# Applying Structural Econometric Analysis to B2B Sequential Dutch Auctions

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**Abstract**

We study multi-unit sequential Dutch auctions in a complex B2B context. Using a large real-world dataset, we apply structural econometric analysis to recover the parameters governing the distribution of bidders' valuations. The identification of these parameters allows us to simulate auction results under different designs and perform policy counterfactuals. Further, we develop a dynamic optimization approach which guides the setting of key auction parameters based on the structural estimation. Given the bounded rationality of human decision makers, we propose to augment auctioneers' capabilities with high performance decision support tools in the form of software agents. Our paper contributes to both theory and practice of auction design. From the theoretical perspective, this is the first study that explicitly models the sequential aspects of Dutch auctions using structural econometric analysis. From the managerial perspective, this paper offers useful implications to business practitioners for complex decision making in B2B auctions.

# 1 Introduction

The introduction of auctions on the Internet has opened vast new opportunities for businesses of all sizes. Unlike traditional auctions that were limited in scope, online auctions have brought this mechanism to the masses, providing them with an all-encompassing selection of products and services. With the tremendous increase of market reach, one of the key challenges is to design an auction that best meets some pre-defined goals (e.g., revenue maximization, allocative efficiency) for the given products or services and the encountered bidder population.

Beginning with the work of Vickrey (1961), a large body of literature has investigated various informational and strategic factors in auction design using the game-theoretic framework (McAfee and McMillan, 1987; Milgrom, 1989; Myerson, 1981). Despite its sharp predictions about the optimal way to design and conduct auctions, most of the existing theoretical work relies on restrictive assumptions regarding bidder behavior and rarely considers the real-world operating environment (Bapna et al., 2004; Rothkopf and Park, 2001). This highlights the necessity of studies addressing the gap between practical auction design and the predictions derived from classical auction theory.

Over the past decade, Information Systems (IS) researchers have made significant contributions to the auction research by empirical investigation of different bidding strategies and price dynamics in various online auctions (Bapna et al., 2003, 2004; Kauffman and Wood, 2006) and creation of test beds to explore different auction designs that cannot be studied analytically (Adomavicius and Gupta, 2005). However, the majority of the empirical work has exclusively focused on B2C or C2C auctions. Comparatively, little attention has been paid to B2B auctions which usually involve much higher stakes and professional bidders that participate in these bidding activities repeatedly over a long period of time.

We address the gap in literature by focusing on the design issues in an information-rich B2B market that necessitates time-critical decision making. Using a large real-world dataset that contains bids submitted through both online and offline channels, we apply structural econometric analysis (Paarsch et al., 2006) to recover the structural properties of the auction model under consideration. We then demonstrate how the structural properties, particularly the underlying distribution of bidders' valuations, can be used to perform policy counterfactuals and develop software agents (Wooldridge and Jennings, 1995) to facilitate auctioneers' decision making.

Our paper contributes to both theory and practice of auction design. From the theoretical perspective, we develop a structural model for multi-unit sequential Dutch auctions in a complex B2B context. To the best of our knowledge, this is the first study that explicitly models the sequential aspects of Dutch auctions using structural econometric analysis. In addition, current research on sequential auctions restricts attention to the sale of a single indivisible unit per round. We on the other hand deal with a more general setting where potential bidders can acquire multiple units in each round. Such multi-unit sale in each transaction makes it difficult to predict the (residual) supply and demand in the upcoming rounds and introduces extra complexities in the modeling process. Therefore, our research adds new insights to the growing literature concerning the structural estimation of auction models. From the managerial perspective, this paper offers useful implications to business practitioners for complex decision making in B2B auctions. In particular, our results suggest that the current heuristic-based approach for determining key auction parameters is far from optimal and there is ample room to improve. Given the cognitive limitations of humans, we propose to augment auctioneers' capabilities by deploying software agents equipped with domain knowledge as well as learning ability (Bichler et al., 2010). These software agents can assist auctioneers in their decision making by offering well-grounded recommendations.

# 2 Research Context

The research context for this paper is the Dutch Flower Auctions. They account for more than 60 percent of the global flower trade and serve as efficient centers for price discovery and exchange of flowers between suppliers and buyers (Kambil and Van Heck, 1998). In 2011, more than 6,000 global buyers participated in these auctions and the annual turnover of auctioned products amounts to 4.16 billion Euros. Flowers are auctioned as separate lots, which are defined as the total supply of a given homogeneous product from a given supplier on a given day. Up to 40 auctions occur simultaneously between 6:00 a.m. and 10:00 a.m. On average, each transaction takes 3 to 5 seconds. In total, roughly 125,000 transactions take place daily.

The Dutch Flower Auctions use the Dutch auction mechanism. They are implemented using fast-paced auction clocks that initially point to a high price, and then quickly tick down in a counterclockwise direction. As the price falls, each bidder, physically present in the auction hall or remotely connected via a remote bidding system, can bid by pressing a button indicating that she is willing to accept at the current price. The first bidder who makes a bid wins. The winning bidder can select the portion of the lot being auctioned (which must exceed the minimum quantity set by the auctioneer). If the winning bidder does not select the entire remaining quantity, the clock restarts at a high price and the auction continues. This process repeats until the entire lot is sold, or until the price falls below the seller's reserve price, in which case any unsold goods in that lot are destroyed.

The auctioneers in the Dutch Flower Auctions represent the growers. As such, their main objective is to realize high revenue. Besides, it is also important to achieve a quick turnaround since flowers are perishable goods. By controlling key auction parameters such as starting prices, minimum purchase quantities and reserve prices, the auctioneers can influence the dynamics of the auction. Currently, these parameters are not optimized because auctioneers cannot process all the available information from the market effectively nor efficiently to make informed decisions. They mainly rely on their experience and use their intuition to decide how to set these key auction parameters. Due to limited availability of proprietary data, empirical research concerning the design issues of the Dutch Flower Auctions is very rare. Our research is among the very first that explicitly models the sequential aspects of these auctions.

# 3 Data Description and Preliminary Analysis

Our dataset contains the transaction details of large roses at a major auction site during May and June, 2011. There are 22 attributes, two of which are bidders' real-time decision variables: price and quantity. The remaining variables can be classified into seven broad categories: (1) product characteristics (e.g., product type, stem length, bundling size and blooming scale, quality); (2) transaction timing (date, time); (3) supply-side information which includes lot size and minimum purchase quantity; (4) the precise market actors (seller and buyer); (5) logistics (stems per unit, units per trolley, number of trolleys); (6) bidding channel (online or offline); (7) clock specification (e.g., clock stand, currency unit).

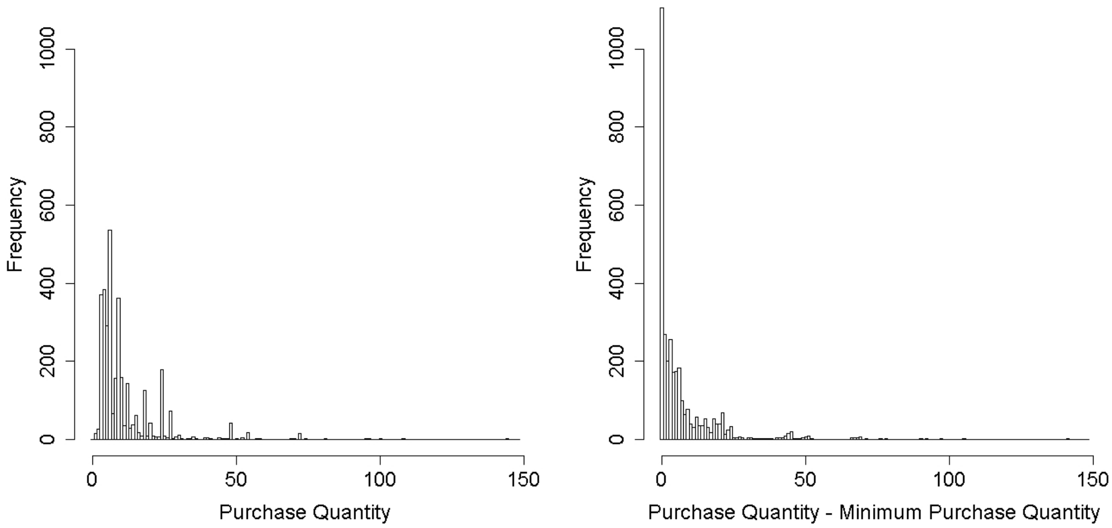
The particular product we chose to study is Avalanche Rose, because its total transaction amount was the largest among the entire assortment, and it was sold steadily throughout the two-month period. In order to rule out potential confounding factors related to flower characteristics in the structural modeling, we created a subsample where the flowers on sale were of the same stem length, bundling size, blooming scale and quality level. This left us with 3279 transactions from 349 auction lots. In total, 35196 units were sold over 43 days. Table 1 summarizes the transaction details for this subsample. We can see that both winning prices and purchase quantities vary a lot.

Table 1: Descriptive Statistics

| | Mean | Standard Deviation | Max | Min |
|---|---|---|---|---|
| Winning Price (Euro) | 0.43 | 0.12 | 1.11 | 0.16 |
| Purchase Quantity | 10.7 | 11.0 | 144 | 1 |

A major difference between the sequential auctions used in various online B2C auctions and the one used in the DFA is that bidders can purchase multiple units in each transaction in the latter setting. For example, it follows from Table 1 that a bidder can buy as much as 144 units via one bid. From the modeling perspective, bidders' purchase quantities serve as good proxy of their demand. Therefore, we also look into the underlying patterns of bidders' purchase quantities.

Figure 1a shows the histogram of bidders' purchase quantity. We can find that in most cases bidders




(a) Histogram of Purchase Quantity

(b) Histogram of Extra Purchase Quantity

Figure 1: Distribution of Purchase Quantity and Extra Purchase Quantity

purchased less than 20 units in each transaction. Further, we plot the distribution of bidders' extra purchase quantity, i.e., purchase quantity subtracted the corresponding minimum required purchase quantity in Figure 1b. The enormous amount of zeros suggests that a large portion of bidders only bought the minimum required units. Therefore, it is important for auctioneers to choose the minimum purchase quantity appropriately as the auction proceeds.

# 4 Structural Model

In this section, we first formalize the auction process and present the structural model. We then discuss the estimation method and empirical results in detail.

**Model Setup:** Consider an auction lot consisting of $l$ units. The number of rounds $K$ it takes to reach the end of the auction varies from a minimum of one, when all units are sold via a single transaction, to a theoretical maximum of $l$, when only one unit is sold via each transaction. In other words, $K$ is endogenous to the auction process. At the beginning of the auction, the clock starts at a price $s_1$ set by the auctioneer, and ticks down until one bidder stops the clock with a bid $b_1$. The winner then chooses the purchase units $q_1$. If the lot is not exhausted, i.e., $q_1 < l$, the auction proceeds to the next round with a new starting price, which is equal to the previous winning price plus an increment $c$. In other words, we have $s_j = b_{j-1} + c$ for $j = 2, \ldots, K$. Winning price $b_j$ in the $j$-th round is always between the starting price and the pre-determined reserve price $b_R$, and the number of units sold, $q_j$, varies from zero (when the price drops below $b_R$) to the total number of available units at the beginning of the $j$-th round. Further, at the beginning of each round, the auctioneer determines the minimum purchase quantity $m_j$ and we have $q_j \geq m_j$ except in the last round where occasionally the remaining units can be less than the minimum purchase quantity.

**Auctioneer's Decision Problem:** Given the $L$-unit auction, an auctioneer's key decision variables in the $j$-th round include: (1) reserve price $b_R$, (2) starting price $s_j$, (3) minimum purchase quantity $m_j$, and (4) clock speed. Currently, the reserve price is set to a negligibly low value which is fixed over the whole year and it has almost no impact on bidders' decisions. The clock speed and the increment $c$ associated with the starting price are also kept constant. Thus in practice, minimum purchase quantity $m_j$ is the only variable that auctioneers can manipulate to influence the bidding dynamics (e.g., the competition level) in a given auction. However, unlike reserve price or clock speed which has been well studied in the auction literature (Katok and Kwasnica, 2008; Levin and Smith, 1996) the effects of minimum purchase quantity is not nearly as well understood. One of the aims of this research is to develop a good understanding about the impact of minimum purchase quantity on bidders' decision-making through structural econometric analysis.

**Bidder's Decision Problem:** Bidder $i$'s decision-making process in round $j$ consists of the following steps: (1) decide whether to participate in the bidding competition, given the minimum purchase quantity $m_j$; (2) submit[1] the bid $b_j^i$, given that he decided to compete in round $j$; (3) choose the purchase quantity $q_j^i$ conditional on the fact that he is the winner of the sub-auction in

[1]All the bidders who are interested in the current round of auction can submit a bid, however, only the first (highest) bid gets revealed and recorded, i.e. we don't observe losing bids.

round $j$.

Suppose there are $N(N > 2)$ potential bidders for the current sub-auction. In the standard symmetric independent private-value (IPV) paradigm, each bidder draws his valuation $v$ independently from the value distribution function $F$ with the corresponding continuous probability density function $f$ and support $[\underline{v}, \overline{v}] \subset \mathbb{R}_+$. The Bayes-Nash, equilibrium-bid function under risk-neutrality is given by:

$$b(v) = v - \frac{\int_{\underline{v}}^{v} F(u)^{N-1} du}{F(v)^{N-1}}. \tag{1}$$

Since the winning bids as well as the winners' ID are revealed during each round of an auction, $F$ is nonparametrically identifiable given that $N$ is known (Athey and Haile, 2002). Unfortunately, it is often difficult to determine the number of potential bidders in a multi-unit sequential Dutch auction. For one thing, only winning bids are observed in Dutch auctions. This is fundamentally different from open-cry English auctions or First-price sealed bid auctions. For another, bidders can easily log in or log out with the current bidding system at any point of an on-going auction, and not all the bidders who have logged in to the current auction are truly interested in the products under auction. Instead, some might be collecting market information and preparing for their bidding in the upcoming auctions by logging in earlier than necessary. Given these considerations, we decided to model the number of potential bidders in a probabilistic way. To start with, we first give the definition of an *active* bidder.

**Definition:** A bidder is considered to be active in round $j$ if his unfulfilled demand is larger than the minimum purchase quantity $m_j$.

Let $N_j$ denote the number of active bidders in round $j$. We have

$$\mathbf{E}(N_j|m_j) = \mathbf{E}(\sum_{i=1}^{N_{total}} x_{i,j}|m_j) \tag{2}$$

where $N_{total}$ is the total number of bidders who have logged in to the current round of auction and

$x_{i,j}$ is a binary variable defined as follows:

$$x_{i,j} = \begin{cases} 0 & \text{if } D^i_j < m_j, \\ 1 & \text{if } D^i_j \geq m_j. \end{cases} \tag{3}$$

Here, $D^i_j$ stands for Bidder $i$'s demand in round $j$. Since most bidders only buy the minimum required units and the empirical distribution of bidders' extra purchase units ($D^i_j - m_j$) is over-dispersed (see Figure 1b), $D^i_j - m_j$ is modeled with zero-inflated negative binomial distribution (Wang and Boutilier, 2003; Winkelmann, 2008):

$$f_{ZINB}(D^i_j - m_j) = \begin{cases} \pi_{i,j} + (1 - \pi_{i,j}) \cdot \text{NegBin}(D^i_j - m_j) & \text{if } D^i_j = m_j, \\ (1 - \pi_{i,j}) \cdot \text{NegBin}(D^i_j - m_j) & \text{if } D^i_j > m_j, \end{cases} \tag{4}$$

where $\pi_{i,j}$ captures the probability of extra zero counts and NegBin is given by

$$\text{NegBin}(Y = y) = \frac{\Gamma(y + \tau)}{y!\Gamma(\tau)} (\frac{\tau}{\lambda + \tau})^\tau (\frac{\lambda}{\lambda + \tau})^y, \ y = 0, 1, \ldots; \lambda, \tau > 0. \tag{5}$$

$\tau$ is a shape parameter which quantifies the amount of over-dispersion, $\lambda = \mathbf{E}(Y)$ and $Y$ is the variable of interest,for example in our case $Y = D^i_j - m_j$.

Using the expected number of active bidders as the proxy of $N$ in Equation 1, we can recover the underlying distribution of bidders' valuation from the observed winning bids using the non-parametric estimation method proposed by Guerre et al. (2000). The general idea is to use the estimation of the distribution of observed bids to construct an estimate of the distribution of bidders' valuation. In the following, we will discuss the details of the estimation procedure.

**Estimation:** Let $G$ and $G_W$ denote the cumulative distribution of bidders' bids (not necessarily revealed in the auction process) and winning bids respectively. Under the symmetric IPV paradigm, we have

$$G_W(w) = G(w)^N. \tag{6}$$

For a random sample of $\mathcal{T}$ observations (denoted by $W_t, t = 1, \ldots, \mathcal{T}$) with identical number of potential bidders, we can estimate[2] $G_W(w)$ by

$$\widetilde{G}_W(w) = \frac{1}{\mathcal{T}} \sum_{t=1}^{\mathcal{T}} \mathbf{1}(W_t \leq w), \tag{7}$$

where $\mathbf{1}(\cdot)$ is the indicator function. The corresponding probability density function of winning bids $g_W(w)$ is then estimated by

$$\widetilde{g}_W(w) = \frac{1}{\mathcal{T}} \sum_{t=1}^{\mathcal{T}} \frac{1}{h} \kappa(\frac{W_t - w}{h}), \tag{8}$$

where $h$ is a sequence of bandwidth parameters such that $h$ goes to zero and $\mathcal{T}h$ goes to infinity as $\mathcal{T}$ goes to infinity. $\kappa(\cdot)$ is a kernel smoothing function. An important issue with the nonparametric estimation in Equation 8 is the trade-off between bias and variances. Here, bandwidth $h$ is similar as the bin width for histograms and it has a strong influence to the estimation results. Following the rule of thumb suggested by Silverman (1986), we choose $h$ equal to $1.06\sigma\mathcal{T}^{-1/5}$ where $\sigma$ is the standard deviation of winning bids[3]. In practice, we can use the sample standard deviation in lieu of $\sigma$.

The valuation of the highest bidder in transaction $t$ can thus be recovered by

$$\widetilde{V}_{(1:N)t} = W_t + \frac{N}{N-1} \frac{\widetilde{G}_W(W_t)}{\widetilde{g}_W(W_t)}. \tag{9}$$

Equation 9 can then by used to estimate the distribution function of the highest valuation using the

[2]In the following, we use a "$\sim$" atop a letter to denote the corresponding estimate.

[3]For more details on appropriate choices of bandwidth parameters and kernel smoothers, see Paarsch et al. (2006).

following relation:

$$\widetilde{F}_Z(z) = \frac{1}{\mathcal{T}} \sum_{t=1}^{\mathcal{T}} \mathbf{1}(\widetilde{V}_{(1:N)t} \leq z), \tag{10}$$

and bidders' value distribution can be estimated by

$$\widetilde{F}(v) = \widetilde{F}_Z(v)^{\frac{1}{N}} = [\frac{1}{\mathcal{T}} \sum_{t=1}^{\mathcal{T}} \mathbf{1}(\widetilde{V}_{(1:N)t} \leq v)]^{\frac{1}{N}}. \tag{11}$$

Similarly, the probability density function of the highest valuation can be estimated by

$$\widetilde{f}_Z(z) = \frac{1}{\mathcal{T}} \sum_{t=1}^{\mathcal{T}} \frac{1}{h} \kappa(\frac{z - \widetilde{V}_{(1:N)t}}{h}) \mathbf{1}(W_{min} + h \leq W_t \leq W_{max} - h), \tag{12}$$

where $W_{min}$ and $W_{max}$ are the minimum and maximum of the observed winning bids in the sample of $\mathcal{T}$. Finally, the probability density function of bidders' valuation can be estimated by

$$\widetilde{f}(v) = \frac{\widetilde{F}_Z(v)^{\frac{1}{N}-1} \widetilde{f}_Z(v)}{N}. \tag{13}$$

**Empirical Results:** Before we present the empirical results, we would like to briefly discuss the applicability of the above theoretical framework to the context of the Dutch Flower Auctions. First of all, according to Milgrom and Weber (1982), the IPV framework suits better than the common value framework in case of nondurable consumer goods such as flowers. In addition, the IPV paradigm can be justified by the market structure: bidders in the DFA are typically serving distinct market segments and they come to the auctions with the willingness-to-pay of their customers. In particular, most bidders have firm-specific marginal revenue curves, which lead to the variation of their valuations. Further, the risk-neutral assumption is appropriate because most bidders do not face strong budget constraints and if they lose an auction, there are often other lots available on the same day which can serve as close substitutes.

Using the transaction data described above, we recovered bidders' valuation of Avalanche Rose during the given period. The cumulative distribution functions under various minimum purchase quantities are presented in Figure 2. Although there seems to be a slightly higher percentage of low-valuation bidders (valuation between 0 and 0.2) when minimum purchase quantity is set to 1, overall, the three estimated distributions are quite similar. In other words, the potential demand heterogeneity does not seem to lead to considerable differences in bidders' value distribution. This also suggests that the way we used to model bidders' decision-making process is appropriate.

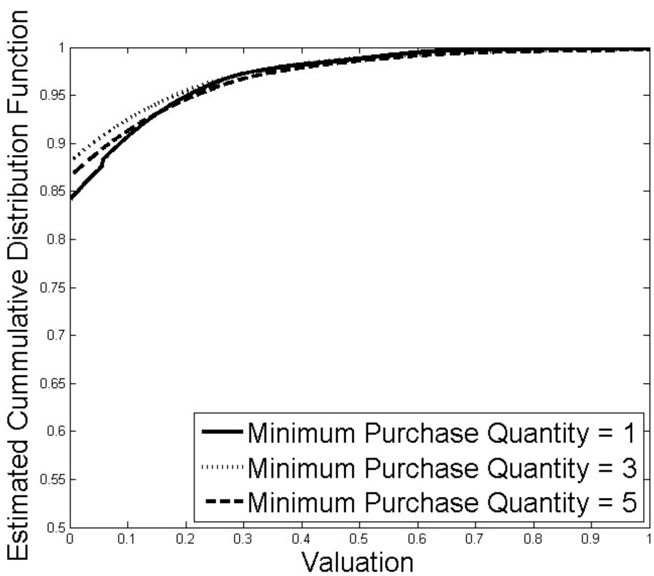



Figure 2: Estimates of Bidders' Value Distribution Functions.

Another important observation from Figure 2 is that a large percentage of logged-in bidders' valuation is below zero, meaning they are not truly interested in the current (sub) auctions they have logged in to. This is consistent with the findings by Van den Berg and van der Klaauw (2007) that while the average number of bidders registered during an auction was around 50, only 5-7 bidders were actually participating in the bidding.

We also compared the estimated bid functions under different required minimum purchase units. The results can be seen from Figure 3. Here, the main observations are: 1) bidders shade their bids considerably below their valuations in all three cases; 2) bidders with higher valuations shade more than low valuation bidders; 3) bidders, especially those with a valuation between 0.5 and 0.8, are expected to bid more aggressively in the case of low minimum purchase quantity. A possible explanation to the expected bid increase under low minimum purchase quantity is that bidders would face tougher competition and higher uncertainty on future supply (Jeitschko, 1998), since a low minimum purchase quantity attracts more bidders to participate in the bidding and opens more possibilities.

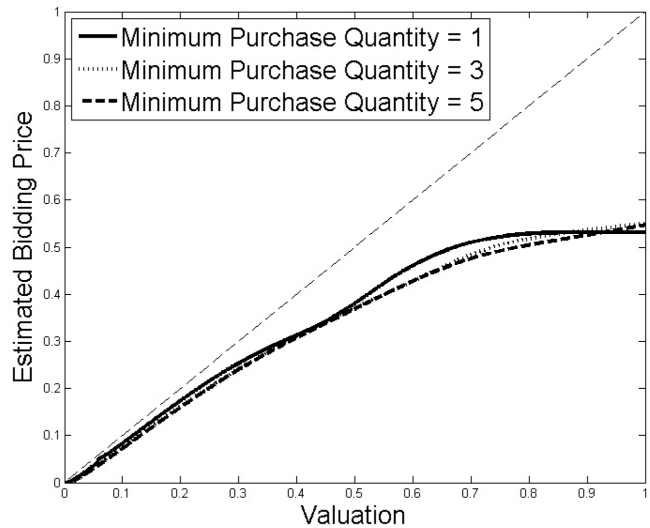



Figure 3: Estimated Bid Functions.

By explicitly recovering the distribution of bidders' valuations, we can simulate auction results under alternative auction designs and compare the resulting revenues from different designs. Further, such structural property can also be used to develop flexible decision support tools. In the next section, we will discuss how to apply the structural estimation results to study policy counterfactuals and facilitate auctioneer's real-time decision making.

# 5 Application of Structural Model

In this section, we first discuss the application of structural econometric analysis on policy guidance with a focus on the determination of minimum purchase quantities in the Dutch Flower Auctions. We then present a structural-based dynamic optimization approach which serves as the basis of the design of decision-support agents for auctioneers.

**Policy Guidance:** As we have already seen before, minimum purchase quantity has a strong impact on the bidding dynamics in the sequential rounds of the Dutch Flower Auctions. On one hand, bidders use the specific minimum purchase quantity in each round as an external reference point when determining their purchase quantities, and they are inclined to purchase the exact amount of minimum required units. Thus increasing minimum purchase quantity is often considered to be an effective way to speed up the auction process. On the other hand, a large minimum purchase quantity might deter potential bidders' entry to an auction and thus leads to less competition and low price.

Currently, auctioneers mainly rely on their intuition and experience to decide the minimum purchase quantity in each round. Typically, they set a relatively low minimum purchase quantity at the beginning and gradually increase it as the auction proceeds. A natural question is whether such heuristic-based strategy is indeed good from revenue-maximization point of view.

With the estimated value distribution, we compared the expected total revenue and market clearing speed, which is measured by the number of rounds needed to finish the given auctions, of three alternative designs where the minimum purchase quantities are set in different ways: 1) fixed design where the minimum purchase quantity is always set to 1; 2) rule-based design where the minimum purchase quantity is monotonically increasing (1, 1, 2, 2, ... and so on); 3) adaptive design where the minimum purchase quantity is determined by dynamic programming[4] with the objective to maximize the expected total revenue. As a benchmark, we also included the observed total revenue and number of rounds from the given dataset. The results are summarized in Table 2.

Table 2: Comparison of Different Auction Designs

| | Total Revenue (in Euro) | Number of Rounds |
|---|---|---|
| Observed Design (Benchmark) | 728,515 | 3,279 |
| Fixed Design | 766,452 | 3,054 |
| Rule-based Design | 704,548 | 2,948 |
| Adaptive Design | 778,207 | 3,035 |

[4] We will explain the details of dynamic programming in the second part of this section.

We can see that the observed design is neither best in terms of revenue maximization nor in terms of market-clearing speed. To our surprise, the fixed design outperforms the observed design substantially both in terms of revenue maximization and market-clearing speed. This suggests that the basic assumption underlying the heuristic strategy currently in use might not hold: increasing the minimum purchase quantity does not necessarily speed up the auction process. In fact, according to Table 2, the rule-based design where the minimum purchase quantity is increased monotonically yields only marginal improvement on market-clearing speed while incurring an extremely high cost with respect to revenue generation.

The adaptive design has the best expected performance: compared with the observed design, the total revenue increases by approximately 7% and the number of rounds reduces by more than 7%. If we compare the minimum purchase quantities set by auctioneers in the observed design and those derived from adaptive design, it turns out that the auctioneer-set minimum purchase quantities are always larger than those resulted from dynamic programming. Specifically, towards the end of an auction, the auctioneer sometimes set the minimum purchase quantity to 6 while in the adaptive design the suggested minimum purchase quantity is at most 3. The observed gap between the heuristic-based choices and the structural-model based ones reinforce our concern that intuition and experience might yield outcomes that are far from optimality in complex environment such as the Dutch Flower Auctions. In the following, we will discuss about effective decision support to auctioneers using a structural-model based dynamic optimization approach.

**Dynamic Optimization of Key Auction Parameters:** Due to cognitive and computational limitations, auctioneers cannot process all the information in the market fast enough to make informed decisions regarding the key auction parameters. A promising way to address these limitations is to augment auctioneers' capabilities with high-performance decision support tools in the form of software agents. In order to be useful, these agents must first be able to make good predictions of the future auction states.

In general, there are two different approaches to solve the prediction problem: the reduced-form approach and the structural-based approach. The former approach aims to characterize bidding dynamics and winning prices using a set of observable variables and the main advantage of this approach is that it can effectively adapt the prediction to the market dynamics. The latter approach, on the other hand, tries to map the observed bids to bidder's valuation and then use the equilibrium bid functions to make predictions. Compared with the reduced-form approach, the structural-based approach can provide normative insights into the auction process itself, and as the result, the predictions often have better interpretations. However, a key question associated with the structural-based prediction is: How can we ensure that the estimated valuation distribution is relevant to the upcoming auctions?

We propose a dynamic prediction method which combines the strengths of pure reduced-form approach and the pure structural approach. The basic idea is to incorporate rich market dynamics into the estimation of bidders' value distribution[5]. This can be done by continuously updating the training data pool: the latest transaction data is added and the earliest transaction data is discarded. Further, we need to put more emphasis on recent data since they are more informative in reflecting the market trend, especially during highly volatile period. In order to capture such change of importance over the time horizon, the transaction data used in the training pool is weighted exponentially with respect to the transaction time.

Figure 4 depicts the most important features of the dynamic training pool. The darker areas indicate higher weights. The data from this updated training pool is used to recover the valuation distribution and predict winning price in the upcoming auctions.

In order to test the performance of such dynamic prediction method, we split the original dataset into 2 parts: the first 2/3 transaction data as the initial training set and the rest 1/3 transaction data as the test set. As soon as we determine the predicted value of winning price in the upcom-

[5]Note that the updating of bidders' value distribution does not influence the validity of IPV assumption since for each bidder, the adjustment in valuation still largely depends on his private information (e.g., customer demands, market channels).

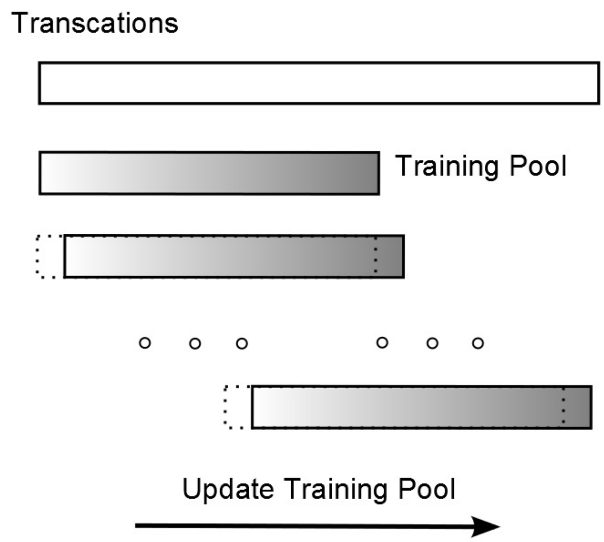



Figure 4: Dynamic Training Pool

ing transaction, the true observation associated with this transaction will be added to the training pool while the earliest observation from the training pool is removed. Therefore, the total amount of transactions used for prediction is constant during the whole procedure. We compared the observed distribution of winning bids on the test set with the estimations from the dynamic prediction method and static method where the prediction is solely based on the original 2/3 transaction data.

In Figure 5, we can see that although both the static and dynamic prediction methods somehow overestimate the proportion of low winning bid between 0 and 0.2, the estimated distribution resulting from the dynamic prediction method shows better fit with the observed distribution. We also performed Kolmogorov-Smirnov test (K-S test) to compare the two estimated distributions and the empirical distribution. For the static model, the resulting p-value is less than 0.01, suggesting the estimated distribution from static model is significantly different from the observed distribution. On the contrary, for the dynamic model, p-value from the K-S test is larger than 0.1. Thus we can conclude that the structural-based dynamic method yields quite accurate prediction. Note that a high prediction accuracy of future auction states under given auction rules and bidder population is the prerequisite for the optimization of key auction parameters and effective decision support.

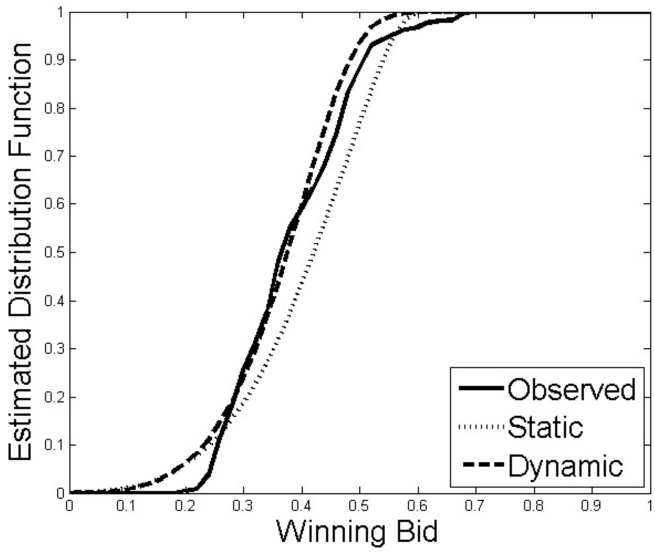



Figure 5: Winning Price Distributions

For the optimization, we also focus on the determination of minimum purchase quantities in the sequential rounds. In order to derive the optimal minimum purchase quantity for each round, we apply the dynamic programming method. Dynamic programming (Bellman, 1957) refers to a useful algorithmic paradigm where a complicated problem is solved by breaking it down into a collection of simpler sub-problems recursively and tackling them one by one. In our case, the problem faced by the auctioneers can be formulated as

$$argmax_{m_j}\mathbf{E}(\textstyle\sum_{j=1}^{K} B_jQ_j - \phi(K)|m_j), \tag{14}$$

$$\text{Subject to } \textstyle\sum_{j=1}^{K} Q_j \leq L, \tag{15}$$

$$\forall j \in \{1, \ldots, K\}, Q_j \geq m_j. \tag{16}$$

$\phi(K)$ is the penalty function depending on the total number of rounds. Since we do not have any information about the operation cost or discount factor associated with the total number of rounds, we first neglect such penalty and focus on the maximization of the expected total revenue. Given that the minimum purchase quantity in the previous rounds can influence both the winning bid and purchase quantity in the future rounds, we choose *backward induction* to solve this optimization problem.

To evaluate the performance of the proposed dynamic optimization approach, we compare its expected revenue with the observed revenue on the test set. It follows from Table 3 that the optimized design yields considerably higher revenue and such improvement does not come at the cost of market clearing speed. In fact, the expected number of rounds needed for the given auctions in the test set reduced by approximately 8% with the optimized design.

Table 3: Performance of Observed Design and Optimized Design on the Test Data

| | Total Revenue (in Euro) | Number of Rounds |
|---|---|---|
| Observed Design (Benchmark) | 237,271 | 1,232 |
| Optimized Design | 243,987 | 1,136 |

Further, we examined the expected winning prices from the dynamic optimization in the sequential rounds. From Figure 6, we can find that the optimized design yield consistently higher winning prices than the observed ones. Despite the seemingly high variation, such improvement in winning prices is significant based on the t-test (p-value $< 0.01$).

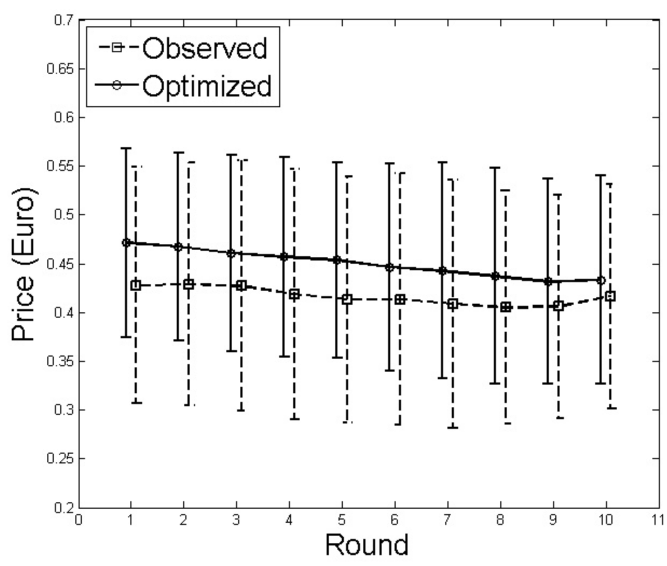



Figure 6: Comparison of Observed and Optimized Design

To this end, we have mainly focused on maximizing the total revenue for given auctions by dynamic optimizing the minimum purchase quantity in each round. However, in real-world auctions, achieving a quick turnaround is often as important as maximizing the revenue. Take the flower auction for example. On peak days such as Valentine's Day, given the extremely high demand of roses, the sellers want to push more products to the market. However, the daily auction schedule is more or less fixed from 6:00 am to 10:00 am. In order to fit in those additional auction lots to the daily schedule, it is necessary to increase the market clearing speed even at the cost of profit margin. At this point, auctioneers can leverage their vast experience to adapt the time (round) dependent penalty function in Equation 14 to the specific market condition (Ketter et al., 2012). The software agents equipped with the dynamic optimization approach can then learn the preferences of the auctioneer and make adjustments to the parametric specification of the objective function in the optimization procedure. In this sense, our dynamic optimization approach bears some similarity with the adaptive design approach proposed by Pardoe et al. (2010) where prior knowledge can be incorporated to enhance the adaptation of auction design, although the performance of the latter approach was tested on simulated data whereas our structural-based approach has demonstrated its effectiveness on the real-world transaction data from a complex B2B market.

# 6 Conclusion

We developed a structural model for multi-unit sequential Dutch auctions in a complex B2B context where auctioning and bidding decisions have to be made within a few seconds. Our work sheds lights on many important aspects in sequential Dutch auctions. For example, according to the estimated bidding functions, bidders with larger valuations tend to shade their bids more than those with lower valuations. Additionally, we also find that when deciding the purchase quantity, bidders tend to use the required minimum purchase quantity in each round as the external reference point. These results provide useful insights for understanding the bidding dynamics in multi-unit sequential Dutch auctions.

Further, we demonstrated how the structural model can be used to study policy changes and evaluate the performance of alternative auction designs. Previous studies have shown that bidders in real-world auctions often exhibit unexpected behavior and deviate from the theoretical prediction. Although a deep understanding of the behavioral aspects in the competitive bidding process will require much more empirical work, the findings from our current research provide a normative benchmark against which alternative designs can be assessed appropriately. In our case, an important finding from the policy simulation is that increasing minimum purchase quantity does not necessarily lead to the speed-up of auction process, although it often incurs a high cost of revenue because of reduced competition. As Klemperer (1999) pointed out, one of the most critical rules in auction design is encouraging entry. Therefore, we suggest that auctioneers should be more cautious when facing the trade-off between revenue and market clearing speed.

From the managerial perspective, our research provides valuable insights to the practitioners, especially the auctioneers, in their decision-making concerning the key auction parameters. In particular, we develop a structural-based dynamic optimization approach which guides the setting of key auction parameters. Given the cognitive and computational limitations of human decision makers, we propose to augment auctioneers' capabilities by deploying intelligent software agents. These agents can assist auctioneers in optimizing the key auction parameters by providing effective decision support under different market conditions.

The main limitation of this work is that we have not considered the observable or unobservable heterogeneity in the bidder population. Note that when bidders' beliefs differ for whatever reasons, i.e., the symmetric assumption does not hold, structural econometric analysis becomes much more challenging-because it is difficult to compute pure-strategy equilibrium bids or there may be no pure-strategy equilibrium bids. Additionally, in sequential auctions, bidders' subsequent valuations might also be influenced by the number of units they have won in the past. In our case, fortunately, bidders are often purchasing on behalf of their clients and they tend to have much stronger sense of valuation as well as willingness to pay. Hence the valuation during the sequential rounds is less likely to vary a lot. Nevertheless, in the future work, we will extend our model to account for heterogeneity in the bidder population and try to address the design issues in a more general setting.

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