Declining Prices in the Sequential Dutch Flower Auction of Roses

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Abstract

According to basic models of sequential private value auctions of identical objects, consecutive prices are on average constant or rising. In empirical studies, prices are often found to decline. Several explanations have been put forward for this declining price anomaly. In this paper we analyze data on sequential Dutch auctions of roses from the largest flower auction in the world. We find that there is a substantial price decline and suggest that the presence of a buyer's option, whereby the winner of the first auction has the opportunity to buy the remaining units at the winning price, is a main determinant of the observed price decline. We advance on the empirical literature on sequential auctions by using formal panel data estimation techniques.

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1   Introduction

In symmetric independent private value auctions of a single object with risk neutral bidders, the English (second price) auction has a strategic simplicity.[1] It is optimal for bidders to reveal their valuation for the object and make bids accordingly. In that case the auction is won by the person with the highest valuation who pays a price equal to the second highest valuation. In a Dutch (first price) auction, this simplicity vanishes. Here winning bidders have to pay their bid. In order to make a profit they shade their bids and bid below their valuation of the object. Somewhat loosely one may state that an English auction is truth revealing, whereas a Dutch auction requires strategic behavior. The simple structure of the one-unit English auction vanishes if two identical objects are auctioned sequentially. Now, in the first round it is optimal for bidders to shade their bids to account for the option value of participating in the subsequent second round (Weber, 1983). Bidders with a higher valuation also have a higher option value. Therefore they shade their bids in the first round by a greater amount than bidders with a lower valuation. As the auction proceeds, the number of bidders decreases. Over the sequence of auctions the number of objects decreases as well. The first has a negative effect on the competition for an object, the second has a positive effect. Both effects cancel out, and prices follow a martingale. As a result, all gains to waiting are arbitraged away and the expected prices in both rounds are the same. The latter result also holds for sequential auctions of more than two objects and does not depend on whether there is an English or a Dutch auction.

This neat theoretical result is not supported by empirical research (see e.g. Ashenfelter, 1989, who finds a price decline in a sequence of auctions of identical lots of wine). Because of the contradiction between theory and empirical studies the declining price is considered to be an anomaly.

A number of recent theoretical studies have given explanations for declining prices in sequential auctions. These can be distinguished according to whether the cause is in the preferences of the bidders, the structure of the auction, or the nature of the objects. An example of the first cause is provided by the existence of a specific type of risk aversion among the buyers (McAfee and Vincent, 1993). For another example, see Branco (1997), who considers an auction of objects of which for some bidders the value is superadditive. An example of the second cause concerns the existence of a buyer's option, whereby the winner of the first auction has the opportunity to buy the remaining objects at the win-

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[1]See McAfee and McMillan, 1987, and Wolfstetter, 1996, for surveys of the auction literature.

ning price (Black and De Meza, 1993). Other examples concern auctions where bidders or auctioneers act as agents who are instructed to win an object at any price up to a specified maximum (Milgrom and Weber, 1982b), or where bidders have to pay participation costs (Von der Fehr, 1994; Menezes and Monteiro, 1997). Engelbrecht-Wiggans (1994), Bernhardt and Scoones (1994), and Gale and Hausch (1994) relate the price decline to heterogeneity of objects. In Section 3 we discuss theoretical studies and their relevance for the present study in detail.

In this study we use data from the Aalsmeer Flower Auction (AFA) on roses to analyze price movements in sequential auctions. AFA is located in The Netherlands and is the largest auction of ornamental plant products (cut flowers, house plants etc.) in the world. AFA uses a Dutch auction to sell products. Products are supplied as "lots", which are defined as the total amount of a given product (or article) supplied by a given grower on a given day. A lot consists of a number of fully identical "units" (a unit is a fixed number of flowers, in our case a bucket of roses). The auctioning of the units of a given lot is sequential, in the following manner. Upon winning the first auction associated with a given lot, the buyer announces how many units he buys at the winning price. If this number falls short of the supplied number of units then the remaining units are auctioned in the same way, until all units are sold. AFA has a buyer's option which is often although not always exercised. Typically, a given lot is auctioned in more than a single round.

We restrict attention to so-called "specialty" roses, that is, rather expensive roses with an exclusive image. The reason for this is that these are auctioned without mandatory minimum purchase quantities. For most other types of roses, the minimum number of units to be bought at the sequential auction of a given lot increases during the sequential auctioning of a given lot. According to a survey questionnaire held among buyers at AFA, this is the main reason for the observed price declines for roses in general (see Kalicharan, 1995). We focus on specialty roses in order to be able to abstract from this potential cause of declining prices. The latter cause would be very difficult to analyze, because the auctioneer may increase the minimum purchase quantity in a way which depends on previous outcomes within the sequential auction.

The setup of our analysis is as follows. First, we establish that there is a price decline in sequential auctions of roses. We relate this to the characteristics of the auction in order to evaluate the relevance of alternative explanations for price declines that are given in the literature. Given the specific nature of the auction, we can dismiss some of these explanations. The estimation results are then used to pinpoint the most likely cause of the price declines we observe. Here,

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we focus on the shape of the price decline and the way in which this is related to observable characteristics of the auction.

There have been a number of empirical studies on sequential auctions (see references in Section 3). Many of these involve sequential auctions of objects that are not fully homogeneous, and sometimes the heterogeneous characteristic is even unobservable for the researcher. Also, many empirical studies consider only sequential auctions of limited size. Usually, only two or three objects are auctioned sequentially. In contrast, our data concern sequential auctions in which the auctioned lots consist of many units, and each lot is fully homogenous. As a result, we are able to investigate the declining price phenomenon in great detail. Our results therefore provide additional insights into the nature of the declining price phenomenon. Another distinguishing feature of the auction we consider is the fact that this is a Dutch (descending first-price) sequential auction, whereas most empirical studies in the literature deal with second-price sequential auctions.

From an econometric point of view, the empirical analysis advances on earlier studies of sequential auction data. Most of those studies analyze data by examining mean prices at different rounds in a sequential auction, or by regressing the price on the rank number of the corresponding round. However, there may be unobserved determinants of the price that are stochastically related to the rank numbers that are observed in the data. If this is ignored then such methods of inference may provide inconsistent estimates of the magnitude and significance of the price decline. To deal with this, we apply methods that are commonly used to estimate panel data. In particular, we use fixed effect regressions and first-difference regressions (see e.g. Hsiao, 1986).

The setup of this paper is as follows. In Section 2 we describe the Aalsmeer Flower Auction in detail. In Section 3 we give an overview of previous work on the declining price anomaly. Section 4 contains the empirical analysis. Section 5 concludes.

2 The Aalsmeer Flower Auction

2.1 General statistics

In this section we give some general statistics concerning the Aalsmeer Flower Auction (AFA), and we provide details of the actual auctioning process. Most of the information on the general statistics is from the Annual Reports of AFA in recent years (see e.g. Bloemenveiling Aalsmeer, 1996a).

AFA is located in Aalsmeer, close to Amsterdam, The Netherlands. It is

the largest auction of ornamental plant products (cut flowers, indoor plants, garden plants etc.) in the world. Its current annual turnover is about 2.5 billion Dutch guilders (about 1.3 billion US Dollars; 1997). AFA is a cooperative owned by about 4000 Dutch *growers* of the auctioned products. The magnitude of AFA reflects the importance of the market for ornamental plant products for the Dutch economy. Indeed, The Netherlands is the world's leading producer and distributer of cut flowers, and flowers are The Netherlands' most important export product. AFA itself employs about 1800 workers, but on a given day about 10,000 individuals do their work in the auction buildings (the latter number includes suppliers and buyers).

To give some further indication of the size of AFA, the current total annual supply consists of about 4.3 billion single flowers, 330 million indoor plants (or houseplants) and 150 million garden plants. The current annual import includes 1.8 billion single flowers. Of these, the largest shares are supplied by Israel, Kenya and Spain. The value of the current annual export of flowers and houseplants equals 4.4 and 1.8 billion guilders, respectively. For flowers, Germany, France and the United Kingdom are the most important markets, while for houseplants these are Germany, France and Italy.

The total number of growers participating in the auctions equals about 7100. Of these, almost 1500 are from abroad. The total number of buyers equals about 1700. The dispersion of their shares in total turnover is enormous. On the one hand, about 50 buyers each buy for more than 10 million guilders a year; together this amounts to about 50% of total turnover. On the other hand, about 725 buyers each buy for less than 0.1 million guilders a year; together this amounts to about 1% of total turnover. These two extremes basically correspond to big exporting companies and small domestic retail shops, respectively. Obviously the large buyers are acting as agents. For cut flowers this dispersion is similar in size. About one third of the buyers each buys for less than 0.05 million guilders per year, which together amounts to only 0.2% of total turnover in cut flowers.

Finally, it should be mentioned that roses are the most important products that are auctioned at AFA. Together, they amount to 33% of the total turnover of cut flowers.

2.2 Institutional features of the auctioning process

AFA uses a Dutch auction to sell products. As a start, consider the auctioning of a certain lot of a homogeneous product. A "lot" is defined as the total amount of a given product (or article) supplied by a given grower on a given day. The

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wall in front of the auctioning room contains a large board with a clock and an electronic display of properties of the product to be auctioned (identity of the grower, name of the product, various quality indicators, length of the stem in case of flowers and size of the flower pot in case of plants) as well as properties of the setup of the auction (monetary unit, minimum price, possibly a minimum purchase quantity). The flowers or plants are transported through the room, and an employee takes a few items from the carriage to show them to the buyers (buyers also have the opportunity to closely examine the flowers some time before the actual auctioning). The auctioneer decides on a starting position for the clock hand which corresponds to an unreasonably high price for the product. He then sets the clock in motion. The value pointed at by the clock hand[2] drops continuously until a buyer stops the clock by pushing the button in front of him. The value pointed at by the clock hand at that moment is the price to be paid by that buyer for a single item. The buyer then announces how many "units" he wants to buy. A "unit" is defined as a fixed amount of single items (e.g., for a particular type of flower, a unit can be defined as 120 flowers; this definition is fixed for a given product). The identity of the buyer is shown on the electronic display in front of the room. If the number of units he buys falls short of the supplied number of units then the clock is reset to a very high value, and the process restarts for the left-over units. If applicable, the auctioneer may decide to stipulate a different[3] minimum purchase quantity than before. Recall however that for the products analyzed in this paper the minimum purchase quantity is always simply 1. This goes on until the whole lot is sold. If the hand of the clock passes the minimum price then the remaining lot is destroyed. Every lot is auctioned in this manner.

The minimum price for a given product is fixed throughout the year (at least,

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[2] Actually, the clock is designed as a circle of small lamps each corresponding to a given monetary value, such that a clockwise movement corresponds to a decrease of this value. If the clock is set in motion then consecutive lamps light up sequentially.

[3] The auctioneers often use standard sequences for the minimum purchase quantity of a given product. For example, for tulips, in about 90% of all auctions, the minimum number of units to be bought at consecutive auctions of a given lot is stipulated according to the series $\{2, 4, 4, 6, 6, 9, 9, 9, 9, ...\}$. For roses this series usually is $\{3, 5, 9, 9, 9, 9, 9, ...\}$. However, an auctioneer may deviate from such sequences, in response to what he perceives as idiosyncratic shocks. He may even decide to deviate from the standard sequence somewhere halfway the sequential auctioning of a given lot. Apparently, the auctioneers use rules of thumb to govern such deviations. For example, they may occasionally stipulate a high minimum purchase quantity in order to try to make buyers believe that supply is short. For a small number of specific products, AFA has decided against minimum purchase quantities. These mostly concern rather expensive flowers.

for the time periods from which our data are). For example, for houseplants, the minimum price in 1996 was 25 cents per single plant, while for roses with large flowers (including specialties) it was 10 cents per flower (i.e., per item). The minimum prices are published in an annual code-book which is distributed among buyers and growers (see e.g. Bloemenveiling Aalsmeer, 1996b).

Now let us go back one step and consider how AFA chooses the order of the auctioning of different lots. AFA uses the term "auction group" to denote a group of products with similar features. For example, about 120 auction groups are defined for the 3500 varieties of cut flowers. The sequence in which auction groups appear at the auction is the same on every day. However, the sequence in which different lots within an auction group appear at the auction is randomized.

The AFA buildings contain four auction rooms. The total number of clocks equals 13. These clocks are often used at the same time, so that simultaneous auctions take place within a room. As a result, it is difficult to observe the number of participants at a given auction. A given individual can only participate in one auction, but a given buyer may of course delegate more than one individual to an auction room. The number of seats in an auction room is about 500. The average duration of a single auction (i.e., one transaction) equals just a couple of seconds. The average number of transactions per day at AFA equals about 30,000.

3 Theoretical analysis

3.1 Theoretical studies

In this section we examine the theoretical literature on prices in sequential auctions. We also investigate to what extent theoretical explanations for the declining price phenomenon apply to the Dutch flower auction.

The theoretical literature on sequential auctions is concerned with the generalization of a basic sequential auction model. This basic model assumes "independent private values" (IPV): a bidder knows his own valuation, but he only knows the distribution from which the rivals' valuations are drawn. The valuations of different bidders are independent random draws from this distribution. There are *two* fully homogeneous objects to be auctioned (so that there are two rounds in the sequential auction), each bidder only wants one object, and the bidders are risk-neutral. The auction design is second-price sealed-bid. Milgrom and Weber (1982b) and Weber (1983) show that in equilibrium, the gains of waiting are arbitraged away so that the expected prices in all rounds are the same.

Weber (1983) shows that this result also applies to the modification of the basic model where the auction design is first-price sealed-bid.

Milgrom and Weber (1982a, 1982b), among others, show that if the IPV framework is replaced by a common-value or affiliated-value framework, then this result does not hold anymore (see also the discussion in Black and De Meza, 1993). Instead, price trajectories are upward trended, notably early on in the sequential auction. Basically, early auctions release information about the value of the good, thereby reducing concerns about the winner's curse in subsequent auctions, and there is a strategic incentive to fool the other bidders into believing that the true value is low.

Ashenfelter (1989) suggests that risk aversion may explain declining prices in sequential auctions. For risk averse bidders, the randomness of the second auction reduces the value of this auction. In case two identical items are auctioned, the expected price in the second period is lower because the price in the first period also contains a risk premium associated with the risky future price. However, the theoretical analysis by McAfee and Vincent (1993) casts doubt on the relevance of risk aversion as an explanation of declining prices. They show both for first-price and for second-price sealed-bid auctions that if the bidders exhibit non-decreasing absolute risk aversion then prices tend to decline within the sequential auction. However, non-decreasing absolute risk aversion is an unsatisfactory characterization of attitudes to risk. But it is necessary to assume non-decreasing absolute risk aversion in order to obtain pure-strategy, monotonic, equilibrium bidding functions. If bidders exhibit increasing absolute risk aversion then no pure strategy equilibria exist, sequential auctions may lead to an inefficient allocation, and in that case there is an incentive for retrading after the auction.

Black and De Meza (1993) extend the basic model in two steps. First, they assume that bidders are interested in the acquisition of more than one object. The value to a bidder of acquiring two objects is assumed to be less than twice the value of a single object. So, the bidders have a high valuation for the first object and a lower valuation for the second object. They examine both second-price sealed-bid auctions and English auctions, and they show that the price tends to increase. For the special case of two bidders, this can be explained intuitively (see also Paarsch and Robert, 1996). The bid of both bidders in the first round is equal to their low valuation. That means that the bidder with the higher valuations (say, the first bidder) gets an object for a price equal to the low valuation of the second bidder. If the high valuation of the second bidder is higher than the low valuation of the first bidder who won the first round, then the

second bidder wins the second auction and pays a price equal to the low valuation of the first bidder. Since the low valuation of the first bidder is higher than the low valuation of the second bidder, the price in the second auction is higher than the price in the first. Similarly, if the high valuation of the second bidder is *lower* than the low valuation of the first bidder who won the first round, then the *first* bidder wins the second auction and pays a price equal to the high valuation of the second bidder. Since the high valuation of the second bidder is higher than the low valuation of the second bidder, the price in the second auction is again higher than the price in the first. In sum, the price tends to increase. Paarsch and Robert (1996) show that this result can be generalized to auctions of more than two objects.

In their second step, Black and De Meza (1993) show that this result can be reversed (i.e., the price tends to decline) if the auction allows for a *buyer's option* whereby the winner of the first auction has the opportunity to buy additional objects at the same price. In that case, the bidder with the lowest valuations can no longer assume that he will win at least one item if his high valuation is higher than his rival's low valuation, because this rival may win the first round and exercise the option. The winner will always exercise the option if the selling price is below his low valuation. The second bidder therefore has an incentive to bid up in the first round in order to prevent the first bidder from exercising the option. But in the two-bidder case, if the option is not exercised, the second price is the first-round winner's low valuation. Hence, the second object must necessarily sell for less than the first. It should be mentioned that if the number of bidders is larger than two then in some cases the price may actually rise, although numerical examples in Black and De Meza (1993) with three buyers suggest that on average the price declines. Interestingly, these examples also suggest that the buyer's option is in the interest of the seller. No results have been derived for auctions of three or more objects if a buyer's option is allowed.

Branco (1997) also considers an auction in which bidders are interested in the acquisition of more than one object. However, contrary to Black and De Meza (1993), he assumes that the value to a bidder of acquiring two objects is assumed to be *more* than the sum of the valuations of the separate objects. This means that preferences are *superadditive*. In his model there are two objects and two bundle bidders. Because a bundle bidder has an extra gain if he succeeds in buying both objects, both bundle bidders are more aggressive in the first auction. In the second auction only the winner of the first auction will bid aggressively. This causes the expected price to decline over the sequence of the auction.

Milgrom and Weber (1982b) argue that a price decline in sequential auctions

may arise from the presence of bidders who act as agents. These agents bid to win an object at any price up to a specific maximum price, so they do not behave strategically. If none of the other bidders bids sufficiently high, the agent with the highest maximum price wins the first auction. If, again, in the second round none of the other bidders has the highest bid the agents with the second highest maximum price wins the second auction at a price which is obviously lower than the winning price in the first auction. In the extreme case where all the bidders act as agents the first auction is won by the agent with the highest maximum price, the second auction is won by the agent with the second highest price etc..

A number of theoretical studies examine sequential auctions of objects that are in some sense perceived to be heterogeneous. It turns out that various forms of heterogeneity are able to generate declining prices (see for example Engelbrecht-Wiggans, 1994; Bernhardt and Scoones, 1994; Gale and Hausch, 1994; and Beggs and Graddy, 1997). This need not concern us here, as in this paper we deal with fully homogeneous objects.[4]

Yet another explanation of declining prices in sequential auctions considers the existence of participation costs (Von der Fehr, 1994; Menezes and Monteiro, 1997). If losing bidders in the first round realize that they only have a small probability of winning, participation costs may induce these bidders to leave the auction, which causes expected prices to decline.

Keser and Olson (1996) use laboratory experiments to study prices in sequential first-price sealed-bid IPV auctions. They too find that prices decline. In the set-up of their experiment there is no heterogeneity of objects and no buyer's option, and the bidders cannot buy more than one object. Furthermore, they find that certain features of the price outcomes cannot be explained by risk aversion, and that bidders who act as agents do not behave differently from other bidders. From this they conclude that declining prices cannot be fully attributed to risk aversion, heterogeneity, a buyer's option, the institutional structure of the English auction, bidders acting as agents, etc.. In this respect the declining price is still an anomaly. Note that the findings by Keser and Olson (1996) do not exclude the buyer's option from being a quantitatively important explanation of observed price declines in real-life auctions. The experiments merely show that even without these explanations there is a "residual" price decline.

As mentioned in the introduction, there have been a number of empirical

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[4]Bernhardt and Scoones (1994) indicate that their model probably does not explain declining prices in the case of wine auctions, for the reason that it is unlikely that a bidder's valuation would differ across identical lots of wine: "a rosé is a rosé is a rosé". This refers to our assumption that "a rose is a rose is a rose".

studies on price changes in sequential auctions, and we end this subsection by briefly mentioning some interesting results. Ashenfelter (1989) finds a mild price decrease in sequential auctions of identical units of wine, and he attributes this to risk aversion of the bidders. These auctions allow for a buyer's option. McAfee and Vincent (1993) also present empirical evidence on sequential wine auctions. They find that, on average, the second unit of wine is sold at a price 1.4% lower than the price of the first unit. Donald, Paarsch and Robert (1997) find price increases in their analysis of timber auctions where bidders are interested in more than one object. These are English auctions of homogeneous objects. The authors assume risk neutrality and decreasing marginal utility, so these results can be interpreted as a strong confirmation of the predictions derived from the Paarsch and Robert's (1996) model and from Black and De Meza's (1993) model without the buyer's option. Ginsburgh (1998) uses data on wine auctions in which the auctioneer acts as an agent for bidders who are not present at the auction. He finds price declines, but apparently the absent bidders enter bids which do not fit with the theory.

The empirical studies by Ashenfelter and Genesove (1992) (see also Laffont, 1997) and Beggs and Graddy (1997) concern heterogeneous objects. They also detect price declines. Jones, Menezes and Vella (1996) find an increasing price, apparently because the composition of the pool of bidders changes over the sequence of the auction in response to heterogeneity of the objects.

3.2   Implications for the Dutch flower auction

Before we move on to our empirical analysis, we evaluate the relevance of the results in the theoretical literature, by examining to what extent the assumptions underlying these results are valid for the Dutch flower auction. As we find strong evidence of declining prices in our data, we are more interested in explanations of price declines than in explanations of price increases.

It seems that the IPV framework is a reasonably accurate description of the valuations of bidders at AFA. Many bidders are retailers with flower shops that serve a local neighborhood. These act as monopolistic competitors on the consumption market for flowers in their neighborhood. From experience, they have an excellent knowledge of the demand functions of the products they sell to the consumers, and these functions differ across different neighborhoods. In addition to these buyers, there are also large buyers who export flowers. These are typically active in a particular geographical region, where they have some market power. Flowers are highly perishable goods, so there is no scope for extensive

retrading after the auction is held.

Are bidders at AFA risk averse, and if so, would it affect their behavior at the auction of a given lot? Often, the price of a given unit covers an extremely small fraction of the budget of a bidder. Most bidders face no strong binding financial constraints. This points towards risk neutrality, but it is difficult to assess whether the argument holds for all bidders. Other lots that are auctioned at the same day may be close substitutes for a given type of flower as supplied by a given grower. This would provide some insurance against the risk at the auction of the lot at hand. However, the "specialty" roses we consider are among the most expensive cut flowers that are available, and the range of substitutes is smaller than for bulk product flowers like most tulips.

Are bidders at AFA often interested in the acquisition of more than one unit? This seems plausible. The size of a unit is often chosen to be rather small and "handy". It is very likely that the value to a bidder of a second unit is always larger than zero. However, it is also likely that the marginal value decreases as more units are bought, so the value of two units is less than twice the value of a single unit.[5]

The AFA always allows for a buyer's option.[6] The units within a lot are fully homogeneous, so any sequential auction at AFA deals with fully homogeneous objects. Also, there may be participants who act as agents (e.g. of international trading companies). Finally, the marginal costs of participation at successive rounds within a sequential auction of a lot are zero.[7]

From all of this, we conclude the following. First, theoretical explanations based on the IPV framework seem relevant. Secondly, (some) bidders might be risk averse. We know from the previous subsection that from a theoretical point of view, risk aversion is a highly unlikely explanation, in particular if there are possibilities of retrading after the auction. Since the latter possibilities are relatively expensive in case of perishable goods like cut flowers, we do not yet exclude the possibility that risk aversion is driving the price decline. A third conclusion is that the buyer's option and/or the presence of bidders acting as agents may well explain the price decline. A fourth conclusion is that explanations

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[5] It could be argued that having multiple units generates efficiency gains in the market where the buyer sells the flowers to the consumers. However, these are probably small, and consumers typically prefer a wide variety of available flowers.

[6] Note that the availability of many close substitutes could reduce the importance of the buyer's option as a determinant of the bidders' behavior. However, recall that one may expect a relatively minor scope for substitution of "specialty" roses.

[7] The auction time is very short. Even the auction of a lot with many units only takes a couple of minutes.

based on stochastic values or heterogeneity of objects or participation costs are irrelevant. The latter is also true for explanations based on super-additivity. Note that super-additivity in combination with a buyer's option would simply imply that the highest bidder buys all the objects in the first round and a declining price could never occur. Because in the Dutch flower auction a buyer's option exists and sequences of auctions frequently occur, superadditive preferences are not present.

As a result, three possible explanations for the declining price phenomenon at the Dutch flower auction emerge: risk averse bidders, the buyer's option, and the presence of bidders acting as agents. We should however point out that the relation between the theoretical models in the literature and the actual setup of the Dutch flower auction is not always very intimate. In particular, most of the theoretical literature on sequential auctions deals with English auctions or second-price sealed-bid auctions rather than Dutch auctions. In addition, this literature often adopts a basic auction setting with a maximum of two objects to be auctioned. It remains a topic for further research to investigate to what extent the theoretical predictions in these studies carry over to sequential Dutch auctions with many objects. We return to this in Subsection 4.3. Finally, the auction setup may provide additional reasons for a price decline which have not yet been discovered, and certain aspects of the bidders' behavior may be missing from the theoretical models.

4 Empirical analysis

4.1 The data set

We use information on auctions of a particular auction group of roses (AFA code 52) for the period June 3 - August 1, 1996. In this period of 44 working days almost 24,000 lots in this group were auctioned, resulting in about 58,000 transactions. So, on average there were 550 auctions per day and 2.4 transactions per auctioned lot. The AFA code 52 roses are so-called "large flower" roses. These are relatively expensive and have an exclusive image. The length of the roses varies from 50 centimeters to over 90 centimeters. On average, the auction price of a rose increases with its length. The color of the roses may be red, brown, green, yellow, orange, purple, white, salmon, et cetera. So, there are obvious differences between the lots. The heterogeneity between the lots is also illustrated by the wide range of the item price (see below).

Figure 1 shows that there is a lot of variation concerning the number of units

per lot offered by the growers. About 3500 lots contain only 1 unit, but there are also for example about 500 lots that contain 10 units. Obviously some of the growers offer their flowers in small quantities, while others offer their flowers in vast quantities. The heterogeneity between the lots is illustrated in the wide range of the number of items (individual roses) per unit. As shown in Figure 2, there are peaks at 80, 100, 120, 140 and 160 items per unit.

Figure 3 presents the distribution of the number of transactions per auctioned lot. About 10,000 lots were auctioned in only 1 transaction, about 5,000 lots in 2 transactions, etc.. Note that to study the phenomenon of the declining auction price we need at least 2 transactions per auctioned lot. Figure 4 shows that about 23,000 transactions only concern 1 unit, about 17,000 transactions concern 2 units, about 8,000 concern 3 units etc..

The minimum price per rose is equal to 10 cents. As shown in Figure 5, for about 100 transactions the auction did not result in a price above this minimum price. About 300 transactions have a price of 11 cents, etc.. There are more than 500 transactions for every price between 20 and 76 cents. The highest price, not included in Figure 5, is 265 cents (attained in only 1 transaction).

4.2   Price determinants in auctions of roses

To proceed, we create a sub-sample in which the range of values of several variables is somewhat limited. The sub-sample contains information about lots that contain less than 11 units and have a number of items per unit of 80, 100, 120 or 140. Furthermore, the length of roses as measured in 10cm is restricted to equal 50, 60, 70, 80 or 90 centimeters. In addition, we restrict attention to the about 20 products for which the number of transactions during the period of analysis is larger than 1000. Finally, we omit information on lots of which part was destroyed because the price fell below the minimum price (13 observations). We also do not use lots in which a minimum purchase quantity was used during the sale (744 observations). The sub-sample contains information on 14,092 transactions.

We analyze the price effects of characteristics of the rose and the auction setup by estimating an equation with the log of the prices as dependent variable and several dummy variables as explanatory variables. The explanatory variables are day of the week, a quality indicator, the number of units per lot, the number of items per unit, the length of the roses and the product code. The reference group concerns Monday, high quality, 1 unit lot, 80 items/unit, length 50 centimeters and one of the product codes.

The estimation results are presented in Table 1. In general, the parameter estimates are highly significant, which is not surprising given the size of the data set. Prices are the highest on Mondays. The lowest prices are recorded on Thursdays when prices are on average 12 percent lower than on Monday. Roses which were labelled to have a low quality are on average 27% cheaper than roses without such a label. Holding everything else constant, lots of one unit have the lowest price. The price increases with more than 10 percent for lots of 2 or 3 units. Table 1 also shows that prices are on average the highest for units which contain 80 flowers. Lots that contain 100 and 120 flowers per unit are about 6 percent cheaper. Lots with 140 flowers per units are 19 percent cheaper. This may very well be caused by unobserved quality effects such that lower quality flowers are offered in larger units. The length of a rose is an important price determinant. Roses of 90 centimeter are 53 percent more expensive than roses of 50 centimeter. There are also large price differences between different product codes.

Table 1 also shows the results of a regression in which the rank number of the transaction within the sequential auctioning of the lot is included as an explanatory variable. The rank number has a positive effect on the price. Units sold in the second transaction are, on average, 1.5 percent more expensive. This results seems to contradict a declining price of sales within a lot. However, this result could be affected by unobserved quality differences. In the next subsection we examine this in more detail.

Table 2 shows the direction of the price movements between subsequent rounds within the sequential auction of a lot, distinguished by the rank number of the transaction. Considering all transactions, the number of instances where the price increases is slightly below the number of transactions where the price decreases. From the first to the second transaction the price more often increases than decreases. The opposite is the case for most of the subsequent transactions. These results do not provide conclusive evidence of either a price decline or increase. In fact, as Keser and Olson (1996) show, a comparison between the number of increases and decreases is not very informative on the importance of price declines.

4.3   Price changes in the sequential auction

A simple regression of the transaction price on the rank number of the transaction can be misleading, for two reasons. To understand the first reason, note that the maximum rank number differs across auctions of different lots. It is plausible

that the value of this maximum rank number is not exogenous, because it is an outcome of the behavior of the auction participants and may depend on realized prices earlier on in the sequential auction. Suppose that there is a characteristic of the rose or the auction setup that is unobserved to us but observed by the auction participants. This may affect both the level of the prices within the sequential auction and the number of rounds in the sequential auction. A result of this may be that a relatively high price throughout the sequential auction often goes together with a relatively large number of rounds. This means that in the data, among the realized prices at transactions with large rank numbers, there are relatively many high prices. The regression coefficient of the rank number is then biased upward (i.e., the price declines more than as suggested by the regression estimate).

A second (related) reason for why a simple regression can be misleading is that the price observations for a given sequential auction are typically not independent. There may be unobserved price determinants which affect all realized prices within a sequential auction. In that case, regressions may generate biased results even if the number of rounds would be the same for all sequential auctions. Note that this criticism also affects the results in Table 1. To a certain extent we dealt with this by allowing for fixed effects for the identity of the product.

To advance, we estimate a fixed effect model for the price as a function of the rank number of the transaction within the sequential auction. This model states that

$$\log p_{i,j} = \alpha_i + \beta_j \cdot d_{i,j} + \varepsilon_{i,j} \tag{1}$$

where $p_{i,j}$ is the price per flower in the transaction with rank number $j = 1, ..., J_i$ in the sequential auction of lot $i = 1, ..., N$. The lot-specific fixed effect α_i captures observed and unobserved heterogeneity between lots. The dummy variable $d_{i,j}$ denotes the rank number of the transaction. The series of $\beta_j (j = 2, \ldots, \max_i J_i)$ coefficients captures the price change within a lot, relative to the first transaction. These are the parameters of interest. We normalize $\beta_1 = 0$, and we define

$$\beta_j^* = \beta_j - \beta_{j-1}$$

Finally, the random variable $\varepsilon_{i,j}$ captures the remaining variation in $p_{i,j}$ and is assumed to be identically and independently distributed across i and j.

By analogy to the fixed-effect panel-data model, the β_j^* coefficients can be estimated by ordinary least squares (OLS) routines. Specifically, the fixed effects

are removed by estimating the model (1) by OLS with variables that are measured in deviation from their average over $j = 1, \ldots, J_i$. Lots that are sold in one round do not contribute to the estimation since in that case the price $\log p_{i,1}$ equals the average of $\log p_{i,j}$. Note that with this estimation approach, the effects of observed characteristics like those examined in the previous subsection are absorbed into the fixed effect and are consequently not estimated along with the β_j^* coefficients.

An alternative method to eliminate the fixed effect from the model is to take first differences of (1) for pairs of consecutive rounds. In this case, the price change from one transaction to the subsequent is directly entered as the endogenous variable in a regression. The price change from the $(j-1)^{\text{th}}$ to the jth round equals

$$\log \frac{p_{i,j}}{p_{i,j-1}} \;=\; \beta_j - \beta_{j-1} + \varepsilon_{i,j} - \varepsilon_{i,j-1} \;=\; \beta_j^* + \varepsilon_{i,j}^* \tag{2}$$

This estimation approach does not impose a priori that the fixed effect is the same in all rounds within the sequential auction of a lot. An advantage of this is that data on auctions that are finished in say j_0 rounds do not play a role in the estimation of the price changes in rounds $j > j_0$. The equations (2) can be estimated directly by OLS. The estimated coefficient is simply the average observed log price decline.

Both estimation approaches only use information on transactions *within* a sequential auction to estimate the effect of the rank number on the price. The resulting estimates are not affected by the possible biases mentioned at the beginning of the subsection.

If the specification of the model equation (1) is correct then the β_j^* estimates obtained with both approaches are asymptotically the same. In fact, they are always exactly the same for β_2^*. Moreover, if J_i does not depend on i then they are even exactly the same for all β_j^* (see Appendix I, which contains a detailed comparison of the two estimation approaches). In general, the estimates based on the fixed effect approach are more efficient than those based on first differencing.

If the sets of β_j^* estimates differ substantially then this suggests that the model is misspecified. In reality, the price may be affected by the interaction between the fixed effect and the rank number of the transaction. This means that unobserved lot-specific determinants of the price *level* also affect the amount of price *change* within the auction of the lot. In that case, auctions with many rounds may also have a different pattern of price changes than auctions that are finished in a few rounds.[8]

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[8] The unobserved lot-specific price determinants may also have a different effect on the price

For both approaches, the estimated coefficients are given in Table 3. Note that the results obtained with first differences are in fact based on separate estimations for each β_j^*, whereas the fixed effect approach estimates all coefficients together.

The empirical analysis provides very strong evidence for declining prices within the sequential auction. The point estimate for the first price change β_2^* is exactly the same under the two approaches (2.2 percent). For the subsequent rounds, the fixed effect approach generally predicts less decreasing prices than the first differences approach. With the fixed effect approach, the price change becomes insignificant after the 5$^{\text{th}}$ round. With first differences, the largest price decline is observed from the 3$^{\text{rd}}$ to the 4$^{\text{th}}$ round (2.8 percent). After that the price declines somewhat less. In Appendix 1 we show that the difference between the two sets of estimates suggests that the price decline per round is smaller in lots that are auctioned in a small number of rounds. We return to this in the next subsection.

4.4   A closer look at the price decline

In this subsection we evaluate empirical evidence for the plausibility of the three remaining explanations for the declining price at the Dutch flower auction: risk aversion, the buyer's option, and the presence of bidders who act as agents. It should be stressed from the outset that the contents of this subsection is rather speculative. Virtually all of the theoretical literature on price changes in sequential auctions deals with English auctions or second-price sealed-bid auctions rather than Dutch auctions. In addition, this literature often adopts a basic auction setting with a maximum of two objects to be auctioned. It is not certain that the theoretical predictions in these studies and the corresponding intuition always carry over to the rather specific sequential Dutch auction we consider in this paper.

The literature on the effect of the buyer's option is a case in point. Recall that Black and De Meza (1993) only examine second-price sealed-bid auctions and English auctions, and only examine auctions of two objects (so the number of rounds is at most two). Moreover, they show that if the number of bidders is larger than two then in some cases the price may actually rise, although numerical

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change at early rounds than on the price change at later rounds. For example,

$$\log p_{i,j} = \alpha_i + \beta_j \cdot d_{i,j} + \gamma_j \alpha_i \cdot d_{i,j} + \varepsilon_{i,j}$$

with additional parameters γ_j. One can think of many alternative generalizations of model (1). We do not pursue the estimation of such general models. However, in the next subsection we estimate some specific departures from model (1).

examples with three buyers suggest that on average the price declines.

In Table 4 we examine the data on lots that consist of two or three units at the beginning of the sequential auction. In particular, we show the relationship between the number of units bought and the price changes at subsequent rounds. For the 1345 two-unit lots there are two possibilities: the lot is sold in one round or in two rounds. The former applies 940 to lots while the latter applies to 405 lots. For the latter lots, the average price decline over the two subsequent auctions is 3.6%. This echoes the results of the previous subsection, and all that can be said is that it does not contradict the predicted effect of a buyer's option.

From the results in Black and De Meza (1993) it follows that the buyer's option is typically exercised if the price at the first round is low in the sense that the valuation of the actual buyer is much larger than the valuations of the other participants. As argued in the previous subsection, we do not use the data on the price levels in the empirical analysis of the price changes, because of possible endogeneity problems. To a certain extent, we can however check this prediction indirectly, using the data on the three-unit lots. If the price at a certain round is low then one may expect the subsequent price decline to be relatively small in absolute size. Therefore, one may expect to see a frequent simultaneous occurrence of the exercise of the buyer's option *with* a small subsequent price decline.

In the data on the 1099 three-unit lots there are four possible trajectories. The first is that the lot is sold in one go. In that case no price change is observed. In the second trajectory, the lot is sold in two rounds, and the buyer's option is exercised in the second round. In the third trajectory, the lot is also sold in two rounds, but the buyer's option is used in the first round when two of the three units are bought. The comparison between the price declines in the latter two trajectories confirms the above hypothesis that the exercise of the buyer's option is often followed by a small price decline.

Now let us turn to the evidence for risk aversion of bidders. Our line of reasoning is the following. If risk aversion is important, it will probably not show up in situations where the auctioned lot consists of many units and the auction has just started. On the other hand, if few units are left, the risk that no more units will be available for a subsequent sale is larger, so price declines may be expected to be larger.

As a first example we investigate auctions of ten-unit lots of which in the first auction 1 unit was sold (total of 71 transactions). This leaves 9 units to be auctioned in the second round. If one unit is sold in the second round the average price decline is 1.1% (32 transactions), if two units are sold the average

price decline is 2.3% (18 transactions), if three units are sold the average price decline is 3.5% (12 transactions). In the latter situation there are still six units left for the third round. So, even in a situation where many units are left to be bought we find a price decline.

Next, we examine the price decline between two rounds as a function of the number of units that are left at the beginning of the first of these two rounds. The results are in the first column of Table 5. Indeed, price declines are larger when there are few units left for sale. To see whether this is a specific result for the first two rounds after the moment at which few units are left, we perform the same exercise for the price change from the second to third round after that moment. The results are in the second column of Table 5. No systematic effects are found between the two columns.

However, we should be careful in deriving conclusions from Table 5. As we already saw in Table 3, price declines are especially large in the beginning of the sequential auction. Table 5 shows that price declines are large when only a few units remain to be sold. Both results can be driven by lots that consist of only a few units. When the auction starts for these lots then already in the beginning a few units remain to be sold. To distinguish between the two effects we estimate a fixed effect model in which we correct both for the rank number of the transaction and for the number of units remaining at the start of each round[9]:

$$\log \frac{p_{i,j}}{p_{i,j-1}} = \gamma_1 + \gamma_2 \cdot (j-2) + \gamma_3 \cdot (k-2) + \varepsilon_{i,j} \qquad j > 1, k > 1 \qquad (3)$$

where j refers to the rank number of the transaction and k refers to the remaining number of units *at the beginning of round $j-1$*. So, for a two-unit lot that is auctioned in two rounds, $j = k = 2$, for a three-unit lot where we consider the price change from the first to the second round $j = 2, k = 3$, for a price change from the second to the third round $j = 3, k = 2$ etc.. The reference case is a two-unit lot that is auctioned in two rounds. In this case we cannot distinguish between the effect of the rank number of the transaction and the effect of the remaining number of units. The value of γ_1 captures the price change for this case. If we find $\gamma_2 > 0$, then this is evidence that the strongest decline is early on in the auction, whereas if $\gamma_3 > 0$, then this is evidence that the strongest decline is where only a few units remain.[10]

The estimation results are in Table 6. The first column shows the estimation results if we impose $\gamma_2 = \gamma_3 = 0$. Then, we measure the average price change over

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[9] For these estimates we use lots containing 2-6 units.

[10] Note that at the end of Subsection 4.3 we found evidence of an interaction effect between j and k on the price decline. We do not pursue this further.

two subsequent auctions within the same lot. It turns out that the average price decline is 2.8%. In the second column we impose $\gamma_3 = 0$. Then, we only consider the effect of the rank number of the transaction. The resulting estimate of γ_1 is $= -2.6\%$. Furthermore, we find that $\gamma_2 < 0$, indicating that the price declines increase at the later rounds. The third column of Table 6 shows the estimation results if we impose $\gamma_2 = 0$. Now, we find that the coefficient $\gamma_3 > 0$ indicating that the fewer the remaining number of units, the larger the price decline. In the fourth column of Table 6 we show the results for the full equation. The results are similar as before albeit that now γ_2 does not differ from zero at conventional levels of significance.

Our conclusion is that the declining price is particularly important in the beginning of a sequential auction irrespective of the number of units to be auctioned. It is true that the decline is stronger the smaller the number of units that remain, but the evidence is not sufficiently unambiguous to conclude that risk aversion is an important determinant of the declining price phenomenon.

Finally, we investigate whether the phenomenon that some bidders may act as agents can explain the declining price.[11] We do this by considering whether there is a systematic difference between large and small buyers. When a purchase is made, the buyer identifier number is registered. As we saw in Section 2, the differences in buyer size are enormous. During the period under investigation, 613 different buyers bought the types of roses we consider here. The largest six buyers are responsible for 20 percent of the total sales. We classify buyers in four groups depending on their total purchase of roses. 558 buyers are classified as small buyers. They represent 30 percent of total sales. 27 buyers are classified as medium. They are responsible for 20 percent of the total sales. 22 buyers are classified as larger. Together they account for 30 percent of total sales. As mentioned, the very large buyers are responsible for the remaining sales.

Table 7 shows the relation between the rank number of the transaction and the type of buyer. No clear relationship can be found. Small buyers tend to buy relatively more often in the second and third round but the differences are small. Table 8 presents the relation between the type of buyer and the number of units that are available at the start of the sequential auction. Large buyers tend to buy more frequently when the number of units that are available is large. Large buyers apparently have a preference for buying many units of the same kind of flowers. If there is only one unit left, the majority of the buyers is small. However even the very large buyers are involved in these one-unit sales.

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[11] Within a sequence of auctions of the same lot bidders typically only buy once. We have 9 observations where a bidder is involved in two transactions within the same lot.

If the large or the very large bidders would behave as agents we would expect them to be active more frequently at the beginning of the auction, and we would expect them to be inactive when only a few units are available. This not being the case we conclude that the phenomenon that bidders act as agents is not a very important determinant of the declining prices we observe over the sequence of auctions.

5   Conclusions

By now there is a substantial literature on price movements in sequential auctions. Theoretical studies often focus on second-price auctions. Empirical analyses are often descriptive. In our paper we analyze data from the Aalsmeer Flower Auction on sequential Dutch auctions of homogeneous lots of roses. Using rather sophisticated econometric techniques, we find that there is a price decline in sequential auctions. We can dismiss some of the explanations put forward in the theoretical literature. It turns out that the explanation in terms of the presence of the buyer's option is consistent with the price declines we find in the data. Since price declines also occur in situations where there are still numerous units to be auctioned we feel that risk aversion is not a very important explanation of the declining prices of roses. From the fact that there does not seem to be a systematic difference in buyer's behavior between small and large buyers we conclude that agent behavior is not a very important determinant of the price decline either. Therefore, after a process of elimination we conclude that the presence of a buyer's option is an important determinant of the price decline of roses.

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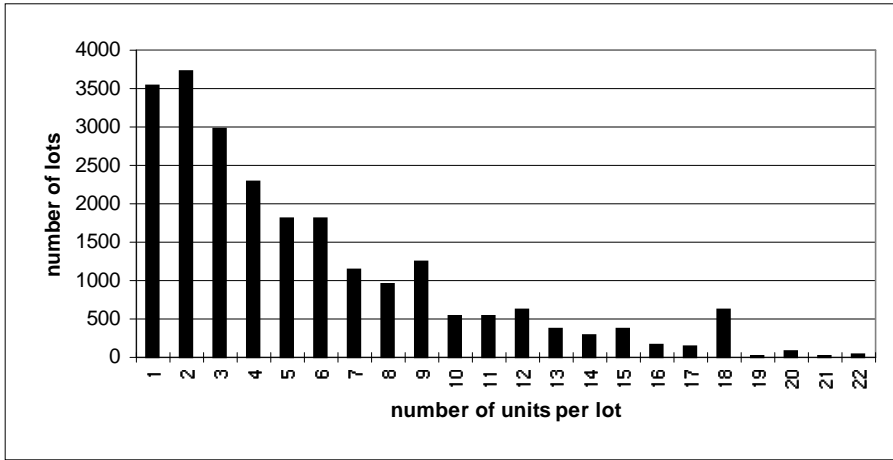Wolfstetter, E. (1996) Auctions - an Introduction, *Journal of Economic Surveys*, 10, 367–420.

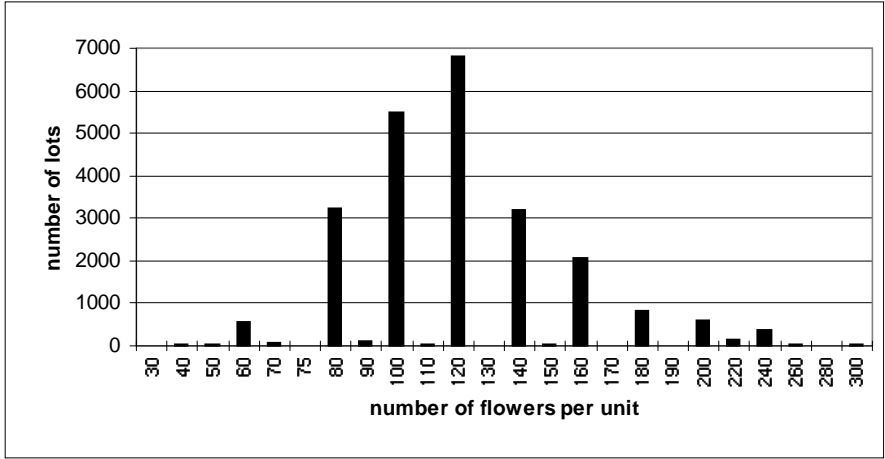Figure 1. Distribution of the number of units per lot

Figure 2. Distribution of the number of flowers (i.e. items) per unit
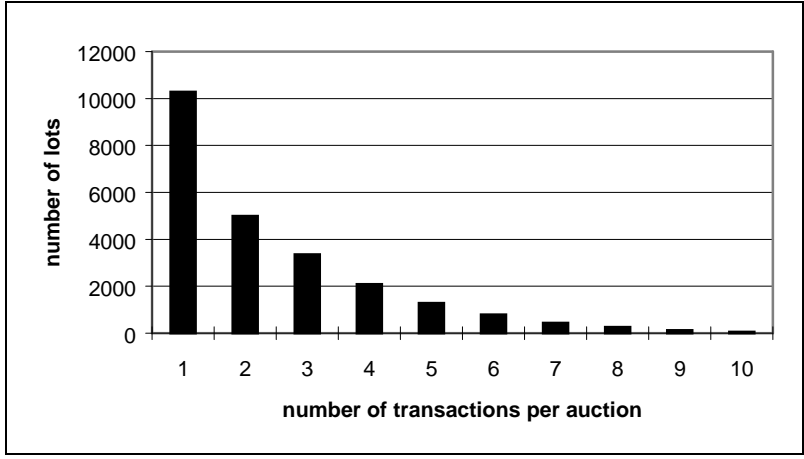

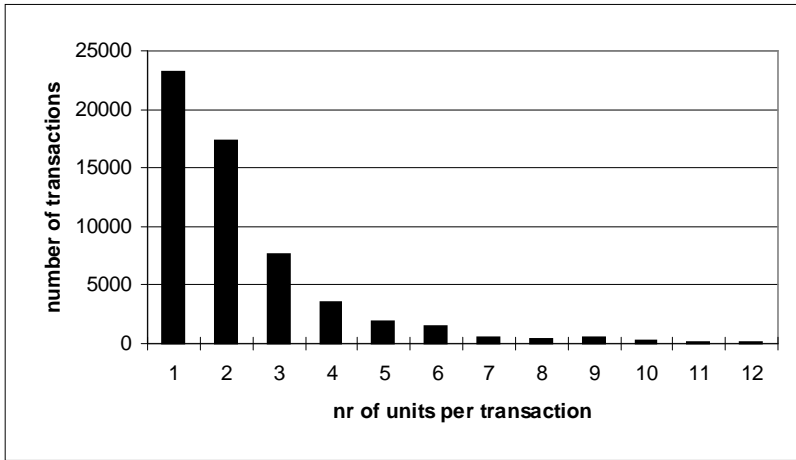Figure 3. Distribution of the number of transactions per auction of a lot

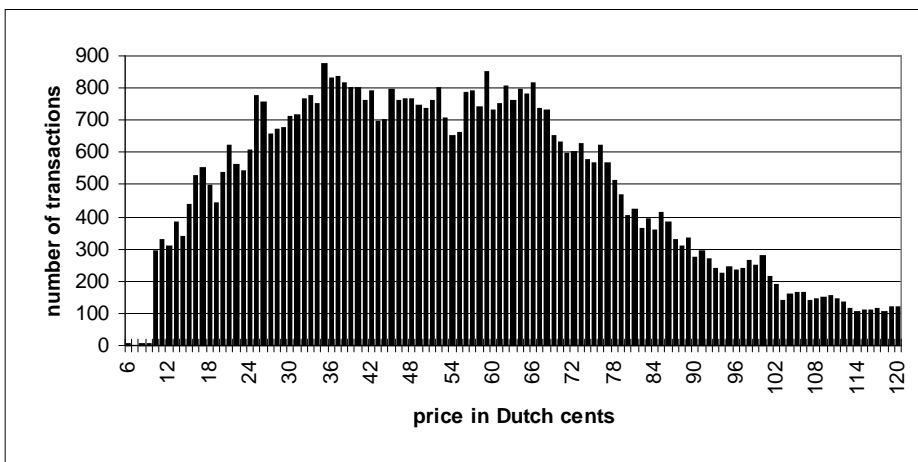Figure 4. Distribution of the number of units per transaction

Figure 5. Distribution of the price of roses

Table 1 Estimation results log price per flower with and without transaction order as regressor (t-values in parentheses)[a]

	coefficient	t-value	coefficient	t-value
Tuesday	-0.073	(-7.46)	-0.074	(-7.57)
Wednesday	-0.088	(-8.72)	-0.088	(-8.73)
Thursday	-0.118	(-11.01)	-0.118	(-11.05)
Friday	-0.032	(-3.23)	-0.033	(-3.37)
Low quality	-0.270	(-21.24)	-0.268	(-21.09)
Lot size (excluded category: 1 unit)				
2 units	0.105	(6.82)	0.103	(6.64)
3 units	0.110	(7.18)	0.104	(6.66)
4 units	0.090	(5.76)	0.079	(4.99)
5 units	0.095	(5.88)	0.081	(4.90)
6 units	0.090	(5.68)	0.073	(4.44)
7 units	0.061	(3.57)	0.041	(2.32)
8 units	0.101	(5.74)	0.076	(4.18)
9 units	0.049	(2.92)	0.021	(1.19)
10 units	0.070	(3.71)	0.040	(2.01)
Number of flowers (items) per unit (excluded category: 80 flowers)				
100	-0.076	(-5.82)	-0.075	(-5.75)
120	-0.065	(-4.73)	-0.064	(-4.65)
140	-0.195	(-11.55)	-0.193	(-11.45)
Length of flower (excluded category: 50 cm)				
60 cm	0.157	(12.62)	0.155	(12.45)
70 cm	0.317	(25.58)	0.311	(25.13)
80 cm	0.440	(32.98)	0.434	(32.47)
90 cm	0.536	(35.94)	0.529	(35.38)
Rank number of transaction (excluded category: 1)				
2			0.015	(1.83)
3			0.035	(3.32)
4			0.054	(3.71)
5			0.071	(3.18)
6			0.145	(3.70)
7			0.160	(2.17)

a)   **The estimated equations allow for fixed effects for each product code (20 in total).**

Table 2 Sign of price changes by rank numbers of the transactions (% of total)

	Rank numbers of transactions						
	1→2	2→3	3→4	4→5	5→6	6→7	all
Decline	34	42	49	47	42	19	39
Constant	20	29	30	31	38	52	24
Increase	46	29	22	22	20	30	37
nr of observations	3777	1953	867	334	100	27	7058

Table 3 Estimated price changes at successive transactions, by rank numbers of the transactions (t-values in parentheses)

	Rank numbers of the transactions					
	1→2	2→3	3→4	4→5	5→6	6→7
fixed effect approach	-0.0223	-0.0200	-0.0217	-0.0170	-0.0085	-0.0057
	(-14.57)	(-10.00)	(-7.55)	(-3.78)	(-1.07)	(-0.37)
first differences	-0.0223	-0.0261	-0.0279	-0.0268	-0.0171	-0.0066
	(-15.37)	(-16.59)	(-12.08)	(-7.86)	(-3.39)	(-0.54)

Table 4 Price changes for lots of two and three units

		price change (%)	
Two-unit lot	nr of lots	from 1st to 2nd round	from 2nd to 3rd
1 round (2 units)	940		
2 rounds (1 and 1 unit)	405	-3.57	

		price change (%)	
Three-unit lot	nr of lots	from 1st to 2nd round	from 2nd to 3rd
1 round (3 units)	463		
2 rounds (1 and 2 units)	267	-4.38	
2 rounds (2 and 1 unit)	241	-2.52	
3 rounds (3 times 1 unit)	128	-0.73	-2.18

Table 5 Price decline by number of remaining units (t-values in parentheses)

	price decline	
nr of units left before sale	first to second	second to third
2	-0.0357 (-7.45)	-0.0266 (-5.49)
3	-0.0294 (-7.94)	-0.0333 (-8.39)
4	-0.0235 (-6.83)	-0.0234 (-6.15)
5	-0.0216 (-5.32)	-0.0307 (-7.68)
6	-0.0206 (-4.87)	-0.0165 (-4.70)
7	-0.0163 (-3.34)	-0.0182 (-4.72)
8	-0.0064 (-1.74)	-0.0269 (-5.02)
9	-0.0194 (-4.10)	-0.0294 (-3.41)
10	-0.0112 (-1.84)	no observations

Table 6 Estimation results for the effects of the rank number of the transaction and the number of remaining units (coefficients * 100; t-values in parentheses)

	1	2	3	4
Constant	-2.75 (20.3)	-2.58 (16.0)	-3.31 (14.4)	-3.13 (11.4)
j-2	-	-0.39 (2.0)	-	-0.24 (1.2)
k-2	-	-	0.31 (3.0)	0.28 (2.5)

Table 7 Size of buyer by rank number of transaction (percentages, number of transactions)

Rank number	size of buyer (row %)				number of transactions
	small	medium	Large	very large	
1	38	17	29	15	7034
2	44	18	27	10	3777
3	45	18	27	10	1953
4	40	18	29	13	867
5	42	21	26	12	334
6	40	16	30	14	100
7	26	17	48	9	23
8	100	0	0	0	4
Total	41	18	28	13	14092

Table 8 Size of buyer by number of units left for sale (percentages, number of transactions)

nr of units left for sale	type of buyer				number of transactions
	small	middle	large	very large	
1	51	15	25	9	2485
2	41	17	29	14	3028
3	40	18	29	13	2281
4	38	19	31	12	1843
5	38	20	29	14	1328
6	37	20	29	15	1148
7	36	19	30	15	740
8	39	19	30	12	549
9	35	22	26	17	477
10	34	19	29	17	213
total	41	18	28	13	14092

Appendix I. Fixed effects versus first differences

First we show that if the number of transactions is the same for each lot, then the fixed effect approach is equivalent to estimation in first differences. Suppressing the error term, the model can be written as

$$y_{ij} = \alpha_i + \sum_{k=1}^{J} I_{ij} \beta_k \qquad j = 1,\ldots,J \qquad i = 1,\ldots,N \tag{1}$$

where
i	= indicator for lot ,
j	= rank number of transaction within lot,
y	= log(price per flower in round j for lot i)
I_{ij}	= 1 if $j=k$,
	= 0 otherwise.

The fixed effects can be eliminated by rewriting this in differences from the cluster (lot) means. In matrix notation

$$My = MX\beta \tag{2}$$

with

$$M = \begin{bmatrix} M_J & 0 & 0 \\ 0 & .. & 0 \\ 0 & 0 & M_J \end{bmatrix} , \quad X = \begin{bmatrix} I_J \\ .. \\ I_J \end{bmatrix}, \quad y = \begin{bmatrix} y_1 \\ .. \\ y_N \end{bmatrix} \text{and } \beta = \begin{pmatrix} \beta_1 & .. & \beta_J \end{pmatrix}'$$

where

$$y_i = \begin{pmatrix} y_{i1} & ... & y_{iJ} \end{pmatrix}' \text{ and } M_J = I_J - \frac{1}{J} \iota_J \iota_J'.$$

The J normal equations can be written as

$$\sum_{i=1}^{N} M_J y_i = N\, M_J \hat{\beta} \tag{3}$$

The estimated price change from the jth to the $(j+1)^{th}$ round is defined as $(\hat{\beta}_j - \hat{\beta}_{j+1})$. The matrix M_J takes differences from the means. By subtracting the $(j+1)^{th}$ from the jth normal equation this mean cancels out. Hence,

$$(\hat{\beta}_j - \hat{\beta}_{j+1}) = \frac{1}{N} \sum_{i=1}^{N} y_{ij} - y_{i(j+1)} \tag{4}$$

The estimated price change from the jth to the $(j+1)^{th}$ round is estimated by the average log price difference from j^{th} to the $(j+1)^{th}$ round. The same estimate results from estimating the model in first differences. Suppressing the error term, the first difference specification for the price change from the jth to the $(j+1)^{th}$ round is

$$y_{ij} - y_{i(j+1)} = \gamma_j \qquad i=1,\ldots,N \tag{5}$$

where γ_j is defined as the price change. It follows directly that

$$\hat{\gamma}_j = (\hat{\beta}_j - \hat{\beta}_{j+1}) \ . \tag{6}$$

In our application, the total number of rounds varies across lots. We show that in that case the estimators with the fixed effect approach and those based on first differences are generally not the same. Define J_i as the total number of rounds for lot i and let $J=\max(J_1,\dots,J_N)$. Maintaining the same notation, the fixed effect equations can now be written as

$$My = MX\beta \tag{7}$$

with

$$M = \begin{bmatrix} M_{J_1} & 0 & 0 \\ 0 & .. & 0 \\ 0 & 0 & M_{J_N} \end{bmatrix} , \quad X = \begin{bmatrix} \tilde{I}_{J_1} \\ .. \\ \tilde{I}_{J_N} \end{bmatrix} , \quad y = \begin{bmatrix} y_1 \\ .. \\ y_N \end{bmatrix} \text{and } \beta = \begin{pmatrix} \beta_1 & .. & \beta_J \end{pmatrix}'$$

where

$\tilde{I}_{J_i} = \begin{bmatrix} I_{J_j} & \varnothing \end{bmatrix}$ with dimension $(J_i \times J)$ and

$y_i = \begin{pmatrix} y_{i1} & \dots & y_{iJ_i} \end{pmatrix}'$ and $M_{J_i} = I_{J_i} - \dfrac{1}{J_i}\iota_{J_i}\iota'_{J_i}$.

The normal equations can now be written as

$$\sum_{i=1}^{N} \tilde{M}_{J_i}\tilde{y}_i = \sum_{j=2}^{J} N_j \tilde{M}_j \hat{\beta} \tag{8}$$

where

$\tilde{M}_j = \begin{bmatrix} M_j & \varnothing \\ \varnothing & \varnothing \end{bmatrix}$, $\tilde{y}'_i = \begin{pmatrix} y'_i & \varnothing \end{pmatrix}$ and

N_j = the number of lots which are sold in j rounds.

Lots which are sold in 1 round are excluded, since the price then equals the fixed effect of the lot. Since all other lots are sold in at least 2 rounds, the estimated price change when going from the first to second round is the same as before

$$\left(\hat{\beta}_1 - \hat{\beta}_2\right) = \frac{1}{\displaystyle\sum_{j=2}^{J} N_j} \sum_{i=1}^{N} \left(y_{i1} - y_{i2}\right) \tag{9}$$

This is identical to the estimator for the first differences approach.

The estimators of the price change when going from the second to third round is not the same for the two approaches. For the fixed effect approach, subtracting the third from the second normal equation yields

$$\sum_{j=3}^{J} N_j\left(\hat{\beta}_2 - \hat{\beta}_3\right) + N_2\left(\hat{\beta}_2 - \tfrac{1}{2}\left(\hat{\beta}_1 + \hat{\beta}_2\right)\right) = \sum_{i=1}^{N}\left(y_{2i} - y_{3i}\right)I_{(J_i>2)} + \sum_{i=1}^{N}\left(y_{2i} - \bar{y}_i\right)I_{(J_i=2)} \tag{10}$$

Rearranging terms yields

$$\sum_{j=3}^{J} N_j \left(\hat{\beta}_2 - \hat{\beta}_3 \right) - \frac{N_2}{2} \left(\hat{\beta}_1 - \hat{\beta}_2 \right) = \sum_{i=1}^{N} (y_{2i} - y_{3i}) I_{(J_i > 2)} + \sum_{i=1}^{N} (y_{2i} - \bar{y}_i) I_{(J_i = 2)} \qquad (11)$$

in which (9) can be substituted. This yields an expression for $\left(\hat{\beta}_2 - \hat{\beta}_3 \right)$.

Taking first differences yields the following estimator for the price change when going from the second to third round,

$$\sum_{j=3}^{J} N_j \left(\hat{\beta}_2 - \hat{\beta}_3 \right) = \sum_{i=1}^{N} (y_{2i} - y_{3i}) I_{(J_i > 2)} \qquad (12)$$

The two estimators are clearly different if $N_2 > 0$ and $N_3 + N_4 + \ldots > 0$. A similar argument can be made for price changes in subsequent transactions.

Using (10) we can say something about how the two estimators compare. If the average price decline from the first to second round is larger in the lots that are sold in two rounds than in the whole sample, then the value of the fixed effect estimate of $\left(\hat{\beta}_2 - \hat{\beta}_3 \right)$ will be more negative than the value of the estimate based on first differences.