to negatively influence auction prices (Y. Lu et al., 2019; Mithas & Jones, 2007).

Supply: While *LOTSIZE* captures the supply information at the lot level, *SUPPLY* captures the substitution and supply information at the market level. For lot *i* of product *p*, *SUPPLY* is measured as the difference between the total units available for product *p* in day *t* and the *LOTSIZE* of lot *i*. Both *SUPPLY* and *QPRE* can take the value of 0, which is undefined after converting to a log scale. Thus, we added a small value (1, in this case) to the measures before performing log transformation.

Auction channel: *CHANNEL* measures the share of the lot quantity that is transacted through the online auction (vs. an on-site auction). Lu et al. (2016) implemented a similar measurement and illustrated that the auction mode can influence bidders' transaction costs, strategies, and, as a result, auction price. In DFA, both auction channels provide identical product information, product pictures, and purchase quantities and use the same auction clocks. However, in on-site auctions, bidders can observe and examine the flowers, which is not possible in online auctions. Koppius et al. (2004) argued that the additional physical cues from the on-site auction channel can lead to a price gap between the two auction modes.

Lot auction time: We accounted for the observed information and the variability in the order and timing of an auction lot. Previous research has found evidence indicating that the price in Dutch auctions tends to decline in subsequent auctions (van den Berg et al., 2001). In addition, the next lots to be auctioned are revealed on the auction clock. Following a similar approach by Lu et al. (2016), we generated *TOEL (time of entry for auction lot),* which normalizes the starting time of an auction lot by the auction time of the product. In other words, for lot *i,* product *p* of grower *g*, on day *t:*

$$TOEL_{igpt} = (Starting\_Time_{igpt} - Starting\_Time_{pt}) / (Closing\_Time_{pt} - Starting\_Time_{pt}).$$

Such normalization indicates how early within the product group the lot is made available for auction.

Presales quantity availability: *PRESALES_AVAI* captures the total quantity that a seller makes available in the presales for lot i on day t. It works as an upper bound for *QPRE* (i.e., $QPRE \leq PRESALES\_AVAI$) since the formal limit of "a third of a flower lot" is not always adhered to by sellers.

Historical price: Historical prices can work as *reference points* for bidders that influence their evaluation and consequently the auction prices (Baucells et al., 2011; Pilehvar et al., 2016). In addition, it can also capture buyers' and sellers' interaction experiences from the buyer's point-of-view since buying cost is still one of the key performance indicators that buyers use to evaluate suppliers' performance in a B2B context (Ho et al., 2010). We follow the widely adopted method for modeling reference price in which the effect is measured as an exponentially smoothed, weighted average of previous prices (Baucells et al., 2011; Baucells & Hwang, 2016; Chen & Nasiry, 2019; Langer et al., 2012). Formally, $EXP_{pt}=\alpha HP_{p,t-1} +(1-\alpha)EXP_{p,t-1,}$ where *HP* is the average price of product p with total N lots on day t: $HP_{pt} = \frac{\sum_1^N TOTALREVENUE_{ipt}}{\sum_1^N LOTSIZE_{ipt}}$. In other words, we expect more recent information to have a stronger effect on buyers' decisions than older information. The value of α is optimized by minimizing the forecasting error of five holdout periods. Here, we calculated the historical prices for each product p, assuming that buyers can take not only prices from the focal sellers but also the prices of other sellers in the market into account. We also conducted a robustness check where the historical prices were measured for each seller-product combination (g,p) or the reference point was based on the focal seller's internal system only. The results are qualitatively consistent.

We also controlled for an extensive set of *fixed effects*, including seller, product, and day fixed effects, as presented in the next section. Thus, our models controlled for other available variables such as sellers' characteristics, reputation, products' characteristics, day of the week, etc., which are fixed across time or fixed across buyers and products, through this estimation. They subsequently become redundant in the models.

We summarize our notation in Table 2. Descriptive statistics are available in Table 3. Nearly 1.5 million lots were traded in 2015—of those, around 360,000 lots were available in the presales. The average auction price per stem was 0.37 EUR, while the average presales price per stem was 0.48 EUR.

Empirical Analysis

The key issue that we address is the effect of presales on auction prices. First, we tested the overall effect of presales listing on auction prices. Next, we teased out the *direct effect* of the *presales price* and *presales quantity* (β_1 and β_3 in Figure 2) and tested the predictions of signaling theory. The conceptual model is presented in Figure 2. The presales price information is available at the beginning of presales and the quantity sold can be determined at the end of presales before the auctions begin. The presales price can influence the presales quantity sold (β_2)—while, as discussed previously, both the presales price and quantity sold can influence the outcome of the auction (β_1 and β_3). In other words, information on the presales quantity sold can *mediate the effect between the presales price and auction outcomes*. We follow the strategy suggested by Baron and Kenny (1986) which has been widely adopted in previous literature to examine the direct and mediation effects. Specifically, if the presales price does not influence the auction price directly but only influences it indirectly by affecting the presales quantity sold (i.e., presales quantity sold is a full mediator between the presales price and auction), by controlling for the presales quantity sold in the same model evaluating the presales price, the effect of the presales price should be insignificant. That is if β_1 does not exist and only β_3 matters, by controlling for *QPRE* when estimating β_1, β_1 will be insignificant. If signaling is the dominant explanation, we are likely to observe a positive and significant β_1 (ex ante prediction of signaling theory). If the barrier to entry is the dominant explanation, we are likely to observe a negative and significant β_1. In addition, we also performed an ex post test (Spence, 1978) where we studied the relationship between the presales price and lot return.

Net Effect of Presales Use on Auction

Empirical strategy and identification

For lot i of grower g, product p on day t, the effect of whether the lots are available in the presales or not (*PRESALES*) on the average auction price (*PAUC*) is estimated using the equation:

$$PAUC_{igpt} = \beta_{00} + \beta_{01}PRESALES_{igpt} + X_{igpt}\delta + f_g + w_p + d_t + \varepsilon_{igpt} \quad (1)$$

The vector of covariates X_{igpt} contains control variables, including lot supply level (*LOTSIZE*), market supply level (*SUPPLY*), the timing of the auction (*TOEL*), auction channel mode (*CHANNEL*), and historical prices and interaction experiences (*EXP*). Vector f_g, w_p, and d_t include grower, product, and time fixed effects. We retested a similar model for *FPR*.

Table 2. Variable Notations	
PAUC	Average auction price per flower stem sold
FPR	Lot's weighted revenue
QPRE	Total quantity sold in the presales for lot *i* on day *t*
PPRE	Presales price per flower stem
PRESALES	Presales use, taking the value of 1 if the lot is in the presales for day *t* and 0 otherwise.
LOTSIZE	Total flower stems available for each lot *i*
SUPPLY	The substitution and supply information at the market level
CHANNEL	Auction channel
TOEL	Lot auction time
PRESALES_AVAI	The total quantity that a seller makes available in the presales for lot *i* on day *t*
EXP	Historical price
Presales_Plant	Presales used for plant products
IV_Sellernum	Number of sellers adopting presales for another flower product market that the focal seller participated in
Disr	Market disruption event
TEMP	Temperature change in the previous month
IV_ppre	Hausman-style instrument, prices of similar products in another market
MAR	Product-group advertisements for the presales channel only
Return	Whether parts of the lot were returned

Table 3. Descriptive Statistics

Statistics	*N*	Mean	Standard deviation	Min	Max
Auction quantity per lot (flower stems)	1,481,314	1,974.072	2,739.549	4	126,000.000
Average auction price per stem per lot (EUR)	1,481,314	0.368	0.363	0.0005	16.450
Presales quantity per lot (flower stems)	363,721	47.735	129.323	0.000	7,200.000
Presales price per stem per lot (EUR)	363,721	0.481	1.928	0.010	450.000
Lot size (flower stems)	1,481,314	1,985.979	2,747.228	4	126,720.000
Total revenue per lot (EUR)	1,481,314	503.329	680.139	0.600	43,811.200

One main challenge of this model is endogeneity, which can come from several sources. First, endogeneity can arise from *reverse causality*. In particular, the auction price on day *t* can reversely influence the presales price on day *t*. However, this is unlikely, since presales decisions are not only made ahead of time prior to the auctions but the two decisions, i.e., presales use and auction price, are also made by distinct groups of people. Presales listing is set by sellers, while auction prices are determined by bidders. This separation in the decision-making process makes it even more unlikely that the auction price on day *t* would influence the presales price on day *t*.

Second, endogeneity can arise from *unobserved factors*. To address this, we included an extensive set of fixed effects, including seller fixed effects, time fixed effects, and product fixed effects. These fixed effects remove unobservable products and sellers' factors that are not expected to change over time such as across-product heterogeneity, starting prices, sellers' reputation, starting price, and across-seller heterogeneity. The specification captures within-seller within-product variance, wiping out the time constant and common sellers' and products' unobservable characteristics. Time fixed effects controlled for unobservable buyer- and product-invariant shocks, such as market seasonality and other market-wide events.

This estimation using seller fixed effects (f_g) assumes that a seller G_g has a similar reputation across all of his products (P_1, P_2, P_3...). As a seller, G_g may have a different reputation for different products (reputation is different for seller G_g - product P_1, seller G_g - product P_2, and seller G_g - product P_3), we further examined more vigorous fixed effects specifications in our robustness tests. These checks employed stricter estimations. For example, in one test, the effect was estimated within the same buyer-product combination (f_{gp}). Hence, unobservable buyer-product factors, such as the seller's reputation for a particular product, were consequently removed. The results of these robust checks are qualitatively consistent with our main analysis. Similarly, product fixed effects estimation assumes that the same products will have similar starting prices. However, starting prices may be similar for the same products during the same time but different across different time periods. Consequently, in one check, we used product-time fixed effects (f_{pt}). We controlled for unobservable product-time factors, such as products' starting prices for a particular time. Overall, we executed 12 models using different fixed effect combinations for both *PAUC* and *FPR* measurements. The results are consistent and can be found in Appendix A1.

Third, although the fixed effect specifications eliminated several sources of unobservability, they may not have covered unobservable seller-product-time variant factors. In addition, there could be selection bias; in other words, presales lots could be different from lots without presales. Hence, we followed Wooldridge (2010) and estimated 2SLS models in combination with fixed effects to tackle endogeneity. We sought instrumental variables (IVs) that correlated with the presales decision but did not directly influence the auction outcome.

First, it is reasonable to assume that the decision to offer lots in presales is driven by the benefit and cost of this action. In particular, $PRESALES_{igpt} = f(v(\varepsilon_{igpt}), c_{igpt})$. As the benefit gained from the presales, $v(\varepsilon_{igpt})$, may correlate with the auction outcome, which is determined by buyers, we searched for variables that correlate with the exclusive cost shifter, c_{igpt}, from the seller side or in this case, variables that shift the distance between the sellers and the presales channel, making it easier or harder for the seller to adopt the channel. Such a cost-shifter strategy for IV development has been widely adopted in previous literature (S. Lu et al., 2019). According to Forman (2005), complementarities, external environment, knowledge spillover, and size are key determinants of internet technology use. Xue et al. (2007) suggested that in the B2C context, channel use depends on customer factors (such as customer's technical skills, time, and opportunity cost), firm factors (such as channel design), and combined factors (such as channel access).

We also focus on variables formulated from product markets, outside of the focal market. Given that we controlled for seller and product fixed effects, the auction price is independent across sellers and products and can only be correlated *within* the same seller and product. This strategy of using different markets and the structure of fixed effect models to source for IVs is motivated by the idea of the widely used Hausman-style instrument (Fisher et al., 2017; Hausman, 1996; Nevo, 2001). Here we report on the testing of our model with two alternative sets of IV.

In the first set of IV (IV with week fixed effects), we used cases where the presales channel limited its access due to technical issues or maintenance (*Disr*). These disruption events acted as external shocks, making it harder for sellers to access the channel or limiting the time the lots were available in presales. This could directly influence *PRESALES*. While *Disr* can be a valid instrument, it is fixed per day and will not work with day fixed effects. Hence, for this analysis, we used week fixed effects instead. We also included day-of-the-week fixed effects since it was evident from the interviews with sellers that there could be an increase in demand on certain days of the week due to export flight schedules. The same control was applied in Y. Lu et al. (2019).

For the second IV set (IV with day fixed effects), we adopted two IVs. First is the decision to use presales for plant products on day *t* ($Presales\_Plant_{gt}$), and second is the number of sellers adopting presales for *another* flower product market, unrelated to the focal product of the focal seller ($IV\_Sellernum_{pt}$).

Based on previous theoretical literature, we expected the decision to use the presales channel for plant products for the day (due to a shock in plant supply, for instance) to entice buyers to use the channel for flower products as well (complementary decision). On previous days, sellers might not have used the channel due to factors such as hassle costs, low perceived benefits, and channel unfamiliarity. However, if they were already using presales for plant sales, listing flowers in presales would only involve a couple of extra clicks. Hence, we expected *Presales_Plant* to correlate with *PRESALES* use for the flower lots. However, since the nature of plants and flowers, are quite different (i.e., one is highly perishable and the other is not), we did not anticipate the shock in the plant markets to correlate with the price of a particular flower.

At the same time, a surge in the number of external sellers from different markets may correlate with presales use due to knowledge spillover (Forman, 2005). Sellers can gain knowledge or tips from using the presales for another product. This can ease the barrier between sellers and presales. Alternatively, presales use in the focal market may correlate with presales use in other markets due to *common cost shifters*, such as workshops that Royal FloraHolland offers to sellers throughout the year to reduce technical barriers. Sellers participating in these workshops might be more likely to adopt the presales channel to sell their different products.

As discussed earlier, such cost-shifter instruments are unlikely to correlate with the error terms. In addition, we controlled for product, seller, and time fixed effects; hence, the error terms are independent across products and are thus unlikely to correlate with our IVs, which are formulated based on different markets.

To further support the suitability of the IVs, we performed several diagnostic tests to examine the essential assumptions (Wooldridge, 2010). These tests included the weak instrument test, which checked whether the IVs are significantly associated with *PRESALES*, and the Sargan test for overidentification restriction, the null hypothesis of which is that the IVs are valid. The results offer support for our IVs. We summarize our IVs used as well as related tests in Table 4.

Additionally, buyers and sellers can be self-selected into different channels. In other words, there may be some unobserved characteristics that make presales-only buyers/sellers behave differently from auction-only buyers/sellers and would consequently explain the positive effect. To tackle this issue, we conducted propensity score matching (PSM) with stratified sampling. We retained one group of buyers who only attend auctions and one group of sellers and products available across all channels. We further conducted stratified matching on this subset to match a lot with presales with a lot without. We first carried out a perfect match for all categorical variables, including time categories variables, product groups, *Presales_Plant*, growers' country of origin, and grower ID. Within each of these groups, we then followed PSM with replacement (Rosenbaum & Rubin, 1985). PSM controls for selection bias and the effects of potential confounding factors (Brynjolfsson et al., 2011). We included all the independent variables and IVs. We performed a balance test, which indicated no significant differences between lots with and lots without presales after matching (Appendix A2). We then reevaluated all models of our analysis.

Furthermore, we exploited the special case of no sales in the presales. This case is interesting in that all buyers are auction buyers and all sales are auction-based. The difference here is that for lots with presales, the seller's information was revealed before the auction, and for the case of no presales, no information was available. All available buyers attended the auctions. This introduced further control for buyers' selection bias.

We also addressed lot-selection bias directly, together with other sources of endogeneity using a Heckman correction in combination with 2SLS (This model is presented together with our presales price and quantity effect estimation).

We accounted for heteroskedasticity, autocorrelation, and the possibility of correlated error terms within different levels by clustering standard errors (Wooldridge, 2010). We tested different error clustering methods, including clustering at different levels (product, time, grower, and multiway clustering), White, and Newey-West. We then selected the most conservative estimation which is the recommended practice of Cameron and Miller (2015) to mitigate bias and the overstatement of our results. The error term was eventually clustered at the grower level.

Results

Results from the pooled and fixed effects estimations can be found in Table 5. Models 1 and 2 do not contain fixed effects. Models 3 and 4 showcase fixed-effect results. The effect of *PRESALES* is positive, significant, and consistent across all models. VIF < 3 does not reveal any high multicollinearity problem. Table 6 presents the results of our 2SLS estimations. Models 1 and 2 use IV with day fixed effects. The first stage is presented in Model 3. Models 4-6 use IV with week fixed effects.

For IV with day fixed effects, as presented in Model 3, both IVs are significantly associated with the *PRESALES* decision. The *F*-statistic on the excluded instruments in the first stage is greater than 10, indicating that the IVs are sufficiently strong for the analysis (Staiger et al., 1997). The Sargan test failed to reject the null hypothesis for the first set, supporting the suitability of the IVs. We found no evidence of IVs correlating with the error term even with our large data size. The results in Models 1 and 2 are qualitatively consistent with the fixed effects estimation in Table 5. We carried out the Durbin-Wu-Hausman test. The residual of the first stage is included in the second stage. The coefficient of the residual is significant (*t*-statistics = -2.849, p-value < 0.05); hence, the 2SLS estimation is preferred. The effect of *PRESALES* is positive and significant. Being listed in presales is associated with 8.8% higher average auction prices ($\beta = 0.088$, $SE = 0.023$) and 9.2% ($\beta = 0.092$, $SE = 0.022$) higher weighted lot revenue. With an average lot size of over 2,000 stems, an average lot revenue of more than 500 euros, and over a million lots transacted per year, the effect size of over 8% gained through simply offering the lot in presales is practically significant in its magnitude. Similarly, for the IV with week fixed effects, the results are qualitatively consistent. Our findings indicate that presales have a significant positive effect on subsequent auction prices.

Table 7 shows the results for the case of no sales in the presales. With no sales in the presales, *PAUC* is the same as *FPR*—i.e., the whole lot is available in the auctions. The coefficients of *PRESALES* in both fixed effects (Model 1) and 2SLS (Model 2) estimations are positive, significant, and consistent with our full model. Lots that were offered in presales yielded 7.6% higher auction prices even without any sales in the presales. This further indicates that buyers pay attention to the signal in the presales channel.

We retested the models using a subsample including one buyer, seller, and product group with matched data. The results are presented in Table 8. For the same group of auction-only buyers, the same products, and sellers with similar auction lots distributed between presales and non-presales, we found a positive effect of *PRESALES* on *PAUC* (Model 1), *FPR* (Model 2), and the case of no sales in the presales (Model 3).

Table 4. Models Summary

Models	**IVs definition**	**Summary**	**Related tests**
Equation (1): *PRESALES →PAUC*	*Presales_Plant:* Whether the growers use the presales channel for plant products on day *t*	The decision to use presales for plant products (due to a shock in plant supply, for instance) can entice buyers to use the channel for flower products (complementary decision). However, since the nature of plants and flowers is very different, the shock in the plant markets is unlikely to correlate with the price of a flower.	*F*-statistic=20.928 Sargan test *p-value* = 0.999 Durbin-Wu-Hausman test *p*-value = 0.003
	IV_Sellernum: number of sellers adopting presales for another flower product market, (unrelated to the focal product) that the focal seller participated in	Presales use in the focal market can correlate with presales use in other markets due to common cost shifters such as training workshops. These cost shifters of *PRESALES* are unlikely to correlate with the error terms in the *PAUC* function. In addition, we controlled for product and seller FE, *PAUC* can only correlate within the same seller and product; the error terms are independent across products. They are unlikely to correlate with IVs formulated from different markets.	
	Other robustness tests: alternative FE specifications, stratified matching, no sales in the presales case Alternative set of IV: *Disr:* Disruption events that limit presales access. These external shocks make it harder for sellers to access the channel or limiting the time the lots are available in presales.		
Equation (2) *PPRE, QPRE → PAUC*	IV for *PPRE:* *TEMP:* level of temperature change in the previous month at the sellers' country of origin	An input cost shifter for flower growers. The increase in input cost can force the sellers to increase the posted price, yet the shift in the cost function of the sellers is unlikely to correlate with buyers' decisions (Berry et al. 1995)	*F*-statistic = 20.394
	IV_ppre: Hausman-style instrument where prices of similar products in another market can be used as the instrument for prices of the product in the focal market	The prices of similar products from different markets are likely to correlate as they share the firm-level cost-shifter shock, but given that the market fixed effects are used, they are unlikely to correlate with the demand side (Fisher et al. 2017)	
	IV for *QPRE* *Mar:* indicates whether similar sellers of the same flower group announce if the products will be available the day before the presales, two days ahead of auctions.	This information advertisement can help to reduce the buyer's search cost (Chen et al. 2009) and hence is likely to correlate with the quantity sold. Further, there is evidence of positive marketing spillover effects—e.g., a Samsung tablet ad can increase the search volume for Apple iPads (Lewis & Nguyen, 2015). The ad is for presales only and is made two days before the auctions. It is the product information that can work as a buyer's preferences shifter (Berry & Haile, 2016), unlikely to directly influence price evaluation—it reflects the marketing decisions of similar sellers, not the focal seller. We controlled for seller FE; *PAUC* can only correlate within sellers and is independent across sellers.	• F-statistic=10.966 • Sargan test *p-value* = 0.194 • Durbin-Wu-Hausman test *p-value* of residuals for *PPRE* = 0.045 • *p-value* of residuals for *QPRE* = 0.011
	Other robustness tests: Use *Disr* as IV for *QPRE* instead of *Mar,* (as an external shock like disruption can influence sales but is unlikely to influence *PAUC*), alternative specification: Heckman + 2SLS.		
Equation (3) *PPRE → QPRE*	IV for *PPRE*: *TEMP & IV_ppre:*	(similar to Equation 2)	• *F*-statistic = 24.331 • Sargan test *p-value* = 0.145 • Durbin-Wu-Hausman test *p-value* = 0.407

Table 5. Net Effect of Presales on Auction Price and Lot-Weighted Revenue				
Independent variables	**(1)** ***PAUC*** **Pool**	**(2)** ***FPR*** **Pool**	**(3)** ***PAUC*** **Fixed effects**	**(4)** ***FPR*** **Fixed effects**
*PRESALES:*1	0.090*** (0.016)	0.095*** (0.016)	0.049*** (0.008)	0.062*** (0.010)
LOTSIZE	-0.076*** (0.005)	-0.076*** (0.005)	-0.085*** (0.005)	-0.085*** (0.005)
CHANNEL	0.162*** (0.016)	0.160*** (0.016)	0.159*** (0.012)	0.157*** (0.012)
EXP	0.929*** (0.009)	0.928*** (0.009)	0.814*** (0.006)	0.812*** (0.006)
TOEL	-0.171*** (0.012)	-0.170*** (0.012)	-0.193*** (0.011)	-0.192*** (0.011)
SUPPLY	0.009* (0.005)	0.009* (0.005)	-0.021*** (0.003)	-0.020*** (0.003)
N	1,481,314	1,481,314	1,481,314	1,481,314
R^2 Adjusted	0.744	0.744	0.808	0.809
FE: time, grower, product	No	No	Yes	Yes

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

Table 6. Net Effect of Presales on Auction Price and Lot-Weighted Revenue with 2SLS and Fixed Effects Estimations						
Independent variables	**(1)** ***PAUC*** **2SLS**	**(2)** ***FPR*** **2SLS**	**(3)** ***PRESALES*** **First-stage**	**(4)** ***PAUC*** **2SLS**	**(5)** ***FPR*** **2SLS**	**(6)** ***PRESALES*** **First-stage**
	IV with day fixed effects			***IV with week fixed effects***		
*PRESALES:*1	0.088*** (0.023)	0.092*** (0.022)		0.071*** (0.023)	0.075*** (0.023)	
LOTSIZE	-0.086*** (0.005)	-0.086*** (0.005)	0.034*** (0.004)	-0.086*** (0.005)	-0.086*** (0.005)	0.034*** (0.004)
CHANNEL	0.158*** (0.012)	0.156*** (0.012)	0.033*** (0.011)	0.159*** (0.012)	0.157*** (0.012)	0.032*** (0.011)
EXP	0.813*** (0.006)	0.812*** (0.006)	0.008 (0.007)	0.813*** (0.005)	0.812*** (0.005)	0.010 (0.007)
TOEL	-0.194*** (0.011)	-0.192*** (0.011)	0.012** (0.006)	-0.193*** (0.011)	-0.192*** (0.011)	0.012** (0.006)
SUPPLY	-0.021*** (0.003)	-0.020*** (0.003)	-0.002 (0.002)	-0.021*** (0.003)	-0.020*** (0.003)	0.0005 (0.002)
Presales_Plant			0.301*** (0.043)			
IV_Sellernum			0.0001** (0.00004)			
Disr						-0.012*** (0.005)
F-statistic			20.928			10.355
Sargan *p*-value	0.999	0.999				
Hausman *p*-value	0.003	0.004		0.001	0.001	
N	1,481,314	1,481,314	1,481,314	1,481,314	1,481,314	1,481,314
Fixed effects: time, grower, product	Yes	Yes	Yes	Grower, product, week, day of the week		

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

Table 7. Net Effect of Presales on Auction Price When There Are No Sales in the Presales		
Independent Variables	**(1)** ***PAUC (FPR)*** **Fixed effects**	**(2)** ***PAUC (FPR)*** **2SLS**
*PRESALES:*1	0.041*** (0.009)	0.076*** (0.022)
LOTSIZE	-0.083*** (0.005)	--0.084*** (0.005)
CHANNEL	0.161*** (0.012)	0.159*** (0.012)
EXP	0.814*** (0.006)	0.814*** (0.006)
TOEL	-0.192*** (0.011)	-0.192*** (0.011)
SUPPLY	-0.020*** (0.003)	-0.020*** (0.003)
N	1,366,257	1,366,257
R^2 adjusted	0.807	
Fixed effects: time, grower, product	Yes	Yes

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

Table 8. Net Effect of Presales on Auction Performance with Same Groups of Buyers, Sellers, and Products			
Independent variables	**(1)** ***PAUC***	**(2)** ***FPR***	**(3)** **No sales in presales**
*PRESALES:*1	0.047*** (0.016)	0.053*** (0.016)	0.036** (0.016)
LOTSIZE	-0.091*** (0.005)	-0.091*** (0.005)	-0.091*** (0.005)
CHANNEL	0.080*** (0.019)	0.076*** (0.019)	0.085*** (0.019)
EXP	0.830*** (0.011)	0.825*** (0.010)	0.835*** (0.011)
TOEL	-0.191*** (0.019)	-0.187*** (0.019)	-0.182*** (0.020)
SUPPLY	-0.031*** (0.003)	-0.030*** (0.003)	-0.028*** (0.003)
N	410,569	410,569	347,610
R^2 adjusted	0.827	0.830	0.827
Fixed effects: time, grower, product	Yes	Yes	Yes

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

Effect of Presales Price and Presales Quantity

Empirical Strategy

We teased out the effect of presales price and presales quantity on auction price by estimating Equation (2).

$$PAUC_{igpt} = \beta_{10} + \beta_{11}PPRE_{igpt} + \beta_{12}QPRE_{igpt} + X_{igpt}\delta + f_g + w_p + d_{t+}\, \varepsilon_{igpt} \qquad (2)$$

We estimated a similar model for *FPR*, the lot's weighted revenue. Vector X_{igpt} comprises control variables (i.e., *LOTSIZE*, *SUPPLY*, *TOEL*, *CHANNEL*, and *EXP*). Vector f_g, w_p, and d_t contain grower, product, and time fixed effects. Similarly to Equation (1), we clustered standard errors at the grower level to address heteroskedasticity and error terms correlated within sellers.

As discussed previously, the extensive set of fixed effects eliminates time-invariant factors as well as product- and grower-invariant factors. Nevertheless, these cannot capture other seller-product-time variant unobservable factors. One concern is that *PPRE* may be endogenous. We estimated a 2SLS model and searched for an IV that could influence *PPRE*, which is the price set by the seller, on *the supply side* but would be unlikely to directly affect *PAUC*, i.e., the outcome on *the demand side*. We followed the IV approach by Berry et al. (1995) for sellers' prices as part of the demand function and searched for an IV that would be an input cost shifter for growers. The increase in input cost could force the sellers to increase the posted price; however, the shift in sellers' cost function is unlikely to correlate with buyers' decisions (Berry et al., 1995). Here, we used the level of temperature change in the previous month (*TEMP*) at the sellers' country of origin which was collected from the FAO database. Temperature plays a great role in agriculture production and is thus commonly used for identification purposes. Temperature fluctuations can increase the cost of flower production (electricity, water, etc.), and may thus be transferred to the posted price set by growers. This cost shifter for growers on a global scale is unlikely to influence the decisions of buyers in the short term. In addition, in line with a widely-used Hausman-style instrument, we used prices of similar products in another market as an instrument for prices of the product in the focal market (Fisher et al., 2017; Hausman, 1996; Nevo, 2001). As suggested by Fisher et al. (2017), the prices of similar products from different markets are likely to correlate, as they share the same firm-level cost shifter shock, but given that the market fixed effects are used, they are unlikely to correlate with the demand side.

We further performed diagnostic tests, including weak instruments and overidentification tests, which offered support for our IVs. There may be a concern that buyers may observe temperature changes. While buyers may be aware of major shifts in weather (captured in day fixed effects), they are unlikely to be aware of the microchanges in temperature in multiple countries around the world, which affect the local day-to-day operation cost. Nevertheless, to test for this, we dropped this IV and the results remain qualitatively consistent.

In addition, since *QPRE* could potentially be endogenous, we searched for a variable that would shift the quantity sold in the presales channel but would be unlikely to directly affect the price determined by buyers in the auction. One strategy used in previous research to identify quantity demand in the willingness to pay function, as reviewed by Berry and Haile (2016), is to seek buyer preference shifters—or in other words, create measures of the "buyer × product" distance. These shifters are attractive as they are classic drivers of changes in quantity demand but do not directly influence the price evaluation. Some examples provided by Berry and Haile (2016) include exposure to product (non-price) advertising and physical distance to retailers or schools to identify shop or school demand.

Following this strategy, we used product group advertisements for the presales channel only (*Mar*), which are made available on Twitter. Sellers use social media to remind buyers that products will be made available on the presales channel (non-price information advertisement for presales only). The information is normally presented with less detail and at higher product group levels [2] (tulip, rose) rather than at the product level that we analyzed, which includes flowers of the same breed and with finer details (such as the big Athena rose) due to the concise nature of Twitter messages and the large number of products that sellers normally offer. Formally, *Mar* indicates whether similar sellers of the same product group (such as tulip, rose, etc. excluding the focal seller) made product group advertisements on Twitter the day before the presales, which occur two days prior to auctions. Such non-price information advertisement can help to further reduce the buyer's search cost (Chen et al., 2009; Erdem et al., 2008), and is hence likely to *correlate* with sales in the presales (Brynjolfsson et al., 2009). Further, there is evidence of positive marketing spillover effects. For example, Lewis and Nguyen (2015) found that a Samsung tablet ad can increase the volume of searches for Apple iPads. Hence, information marketing can have a spillover effect and, in our case, may correlate with the sales of the focal seller in the presales.

As only the product group level can be traced and *Mar* captures decisions of similar sellers (in the same product group), we questioned the effect of the instrument and whether the instrument might suffer from a weak-instrument problem. Here, as shown in the first-stage model (Table 10, Model 4), *Mar* is statistically significantly correlated with *QPRE*, which ensures the strength of the correlation. There may also be a concern that this marketing decision may correlate with the unobserved quality of the lot and hence the error terms in Equation (2). First, it is important to note that the ad is for presales only; it does not relate to the auction and is placed the day before the presales, which is two days before the auctions. It is product information and, as discussed previously, evidence from previous literature indicates that information marketing can work as a buyer preference shifter; hence, it is unlikely to directly influence buyers' price evaluations. This provides a case in which to employ *Mar* as an IV. Second, it is the marketing decision of similar sellers, not the focal one. Given that we controlled for seller fixed effects, the auction valuation can only correlate within sellers and is independent across sellers. Third, we tested an alternative IV for *QPRE*.

[2] We utilize the group categorization done by experts at the market. In DFA, the same flower breed is made up of one product and similar flower breeds are grouped into one product group. Product group is a higher categorization. Different breeds even in the same product group can have a very different cost structure and can be priced and valued significantly differently.

We used *Disr*, or the days on which maintenance was carried out for the presales. This limited the ability of sellers to offer lots in the presales and the time the lots were available; this external shock limiting access could also influence the total presales quantity sold for a lot. Similarly, as in the case of net effect estimations, we relaxed the day fixed effects and used week fixed effects.

As *QPRE* is censored and estimated through a Tobit model, the standard 2SLS estimation procedure where the fitted value of *QPRE*, a nonlinear variable, is used in the second stage will result in forbidden regression (Wooldridge, 2002). Following the modified 2SLS approach suggested by Wooldridge (2002, §18, §9) and Wooldridge (2008), we first used IV to estimate the fitted value of the endogenous variables, and these fitted values were used as the new instruments in the 2SLS model.

To further tackle selection bias, we also tested another model specification, where 2SLS is combined with Heckman correction (Wooldridge, 2002). A motivation for this specification is that we only observed *PPRE* for lots with presales; thus, to tease the effect of *PPRE* and *QPRE*, we truncated the data, considering only lots with presales. Wooldridge proposes a procedure to additionally tackle bias from truncation in addition to endogeneity by incorporating a Heckman correction (Heckman, 1981)—an approach to address selection bias—to the 2SLS (Wooldridge, 2002, §17). Specifically, we tested the selection model using the full data sample based on which the inverse Mills ratio is estimated. Then, we added the Mills inverse ratio term to the 2SLS estimations of Equation (2).

Finally, motivated by Lin et al. (2013) and Spence (1978), we also conducted an ex post test where we correlated the presales price with the lot return. Quality is closely related to returns and it is reasonable to expect that higher-quality lots will have a lower likelihood of being returned than lower-quality lots (Li et al., 2013). Hence if the presales price reflects a credible signal of quality, we would expect a negative correlation between the presales price and the lot return.

Results

We present the effects of *PPRE* and *QPRE* on *PAUC* and *FPR* under fixed effects estimation in Table 9. The result supports our hypothesis development in that both *PPRE* and *QPRE* have a positive significant effect on auction price and lot-weighted revenue.

Table 10 presents the results from the 2SLS estimations (Models 1-2) and the results of integrating the Heckman correction with 2SLS (Models 5-6). First, all of our IVs are significantly correlated with *PPRE* and *QPRE*. The results found in Models 3 and 4 support the suitability of the IVs. Similar to the fixed effects estimation in Table 9, we found that *PPRE* and *QPRE* are positively associated with auction price and lot-weighted revenue. An increase in the presales price of 1% is associated with a direct increase of 0.84% (β = 0.841 *SE* = 0.134) in auction price and lot-weighted revenue. An increase of 1% in presales quantity sold is associated with a 0.26% increase in the auction price (β = 0.260 *SE* = 0.131) and a similar increase in lot-weighted revenue. We also rechecked our 2SLS estimations using *Disr*, an alternative IV for *QPRE*. The results are consistent and can be found in the Appendix. Table 11 presents the ex post test result. Consistent with our hypothesis development, *PPRE* is negative and statistically significant (β = -0.086, *SE* = 0.030). Lots with higher presales prices are associated with a lower likelihood of returns.

Overall, through empirical analyses, we found that both presales price and presales quantity have a positive effect on auction prices. In addition, we also found a negative correlation between presales price and return likelihood.

Interviews with Flower Sellers

We conducted follow-up semi-structured open-ended interviews with growers at Royal FloraHolland. The aim was to obtain insights into how they use presales, how the prices are set, their experiences with the presales channel, and whether the presales price can work as a credible signal. Each in-depth interview was around 60 minutes long and conducted in Dutch. The data was then processed anonymously. The interviews with the sellers revealed that presales prices are based on historical prices, the trend in the market including special occasions (such as Valentine's Day), and the quality of particular products. Growers generally agree that quality characteristics play an important role in the price decision process with lower-quality means lowering the price. Sellers normally encounter more difficulty in successfully selling lower-quality lots unless they reduce their prices. A grower even indicated that quality can be part of the consideration of whether to make the lots available in the presales or not.

> *You have the least trouble if the presales have the best quality. So, the lower the quality, the harder it is to sell, or you have to list it at an extremely low price.*
>
> *I do not put them [lower-quality products] immediately in the presales because I think yes, if I list them a lot cheaper in the presales, that will send a signal that they are different than usual.*

Table 9. Effect of Presales Price and Presales Quantity on Auction Price and Average Lot-Weighted Revenue

Independent variables	(1) *PAUC* – Fixed effects	(2) *FPR* – Fixed effects
PPRE	0.821*** (0.022)	0.822*** (0.022)
QPRE	0.015*** (0.001)	0.018*** (0.001)
LOTSIZE	-0.057*** (0.004)	-0.058*** (0.004)
CHANNEL	0.088*** (0.023)	0.081*** (0.021)
EXP	0.264*** (0.021)	0.256*** (0.021)
TOEL	-0.097*** (0.007)	-0.093*** (0.007)
SUPPLY	-0.023*** (0.004)	-0.022*** (0.003)
N	363,721	363,721
$R2$ adjusted	0.901	0.908
Fixed effects: time, grower, product	Yes	Yes

Note: ****ρ* < 0.01, ***ρ* < 0.05, **ρ* < 0.1

Table 10. Effect of Presales Price & Quantity on Auction Price with Alternative Estimations

Independent Variables	(1) *PAUC* 2SLS	(2) *FPR* 2SLS	(3) *PPRE*	(4) *QPRE*	(5) *PAUC* 2SLS+Heckman	(6) *PPRE* 2SLS+Heckman
PPRE	0.841*** (0.134)	0.839*** (0.132)			0.820*** (0.203)	0.819*** (0.198)
QPRE	0.260** (0.131)	0.250** (0.125)			0.259* (0.147)	0.249* (0.138)
LOTSIZE	-0.161*** (0.051)	-0.157*** (0.048)	-0.100*** (0.002)	1.197*** (0.018)	-0.180*** (0.058)	-0.175*** (0.054)
CHANNEL	0.319*** (0.119)	0.299*** (0.113)	0.077*** (0.002)	-3.767*** (0.047)	0.303** (0.128)	0.284** (0.119)
EXP	0.277*** (0.085)	0.271*** (0.083)	0.670*** (0.008)	-0.325*** (0.053)	0.286** (0.131)	0.280** (0.128)
TOEL	-0.152*** (0.026)	-0.146*** (0.025)	-0.111*** (0.002)	0.838*** (0.038)	-0.161*** (0.032)	-0.154*** (0.030)
SUPPLY	0.003 (0.014)	0.002 (0.013)	-0.002 (0.002)	-0.339*** (0.021)	0.003 (0.015)	0.003 (0.014)
TEMP			0.006*** (0.001)	-0.038** (0.017)		
IV_ppre			0.146*** (0.015)	-0.344*** (0.109)		
MAR			-0.013 (0.008)	0.146** (0.071)		
IMR					-0.138** (0.060)	-0.132** (0.056)
F-statistics			20.394	10.966		
Sargan *p*-value	0.194	0.183				
Hausman *p*-value	PPRE: 0.045 QPRE: 0.011	PPRE: 0.049 QPRE: 0.012				
N	363,721	363,721	363,721	363,721	363,721	363,721
Fixed effects: time, grower, product	Yes	Yes	Yes	Yes	Yes	Yes

Note: ****ρ* < 0.01, ***ρ* < 0.05, **ρ* < 0.1

Table 11. Presales Price and Return	
Independent variables	**Return**
PPRE	-0.086** (0.030)
LOTSIZE	0.116*** (0.013)
CHANNEL	-0.323*** (0.028)
EXP	0.213*** (0.039)
TOEL	0.012 (0.025)
SUPPLY	-0.011 (0.012)
Intercept	-4.025*** (0.873)
N	363,721
Fixed effects: time, grower, product	Yes

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

Buyers do notice the effect of quantity sold, which can raise the auction prices as it can create a scarcity indication for buyers*:* "If you already sold in the presales, more and more people are getting nervous because there is less time available on the clock. Meaning that if it [the products] becomes scarcer, they will have to bet higher because otherwise they will have nothing." This further demonstrates that sellers observe buyers taking presales information into account. Consistent with our empirical analysis, some interviewees indicated that price can send a signal to buyers and some even used this to their advantage:

> *For example, a certain segment [on the clock] earns 4 euros, and we indicated in the clock presales that you [buyers] can have it for 4.20 or 4.25. When we go above 4 euros, we notice that many customers notice it and [the auction price] is ultimately 4.25. I sometimes say that it seems like it sticks to the buyers, that 4.25 is already in their heads. As soon as they start to bet, they are already around 4.25.*
>
> *You have to pay attention to make sure that you are not going to end up in a position thinking: let me drop the price because I have to get rid of them.*
>
> *[When presales were first introduced], we were in the learning process, learning what we should do: Should we set the price low or should we learn to set a higher price? Most growers set a low price to end up losing the trade while we experience if you set a low price, buyers will use it in the clock. That is what I have learned over the past three years.*

Other Robustness Tests

Our analysis is based on a big data set of nearly 1.5 million auction lots. While big data provides excellent opportunities to capture patterns that may not be observed in a smaller sample, big data analyses may face the risk of the "*p*-value problem" that picks up subtle differences with no practical value (Lin et al., 2013a). Here, as analyzed previously, an 8% increase in auction price is practically significant. Lin et al. (2013a) further suggested that when dealing with big data, a more conservative confidence interval (95% and higher) should be reported. This holds in this case, as the majority of our results are significant at the 99% level. We further reran our analysis for one randomly chosen product. The results are consistent and available in the Appendix. Lots with presales were found to have significantly higher weighted revenues and auction prices.

Additional Analysis: Sell High or Sell More

The presales quantity sold (*QPRE*) can mediate the effect of the presales price (as presented in Figure 2). The presales price (*PPRE*) can affect the presales quantity sold (β_2, can be negative and significant). At the same time, both *PPRE* and *QPRE* have effects on auction prices (β_1 and β_3 are positive and significant). Thus, the presales price, besides the direct signaling effect (β_1), can influence the auction outcome indirectly via the presales quantity sold (roughly, $\beta_2 \times \beta_3$).

Ceteris paribus, sellers face two strategies. First, they can sell high, meaning that they can increase the presales price, amplifying the direct effect of the presales price on the auction.

However, in this case, we would expect the presales quantity to decline. An alternative strategy would be to reduce the price to sell more in the presales. This reduces the direct effect of presales price but increases the effect of the quantity sold on auction outcomes. Which strategy to use depends on not only the direct effect of presales price and presales quantity but also the price elasticity in the presales, β_2.

We evaluated β_2 in this section. The direct effects of *PPRE* and *QPRE* on auction price (or β_1 and β_3) and the lot's weighted revenue were already estimated. We then followed the framework from Baron and Kenny (1986) to affirm the mediator role of *QPRE* and estimate the *total effect*, which combined both the direct effect and the indirect effect of *PPRE* on auction outcomes (roughly, $\beta_1 + \beta_2 \times \beta_3$). If the total effect of *PPRE* is positive, on average, it indicates that the selling high strategy is still more favorable than discounting the price to obtain a high auction price and a high lot revenue.

QPRE is censored in nature. Specifically, it is 0 or positive. In addition, a large proportion of this observation is at 0 (only 8% of all the lots, or around 31% of lots listed in the presales, were sold) and there is a limit to *PRESALES_AVAI* set by the grower. Such data is censored and an OLS application would hence provide inconsistent estimation (Ghose & Yao, 2011; Venkatesh & Vitalari, 1992). Even with log transformation rescaling and shifting the data set, the bounded problem remains. Thus, Tobit, which is a model technique for censored terms (further review in McDonald & Moffitt, 1980), was used to estimate the underlying effect of the presales price on the presales quantity sold. The estimated model is presented below.

$$QPRE^{*}_{igpt} = \begin{cases} X_{igpt}\delta + \varepsilon_{igpt}, \ if\ 0 < X_{igpt}\beta + \varepsilon_{igpt} < PRESALES\_AVAI_{igpt} \\ 0, \quad if\ X_{igpt}\beta + \varepsilon_{igpt} \le 0 \\ PRESALES\_AVAI_{igpt}, \ if\ X_{igpt}\beta + \varepsilon_{igpt} \ge PRESALES\_AVAI_{igpt} \end{cases} \quad (3)$$

X_{igpt} is the vector of our estimated variables, which include *PPRE*, *LOTSIZE*, *SUPPLY*, *EXP*, *GROWER*, *PRODUCT* and *TIME* fixed effects.

As a price-quantity model can inherit an endogeneity risk, we implemented a two-stage Tobit model using a control function approach (Wooldridge, 2002, §16). In the first stage, *PPRE,* the endogenous variable, was estimated using an IV. The residual from this estimation was included in the Tobit model in the second stage. The *t*-test of the coefficient of this residual term can also be used as a test for endogeneity in which the null hypothesis is that *PPRE* is exogenous (Wooldridge, 2002, §16). There are several benefits of this control function approach in estimating a Tobit model with an endogenous variable. As Phillips et al. (2015) remarked, while 2SLS models are widely used in the case of endogeneity in linear models, they cannot be easily implemented in nonlinear models. The control function approach fits well with our analyses and provides a way to test and estimate the model at the same time.

We followed the strategy from Berry et al. (1995) and used an IV that would shift the cost on the supply side but would be unlikely to shift the demand side. Sellers with cost shifts will be more likely to increase prices, but this would not influence the demand of buyers. As analyzed previously, we used temperature change and the Hausman-style instrument as IVs for our model. Both factors have been widely adopted in the previous literature (Fisher et al., 2017; Hausman, 1996; S. Lu et al., 2019; Nevo, 2001). The *F*-test supports the suitability of the instruments. The endogeneity test fails to reject the null hypothesis of exogeneity. The coefficient of the residual term is insignificant; hence, the standard Tobit model is preferred. The results of the Tobit and two-stage Tobit model illustrated in Table 12 are consistent. As the presales price increases by 1%, the quantity sold in the presales is reduced by -2.47%.

We summarize our findings in Figure 5. We observe that *PPRE* has a direct positive effect (β_1) on *PAUC*, but has a negative indirect effect via *QPRE* (roughly $\beta_2 \times \beta_3$). To confirm the total effect of *PPRE* on *PAUC* and *FPR*, we ran the generalized mediation analysis[3] developed by Imai et al. (2010) and Tingley et al. (2014). We bootstrapped 200 times. For a 1% increase in the presales price, the total effect of *PPRE* on *PAUC* is estimated at 0.222% (with a 95% confidence interval of 0.154%-0.320%) and the total effect on *FPR* is 0.174% (95% confidence interval of 0.097%-0.240%). The total effects, which combine both the direct route from signaling and the indirect root via quantity, are both significantly positive. Overall, we found that, on average, selling high is still more beneficial than selling more by discounting prices. For the robustness check, we used the causal mediation approach by Dippel et al. (2020). We note that this method assumes that *QPRE* can be modeled linearly. The results are consistent, positive, and significant (a 0.65% increase on *PAUC, SE* = 0.078, and a 0.64% increase on *FPR*, *SE* = 0.079)

[3]In our case, the mediation models involve a Tobit model with censored outcome; hence, to confirm the total effect of *PPRE*, the generalized mediation analysis approach developed by Imai et al. (2010) and Tingley et al. (2014) was used.

Table 12. Effect of Pre-sales Price on Pre-sales Quantity

Independent Variables	(1) *QPRE* *(Tobit)*	(2) *QPRE* *(Two-stage Tobit)*
Intercept	-8.488*** (1.208)	-8.879*** (1.237)
Exp	1.151*** (0.063)	0.765 (0.509)
PPRE	-2.474*** (0.049)	-1.927*** (0.737)
LOTSIZE	0.756*** (0.019)	0.819*** (0.072)
SUPPLY	-0.265*** (0.022)	-0.265*** (0.021)
Residual		-0.613 (0.739)
F-statistic		24.331
Sargan *p*-value		0.145
N	363,721	363,721
Fixed effects: time, grower, product	Yes	Yes

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

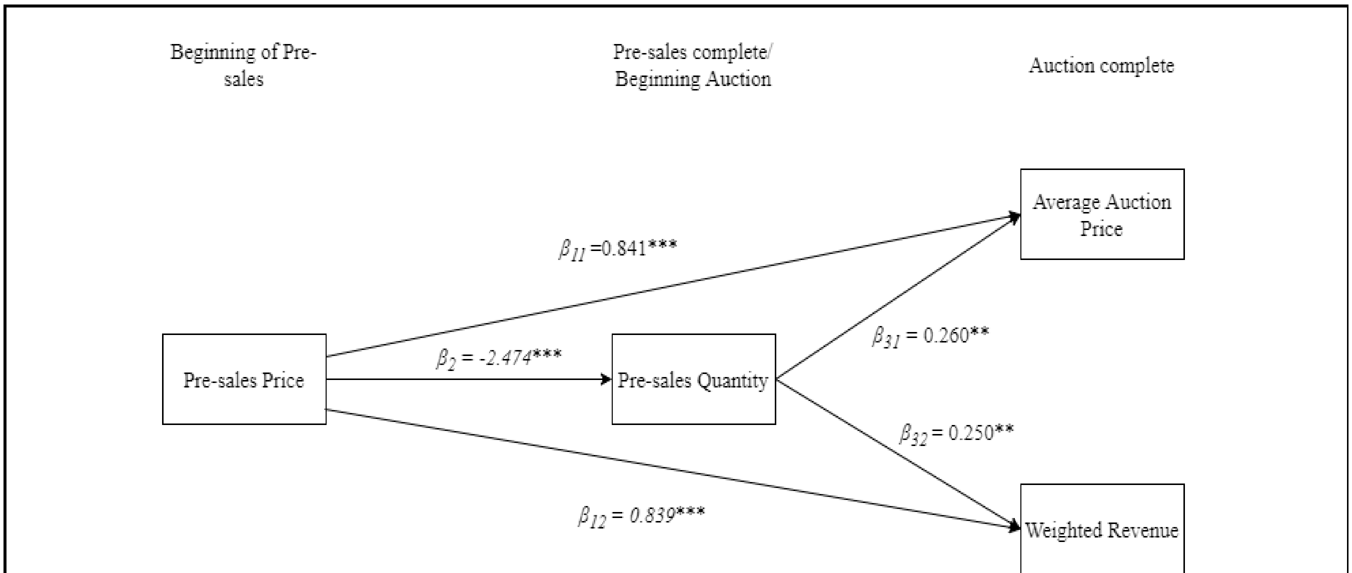

Figure 5. Mediation Results

Discussion and Conclusion

Sellers today are increasingly adopting more complex systems that involve multiple trading mechanisms. We analyzed data from 2015 on nearly 1.5 million lots of cut flowers and investigated how an online posted-price presales channel can be sequentially incorporated into a B2B multichannel Dutch auction system. As far as we are aware, this unique setting involving both the posted price and the century-old Dutch auction system, which is being increasingly adopted in B2B agricultural trade (such as in the coffee and fishery markets), remains unexplored. This is a key differentiator of our research from previous studies that compare the performance of different trading mechanisms (Wang, 1993) and examine interactions across multiple auctions (Bapna et al. 2009).

This study investigates the effect of the presales channel on auction performance. Our results indicate a positive effect of presales on growers' auction prices and lot-weighted revenue. Even when no sales occur in the presales, lots listed in presales still have a higher auction price than lots not listed in presales. This is a novel and surprising result that differs from the findings of previous studies where subsequent auctions tend to have lower prices (Ashenfelter, 1989; van den Berg et al., 2001). This work offers evidence that a multichannel auction system can provide benefits to sellers.

We explain why the presales channel matters. In a market with a high level of information asymmetry where sellers have more information about the products than buyers, as in the case of DFA, adverse selection can occur. Generally, adverse selection results in market inefficiencies and overall welfare loss. Sellers who cannot communicate their high quality fail to obtain adequate prices for their products. This can prevent transactions from taking place, and if it persists for a substantial period, sellers may drop out from the market, no longer sell the products, or reduce their prices and opt to sell products of lower quality (Akerlof, 1970; Lin et al., 2013b; Spence, 1978). We found evidence that sellers can use presales prices as quality signals for buyers, which increases auction prices. Information signaling helps to reduce adverse selection and, consequently, increases the seller's surplus and reduces market welfare loss. The results demonstrate how a posted-price presales channel, which previous research has suggested is less preferred than auctions (Wang, 1993), can add value to auction channels. Along the same lines as the parallel system in B2C (Kuruzovich & Etzion, 2017), we found a positive effect of the posted-price channel on auction prices for the B2B market. We contribute empirical evidence to the research stream and also extend it to a B2B sequential multi-unit Dutch auction system.

We further disentangle the effects of the presales price, presales quantity and auction price, and lot-weighted revenue. As previous studies have largely addressed single-unit auctions, the quantity problem is rarely discussed. We found that the presales price not only has a direct effect on auction price through a signaling mechanism, but it also can influence auction prices indirectly via the quantity sold in the presales. Our empirical estimation reveals that there is a negative indirect effect from the presales price on the auction price via presales quantity. However, this trade-off does not outweigh the positive direct effect of the presales price on the auction price. Thus, although increasing presales prices, which could reduce the quantity sold in presales, might not seem like an obvious strategy to follow, overall, it still outperforms the strategy of dropping prices in presales to produce higher sales volumes. This result offers valuable insights into information signaling and information disclosure strategies in auctions, which are still underexplored (Arora et al., 2007; Granados et al., 2010).

From the platform owner's perspective, our study evaluates the impact of the new online posted-price presales channel on auction prices and lot-weighted revenues. While there has been growth in online posted-price channels in Dutch auction markets in, for example, the agriculture sector in recent years, there is little research and few guidelines available on how the market maker should incorporate the posted-price channel. Our study addresses this issue, and the results suggest that sequential design (conducting presales prior to multi-unit Dutch auctions) is promising and worth considering for a broad range of multi-unit Dutch auction marketplaces confronting similar digitization trends. Given their positive effect on auction prices and revenue, growers should incorporate presales into their overall strategies. In addition, the results indicate that buyers pay close attention to pricing information set by sellers. The results demonstrate that it is important for growers and auctioneers participating in DFA (and multichannel Dutch auction markets in general) to not only take advantage of presales price signals but to also develop information revelation strategies that use different sources of seller-controlled information. Finally, there is evidence that the information signal can spill from one channel to another and that growers can benefit from selling high in presales rather than selling more by discounting prices.

There are many interesting potential directions for extending this research. First, the analysis is based on historical transaction data; thus, further field or laboratory experiments could be beneficial to test the results and affirm the causality. Other interesting research directions might include how the effect of presales prices on auctions changes over time and what the long-term effects might be. While our research indicates that a sell-high strategy is preferable, if presales prices are consistently kept at a (very) high level, it is questionable if the significant positive effect of presales will still hold and for how long. An analysis in this direction would be useful for sellers seeking to develop strategies for the posted-price presales channel. While we focus on the price information signal in this study, there are opportunities to further investigate the quantity side. Our interviews with the sellers suggest that scarcity is the key mechanism explaining the effect. Future work could further assess this to gain insights into how quantity information from a posted-price channel can affect auction performances in a multichannel system. Finally, it is questionable whether the effect would be homogeneous across different product groups and different customer groups. Signal effects might be more prevalent for certain markets and product segments and more harmful in other segments. The identification of such potential heterogeneous effects could help sellers to develop suitable information revelation strategies.

Acknowledgments

We would like to thank the senior editor, Siva Viswanathan, the associate editor, and the three anonymous reviewers for their valuable comments and suggestions during the review process. This research would not have been possible without the collaboration of Royal FloraHolland in the Artificial Intelligence in the Floriculture Chain (iFlow) project (2015-2020). This project was funded by Top Sector Horticulture and Starting Materials, the Netherlands.

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Appendix

Table A1. Different Fixed Effects Specifications

Independent variables	(1) *PAUC*	(2) *FPR*	(3) *PAUC*	(4) *FPR*	(5) *PAUC*	(6) *FPR*	(7) *PAUC*	(8) *FPR*
*PRESALES:*1	0.072*** (0.025)	0.079*** (0.025)	0.046*** (0.008)	0.051*** (0.008)	0.074*** (0.019)	0.080*** (0.018)	0.047*** (0.011)	0.052*** (0.012)
LOTSIZE	-0.091*** (0.008)	-0.091*** (0.008)	-0.087*** (0.005)	-0.087*** (0.005)	-0.087*** (0.006)	-0.088*** (0.006)	-0.087*** (0.005)	-0.087*** (0.005)
SUPPLY	-0.092 (0.073)	-0.092 (0.073)	-0.022*** (0.003)	-0.022*** (0.003)	-0.023*** (0.003)	-0.023*** (0.003)	-0.059 (0.044)	-0.059 (0.044)
CHANNEL	0.136*** (0.014)	0.134*** (0.014)	0.163*** (0.012)	0.161*** (0.012)	0.149*** (0.012)	0.147*** (0.012)	0.148*** (0.012)	0.146*** (0.011)
TOEL	-0.239*** (0.019)	-0.238*** (0.019)	-0.195*** (0.011)	-0.193*** (0.011)	-0.209*** (0.013)	-0.208*** (0.013)	-0.220*** (0.012)	-0.218*** (0.012)
Exp			0.810*** (0.006)	0.809*** (0.006)	0.744*** (0.011)	0.742*** (0.011)		
N	1,481,314	1,481,314	1,481,314	1,481,314	1,481,314	1,481,314	1,481,314	1,481,314
*R*2	0.840	0.841	0.814	0.815	0.827	0.828	0.827	0.828
Fixed effects	Grower-Product-Time	Grower-Product-Time	Grower-Product, Time	Grower-Product, Time	Grower-Time, Product	Grower-Time, Product	Product-Time, Grower	Product-Time, Grower

Note: ***$\rho < 0.01$, **$\rho < 0.05$, *$\rho < 0.1$

Table A2. Stratified Matching Balance Test

	Before matching			After matching		
Variable	**Mean treatment**	**Mean control**	***t*-statistic**	**Mean treatment**	**Mean control**	***t*-statistic**
LOTSIZE	6.4052	6.4674	-22.137***	6.4055	6.1013	1.1608
CHANNEL	0.7259	0.7144	15.317***	0.7283	0.7270	1.3176
SUPPLY	9.1321	9.3331	-51.673***	9.5447	9.5497	-1.0894
TOEL	0.4286	0.3891	47.456***	0.3820	0.3811	1.2357
Exp	0.3533	0.3207	50.035***	0.3556	0.3560	-0.4350
IV_Sellernum	252.0071	229.3774	37.579***	244.6826	245.1501	-0.5861

Note: ***$\rho < 0.01$, **$\rho < 0.05$, *$\rho < 0.1$

Table A3. One Random Product Result- Big White Athena Rose

Independent variables	(1) *PAUC*	(2) *FPR*	(3) PAUC	(4) *PAUC*	(5) *FPR*	(6) *QPRE*
*PRESALES:*1	0.057*** (0.011)	0.060*** (0.011)	0.056*** (0.009)			
LOTSIZE	-0.106*** (0.004)	-0.106*** (0.004)	-0.109*** (0.003)	-0.050*** (0.006)	-0.050*** (0.006)	0.317* (0.189)
SUPPLY	3.813*** (0.251)	3.807*** (0.251)	3.140*** (0.321)	0.461* (0.246)	0.431* (0.244)	16.602 (10.184)
CHANNEL	0.059*** (0.010)	0.059*** (0.010)	0.056*** (0.006)	-0.014 (0.028)	-0.015 (0.026)	
TOEL	-0.383*** (0.013)	-0.383*** (0.013)	-0.383*** (0.013)	-0.126*** (0.031)	-0.123*** (0.030)	
PPRE				0.859***	0.863***	-5.849***
				(0.036)	(0.035)	(0.481)
QPRE				0.010*** (0.002)	0.011*** (0.002)	
N	25,380	25,380	23,804	4,451	4,451	4,451
Fixed effects	Yes	Yes	Yes	Yes	Yes	

Note: ***$\rho < 0.01$, **$\rho < 0.05$, *$\rho < 0.1$

Table A4. Effect of Presales Price / Presales Quantity on Auction Price and Lot-Weighted Revenue

Independent variables	(1) *PAUC*	(2) *FPR*	(3) *PAUC*	(4) *FPR*
PPRE	0.678*** (0.097)	0.682*** (0.096)		
QPRE			-0.345*** (0.101)	-0.353*** (0.100)
LOTSIZE	-0.064*** (0.010)	-0.064*** (0.010)	0.018 (0.047)	0.022 (0.047)
CHANNEL	0.085*** (0.024)	0.074*** (0.022)	-0.191* (0.104)	-0.209** (0.101)
EXP	0.359*** (0.071)	0.350*** (0.070)	0.785*** (0.017)	0.777*** (0.017)
TOEL	-0.152*** (0.026)	-0.146*** (0.025)	-0.104*** (0.030)	-0.098*** (0.030)
SUPPLY	-0.024*** (0.004)	-0.024*** (0.003)	-0.061*** (0.011)	-0.061*** (0.011)
N	363,721	363,721	363,721	363,721
Fixed effects: time, grower, product	Yes	Yes		

Note: ***$\rho < 0.01$, **$\rho < 0.05$, *$\rho < 0.1$

Table A5. Effect of Presales Quantity on Auction Price and Lot-Weighted Revenue Using an Alternative IV for QPRE

Independent variables	(1) *PAUC* 2SLS	(2) *FPR* 2SLS	(3) *PPRE*	(4) *QPRE*
PPRE	0.697*** (0.029)	0.705*** (0.028)		
QPRE	0.051** (0.024)	0.059** (0.024)		
LOTSIZE	-0.085*** (0.010)	-0.087*** (0.009)	-0.100*** (0.009)	1.205*** (0.019)
CHANNEL	0.132*** (0.022)	0.129*** (0.022)	0.077*** (0.002)	-3.774*** (0.047)
EXP	0.350*** (0.019)	0.271*** (0.083)	0.673*** (0.010)	-0.252*** (0.051)
TOEL	-0.120*** (0.005)	-0.116*** (0.005)	-0.111*** (0.002)	0.842*** (0.038)
SUPPLY	-0.020*** (0.002)	-0.018*** (0.002)	-0.001 (0.005)	-0.305*** (0.021)
TEMP			0.005*** (0.002)	-0.047*** (0.017)
IV_ppre			0.148*** (0.019)	-0.309*** (0.109)
Disr			-0.002 (0.003)	0.208*** (0.063)
N	363,721	363,721	363,721	363,721
FE: grower, product, week, day of the week	Yes	Yes	Yes	Yes

Note: ***$\rho < 0.01$, **$\rho < 0.05$, *$\rho < 0.1$