The Declining Price Anomaly in Dutch Dutch Rose Auctions

By Gerard J. van den Berg, Jan C. van Ours, and Menno P. Pradhan*

In symmetric, independent, private-value auctions of a single object, with risk-neutral bidders, the English (second-price) auction has strategic simplicity.1 It is optimal for bidders to reveal their valuation of 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. 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 (Robert J. 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 do 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 fact has a negative effect on the competition for an object and the second has a positive effect. Both effects cancel out and prices follow a martingale. As a result, all gains to waiting are arbitrated 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 the auction is English or Dutch.

This neat theoretical result is not supported by empirical research, which usually finds price declines. Orley Ashenfelter (1989) found a mild price decrease in sequential auctions of identical units of wine. McAfee and Daniel Vincent (1993) also present empirical evidence on sequential wine auctions. They found that, on average, the second unit of wine was sold at a price 1.4 percent lower than the price of the first unit. Victor Ginsburgh (1998) uses data from wine auctions in which the auctioneer acted as an agent for bidders who were not present at the auction. He found price declines but, apparently, the absent bidders entered bids that did not fit with the theory. Empirical studies by Ashenfelter and David Genesove (1992) (see also Jean-Jacques Laffont, 1997) and Alan Begg and Kathryn Graddy (1997) concern heterogeneous objects. They also detected price declines. Because of the contradiction between theory and empirical studies, the declining price phenomenon is regarded to be an anomaly.2,3


2. A few empirical studies find price increases. Stephen G. Donald et al. (1997) find this in their analysis of timber auctions where bidders were interested in more than one object. These were English auctions of homogeneous objects. Chris Jones et al. (1996) find an increasing price, apparently because the composition of the pool of bidders changed over the sequence of the auction in response to heterogeneity of the objects.

3. A number of recent theoretical studies provide explanations for declining prices in sequential auctions. For example, McAfee and Vincent (1993) require the existence of an unconventional type of risk aversion among buyers. Fernando Branco (1997) assumes that the value of the objects is superadditive for some bidders. Jane Black and David de Meza (1992) assume the existence of a “buyer’s option” or “parcel option” whereby the winner of the first round has the opportunity to buy the remaining objects at the winning price. Incidentally, Ashenfelter (1989) shows

* van den Berg: Department of Economics, Free University Amsterdam, De Boelelaan 1105, 1081 HV Amsterdam, Tinbergen Institute, and CEPR (e-mail: gberg@econ.vu.nl); van Ours: Center for Economic Research, Tilburg University, P.O. Box 90153, 5000 LE Tilburg, The Netherlands, and CEPR (e-mail: vanours@kub.nl); Pradhan: Economic and Social Institute, Free University Amsterdam, De Boelelaan 1105, 1081 HV Amsterdam (e-mail: mpradhan@econ.vu.nl). The authors thank the Aalsmeer Flower Auction for the use of their data, helpful suggestions, and financial support; Maarten Cornet, Victor Ginsburgh, Jan Potters, Michael Visser, and two anonymous referees for comments; Baukje Gietema for computational assistance; and participants of seminars and workshops in Austin (TU), London (UCL), Berlin (ESEM 98), and Louvain-la-Neuve for comments.
The present paper contributes to the empirical literature on declining prices. We use data on roses from the Aalsmeer Flower Auction (AFA) to analyze price movements in sequential auctions. The AFA is located in The Netherlands and uses a Dutch (descending first-price) 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. Typically, there is more than one round per auction.

Many of the earlier empirical studies of sequential auctions consider the auctioning of objects that are not fully homogeneous; sometimes the heterogeneous characteristic was unobservable to the researcher. Also, many empirical studies restrict their attention to sequential auctions of limited size. Usually, only two or three objects are auctioned sequentially. In contrast, our data concern sequential auctions in which auctioned lots consist of many units and each lot is fully homogenous. Our results therefore provide additional insight into the nature of the declining-price phenomenon. Another distinguishing feature of the auction under consideration is the fact that it is a Dutch (descending first-price) sequential auction whereas the other empirical studies in the literature deal with second-price sequential auctions.

Most of the earlier studies of sequential auction data examine mean prices at different rounds in a sequential auction and/or regress the price on the rank number of the corresponding round. However, there may be unobserved determinants of price that are stochastically related to the rank numbers that are observed in the data. If this is ignored, such methods of inference may provide inconsistent estimates of the magnitude and significance of price decline. In our empirical analysis, we take this heterogeneity into account.

I. The Aalsmeer Flower Auction

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

The 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. In 1997, approximately 4.3 billion single flowers, 330 million indoor plants (or houseplants), and 150 million garden plants were traded. The value of the current annual export of flowers equals 4.4 billion guilders (about 2 billion U.S. dollars). Roses are the most important products that are auctioned at the AFA. They amount to 33 percent of the total turnover of cut flowers.

The total number of growers who bring products to the auction is approximately 7,100. The total number of buyers per year is approximately 1,700. The dispersion of their shares in total turnover is enormous. On the one hand, approximately 50 buyers each buy more than 10 million guilders worth of merchandise a year; this amounts to approximately 50 percent of total turnover. On the other hand, approximately 725 buyers each buy less than 0.1 million guilders worth of merchandise a year; this amounts to approximately 1 percent of total turnover. These two extremes basically correspond to big exporting companies and small domestic retail shops, respectively. Obviously, some of the large buyers resell to other companies (abroad). For cut flowers, the dispersion in size is similar. Approximately one-third of the buyers each buy less than 0.05 million guilders worth of merchandise per year, which amounts to only 0.2 percent of the total turnover in cut flowers.

The AFA uses a Dutch auction to sell products. As a starting point, consider the auctioning of a certain “lot” of a homogeneous product. The wall in front of the auctioning room contains a large board with a clock and an electronic display of the properties of the product to

that this does not explain the price decline in the data. Paul Milgrom and Robert J. Weber (1982) assume that bidders or auctioneers acts as agents who are instructed to win an object at any price, up to a specified maximum. Nils-Henrik M. von der Fehr (1994) and Flavio M. Menezes and Paulo K. Monteiro (1997) assume that bidders have to pay participation costs. Dan Bernhardt and David Scoones (1994), Richard Engelbrecht-Wiggans (1994), and Ian L. Gale and Donald B. Haush (1994) explain the price decline by heterogeneity of the objects.
be auctioned (identity of the grower, name of the product, various quality indicators, length of the stem for flowers and size of the flower pot for plants) as well as properties of the setup of the auction (monetary unit, minimum price). 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 that corresponds to an unreasonably high price for the product. He then sets the clock in motion. The value pointed at by the clock hand\(^4\) drops continuously until a buyer stops the clock by pushing a 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, so there is a “buyer’s option” or “parcel option.” 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, the clock is reset to a very high value and the process restarts for the remaining units. This goes on until the whole lot is sold. So, there is a buyer’s option at each round unless only one unit is left. If the hand of the clock passes the minimum price, the remainder of the lot is destroyed. Each lot is auctioned in this manner.

The minimum price for a given product is fixed throughout the year (at least for the time periods from which we extracted our data). For the products in our analysis, the minimum price equals 10 cents per flower (i.e., per item; a Dutch cent equals 0.01 guilder). The minimum prices are published in an annual codebook that is distributed among buyers and growers (see, e.g., Bloemenveiling Aalsmeer, 1996b).

Now, let us go back one step and consider how the AFA chooses the order of the auctioning of different lots. The AFA uses the term “auction group” to denote a group of products with similar features. For example, approximately 120 auction groups are defined for 3,500 varieties of cut flowers. The sequence in which auction groups appear at the auction is the same every day. However, the sequence in which different lots within an auction group appear at the auction is randomized. Note that, by definition, different lots concern different products, if only because the identity of the grower is different.

The AFA buildings contain four auction rooms and a total of 13 clocks. 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 approximately 500. The average duration of a single auction (i.e., one transaction) is just a couple of seconds. The average number of transactions per day at the AFA is approximately 30,000.

II. Empirical Analysis

A. 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. This concerns so-called “large flower” roses, which are relatively expensive and have an exclusive image. We restrict our attention to these products because the mandatory minimum purchase quantity does not change during successive rounds of a sequential auction of a given lot, contrary to most other types of roses where the auctioneer may decide to increase this quantity. According to a survey of buyers at the AFA, the latter fact is the main reason for observed price declines for the corresponding products (Anil Kalicharan, 1995). By restricting our attention to large flower roses, we are able to abstract from this a potential cause of declining prices. In the data period of 44 working days, almost 24,000 lots were auctioned, resulting in approximately 58,000 transactions (see Table 1). So, on average, there were 550 auctions per day and 2.4 transactions per auctioned lot. The average number of units per lot was 6.0, which

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\(^4\) 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, consecutive lamps light up sequentially.
illustrates that the buyer’s option is frequently exercised. The length of the roses varied from 50 centimeters to more than 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, etc. Approximately 3,500 lots contained only one unit but approximately 500 lots contained 10 units. Obviously, some growers offer their flowers in small quantities whereas others offer their flowers in bigger quantities. The heterogeneity between lots is further illustrated by the range of the number of items (i.e., individual roses) per unit. In most cases, this number equaled 80, 100, 120, or 140. For approximately 15 percent of the lots, this number was outside this range. The average price per rose was 56.8 cents. Note that the minimum price per rose was equal to 10 cents. The highest price was 265 cents (attained in only 1 transaction).

To proceed, we create a subsample in which the range of values of several variables is somewhat restricted. We only consider lots that contained less than 11 units and that had 80, 100, 120, or 140 items per unit. Furthermore, the length of roses, as measured in tens of centimeters, is restricted to the range 50–90 cm. In addition, we restrict our attention to the 20 products for which the number of transactions during the period of analysis was more than 1,000. We omit information on lots that were partially destroyed because the price fell below the minimum price (13 lots). Finally, we do not use lots when a minimum purchase quantity larger than 1 was used during the auction (744 observations). As a result, we are left with 14,092 transactions based on 7,034 lots. Table 1 contains summary statistics on the subsample. Note that this subsample contains 3,257 lots that were auctioned in one transaction and that these cannot be used to study price movements. Table 2 shows the direction of 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 increased is slightly less than the number of transactions where the price decreased. From the first to the second transaction, the price more often increased than decreased. The opposite is the case for most of the subsequent transactions. These results do not provide conclusive evidence either of a price decline or increase. In fact, as Claudia Keser and Mark Olson (1996) show, a comparison between the number of increases and decreases is not very informative concerning the importance of price declines.

### Table 1—Descriptive Statistics

<table>
<thead>
<tr>
<th>Unit of Observation</th>
<th>Gross Sample</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>Subsample</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Price in Dutch cents (cents per rose)</td>
<td>Transaction</td>
<td>57,981</td>
<td>56.80</td>
<td>29.58</td>
<td>14,092</td>
<td>60.72</td>
<td>25.55</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of units per transaction</td>
<td>Transaction</td>
<td>57,981</td>
<td>2.45</td>
<td>2.34</td>
<td>14,092</td>
<td>2.08</td>
<td>1.47</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of units per lot</td>
<td>Lot</td>
<td>23,775</td>
<td>5.98</td>
<td>5.87</td>
<td>7,034</td>
<td>4.17</td>
<td>2.55</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of transactions per lot</td>
<td>Lot</td>
<td>23,775</td>
<td>2.44</td>
<td>1.88</td>
<td>7,034</td>
<td>2.00</td>
<td>1.22</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of transactions per lot if &gt;1</td>
<td>Lot</td>
<td>13,489</td>
<td>3.54</td>
<td>1.86</td>
<td>3,777</td>
<td>2.87</td>
<td>1.07</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of items per unit</td>
<td>Unit</td>
<td>142,233</td>
<td>120</td>
<td>34</td>
<td>29,320</td>
<td>109</td>
<td>20</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

5 The restriction to 20 products entails a loss of 29,000 transactions in the data. The restriction to lots of less than 11 units entails an additional loss of approximately 10,000 transactions.

6 See van den Berg et al. (1999) for additional sample characteristics.
number is not exogenous because it is an outcome of the behavior of the auction participants and may depend on prices realized earlier in the sequential auction. Suppose that there is a characteristic of the rose or the auction setup that is unobserved by us but is observed by the auction participants. This might affect both the level of the prices and the number of rounds in the sequential auction. A result of this might be that a relatively high price throughout the sequential auction often accompanies a relatively large number of rounds. This means that in the data, among the prices realized 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 is suggested by the regression estimate).  

A second (related) reason as to why a simple regression can be misleading is that price observations for a given sequential auction are typically not independent. There may be unobserved price determinants that affect all realized prices within a sequential auction. In that case, regressions might generate biased results even if the number of rounds was the same for all sequential auctions. To advance, we use 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

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

where $p_{i,j}$ is the price per flower in the transaction, with rank number $j = 1, \ldots, J_i$ in the sequential auction of lot $i = 1, \ldots, N$. The lot-specific fixed effect $\alpha_i$ captures observed and unobserved heterogeneity between lots. The dummy variable $d_{i,j}$ denotes the rank number of the transaction. The series of $\beta_j$ ($j = 2, \ldots, \max J_i, J_j$) coefficients captures the price change within a lot, relative to the first transaction. Finally, the random variable $\epsilon_{i,j}$ captures the remaining variation in $p_{i,j}$ and is assumed to be identically and independently distributed across $i$ and $j$. We eliminate the fixed effect from the model by taking first differences of equation (1) for pairs of consecutive rounds. In this case, the price change from one transaction to the next is the endogenous variable in a regression. The price change from the $(j-1)$th to the $j$th round equals

$$\log \frac{p_{i,j}}{p_{i,j-1}} = \beta_j^* + \epsilon_{i,j}^*$$

where $\beta_j^* = \beta_j - \beta_{j-1}$ and $\epsilon_{i,j}^* = \epsilon_{i,j} - \epsilon_{i,j-1}$. 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 price changes in rounds.

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**Table 2—Signs of Observed Price Changes and Estimated Magnitudes of Price Changes by Rank Number of the Transaction**

<table>
<thead>
<tr>
<th>Rank numbers</th>
<th>1→2</th>
<th>2→3</th>
<th>3→4</th>
<th>4→5</th>
<th>5→6</th>
<th>6→7</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Sign (Percentage of Total)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Decline</td>
<td>34</td>
<td>42</td>
<td>49</td>
<td>47</td>
<td>42</td>
<td>19</td>
<td>39</td>
</tr>
<tr>
<td>Constant</td>
<td>20</td>
<td>29</td>
<td>30</td>
<td>31</td>
<td>38</td>
<td>52</td>
<td>24</td>
</tr>
<tr>
<td>Increase</td>
<td>46</td>
<td>29</td>
<td>22</td>
<td>22</td>
<td>20</td>
<td>30</td>
<td>37</td>
</tr>
<tr>
<td><strong>Average Percentage Change</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Estimate (t-statistic)</td>
<td>-2.2 (15.4)</td>
<td>-2.6 (16.6)</td>
<td>-2.8 (12.1)</td>
<td>-2.7 (7.9)</td>
<td>-1.7 (3.4)</td>
<td>-0.7 (0.5)</td>
<td>-2.4 (25.3)</td>
</tr>
<tr>
<td>Number of observations</td>
<td>3,777</td>
<td>1,953</td>
<td>867</td>
<td>334</td>
<td>100</td>
<td>27</td>
<td>7,058</td>
</tr>
</tbody>
</table>

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7 In van den Berg et al. (1999), we show that this is the case for our data. In a log price regression, with the explanatory variables day of the week, lot size, number of items per unit, and length of the flower, we also include the rank number of the transaction. Then the price was estimated to increase with the rank number.
Equation (2) can be estimated directly by ordinary least squares. The estimated coefficient is simply the average observed log price decline.

The estimation approach only uses 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 this subsection.

The estimated coefficients are given in Table 2. They provide very strong evidence for declining prices within the sequential auction. The point estimate for the first price decline \( b_2 \) is 2.2 percent. The largest price decline is observed from the 3rd to the 4th rounds (2.8 percent). After that, the price declines somewhat less. The price change becomes insignificant after the 6th round.

C. A Closer Look at the Price Decline

We take a closer look at the price decline between two rounds by distinguishing between the effect of the number of units remaining and the rank number of the transaction. To distinguish between the two effects, we estimate a regression equation 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.

\[
\log \frac{p_{ij}}{p_{ij-1}} = \gamma_1 + \gamma_2 \cdot (j - 2) + \gamma_3 \cdot (k - 2) + v_{i,j} \quad j > 1, \quad k > 1,
\]

where \( j \) refers to the rank number of the transaction, \( k \) refers to the remaining number of units at the beginning of round \( j - 1 \) (for convenience, we suppress index \( i \) for \( j \) and \( k \)), and \( v_{i,j} \) is the error term. 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 rounds, \( j = 2, k = 3 \); for a price change from the second to the third rounds, \( j = 3, k = 2 \), etc.

The reference case is a two-unit lot that was 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 \( \gamma_1 \) captures the price change for this case. If we find \( \gamma_2 < 0 \), this is evidence that the strongest decline is early in the auction whereas if \( \gamma_3 > 0 \), this is evidence that the strongest decline occurs when only a few units remain. The estimation results are in Table 3. Column 1 shows the estimation results if we impose \( \gamma_2 = \gamma_3 = 0 \). Then, we measure the average price change over two subsequent auctions within the same lot. It turns out that the average price decline is 2.4 percent. In column 2, we impose \( \gamma_3 = 0 \) so we only consider the effect of the rank number of the transaction. The resulting estimate of \( \gamma_1 \) is -2.3 percent. Furthermore, we find that \( \gamma_2 < 0 \), which indicates that the magnitude of price decline becomes larger at later rounds. However, the estimate of \( \gamma_2 \) is insignificantly different from zero. Column 3 shows the estimates if \( \gamma_2 = 0 \) is imposed. Now, we find that the coefficient \( \gamma_3 \) is significantly larger than zero, which indicates that the fewer the remaining number of units, the larger the price decline. In column 4, we list the results for the full equation. These agree with those in columns 2 and 3.

We conclude that the declining price is particularly important when going from the first to the second round of a sequential auction, irrespective of the number of units to be auctioned.

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-2.41 (25.3)</td>
<td>-2.32 (19.5)</td>
<td>-3.13 (19.3)</td>
<td>-3.12 (16.3)</td>
</tr>
<tr>
<td>( j - 2 )</td>
<td>-0.12 (1.2)</td>
<td>0.24 (5.4)</td>
<td>0.24 (5.3)</td>
<td></td>
</tr>
<tr>
<td>( k - 2 )</td>
<td></td>
<td></td>
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</table>

Notes: Parentheses indicate \( t \)-statistics. Total of 7,058 observations.
III. Conclusions

Data from sequential Dutch auctions of roses allowed us to advance understanding of the declining price phenomenon in sequential auctions. First, the products are fully homogeneous. Second, in contrast to previous studies that consider only sequential auctions of limited size, the data contain long sequences of transactions. Third, the data concern Dutch (first price) auctions. We found price declines in these sequential auctions. Moreover, even in long sequences of auctions, there is a declining price. In addition, at any round, the decline is stronger if the number of remaining units is smaller.

A number of theoretical studies provide explanations for declining prices. However, the relation between the models in the literature and the actual setup of the Dutch flower auction is not very close. Virtually all of the literature deals with English auctions or second-price sealed-bid auctions rather than Dutch auctions. In addition, the literature often adopts a basic auction setting with a maximum of two objects to be auctioned. It is a topic for further research to investigate to what extent the predictions of the literature carry over to sequential Dutch auctions with many objects and, more specifically, to what extent the empirical results in the present paper can be reconciled with these predictions.

REFERENCES


