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**Tables and figures are presented at the end of the paper**

## **Sealed-Bid Auctions: Case Study**

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## **Abstract**

Auctions are an important link in supply chains. This paper presents an empirical investigation of a single-shot simultaneous or sealed-bid auction. This case study concerns the mussel trade in Yerseke, the Netherlands. It surprisingly demonstrates that companies buying large quantities of mussels pay higher unit prices. It also reveals that auction prices react sharply to changes in annual supply and that seasonality causes a bullwhip effect. Finally, purchase managers perform significantly differently from each other, when accounting for the above price factors and “hedonic price” factors, which represent objectively measured product characteristics. To derive these conclusions, this paper uses a simple linear regression model that: (i) extracts information from a database of 28,017 mussel lots enabling the rejection of four intuitive null-hypotheses; (ii) has signs for all explanatory variables that are correct from the viewpoint of economics or marine biology; and (iii) provides a novel tool for objective performance evaluation of purchase managers.

(Auction, supply chain, performance measurement, purchasing)

### **1. Introduction**

This paper presents the results of our investigation into the role of auctions in supply chains (SCs). An SC is a flow of goods, services, and information in a single organization or between organizations. Organizations benefit significantly by coordinating their activities and sharing information. The aim of supply chain management (SCM) is to organize the SC in such a way that it can efficiently respond to the requirements of the ultimate customer. More specifically, a common theme in the SCM literature is the question of how can a purchase manager gain control over quantity, quality, timing, and price in the SC.

Indeed, it is the purchasing activity that is one of the corporate functions most affected by SCM. The company can realize significant cost savings through reductions in total purchase expenditure and inventory (see Rajagopal and Bernard 1993). We focus on how a purchasing company can manage the flow of goods when an auction is part of the SC. There are many theoretical and empirical studies of auctions in general (see Milgrom and Weber 1982 and the references in Van Heck et al. 1997). We address the following four SCM issues.

(i) From a SCM standpoint, it is important to know whether the price discovery at an auction *handicaps big buyers*. If this is true, buyers with large market shares should try to avoid bidding at auctions. They could, for example, pre-arrange prices with suppliers. In practice, large retailers indeed try to circumvent auctions, as exemplified by SCs for vegetables, fruit, and flowers.

(ii) The relationship between *supply quantities* and *auction prices* may imply that abundant supply lowers auction prices, or that high auction prices prompt sellers to increase supply. If there is a strong negative relationship between auction prices and supply, buyers should stabilize prices to make the supply follow a pattern compatible with market demand.

(iii) Prices and quality may vary with the time of the year. This *seasonality* implies that buyers should increase their demands during periods when prices are relatively low and quality is relatively high. Lee et al. (1997) discuss the bullwhip effect of seasonality. Indeed, in our case study the variation of monthly auction sales exceeds the variation of monthly consumption; see Figure 1.

(iv) The *purchase manager's performance* may affect price determination. If that is the case, the buying company should improve the quality of its purchase manager by, for example, training and providing decision support tools. We calculate a “hedonic” price by means of a regression model; this price is the implicit price of objectively measured characteristics of a differentiated product (see Rosen 1974).

Our main conclusions are: (i) bigger buyers pay higher prices; (ii) prices react sharply to changes in supply and demand; (iii) seasonality causes a bullwhip effect; and (iv) purchase managers perform significantly differently from each other.

These conclusions are based on a novel linear regression model that extracts information from a huge database of 28,017 mussel lots and provides a tool for objective performance evaluation of purchase managers.

We have organized the remainder of this article as follows. In Section 2, we present our a priori hypotheses on the four SCM issues presented above. In Section 3, we seek greater understanding of this auction and provide background information on the mussel industry. In Section 4, we describe the organization of the mussel auction and the challenges faced by purchase managers who attend it. In Section 5, we describe our regression model, its dependent variable, and its twelve independent variables. In Section 6, we discuss our data source and sample selection procedure. In Section 7, we present the results of our regression analysis accounting for autocorrelation that enables us to test our four hypotheses. In Section 8, we investigate the predictive usage of our regression model. Finally, we give in Section 9 our conclusions and topics for future research. More details are given by Van Schaik and Kleijnen (2001).

## **2. Four Hypotheses**

We formulate four hypotheses in the null-form, as is standard in mathematical statistics. This type of formulation implies that the hypotheses are rejected only if there is strong evidence against them: the type I error probability is only  $\alpha$ , for example, 5%.

## **2.1 Market Share and Price**

Normally, the buyer who purchases larger quantities pays a lower price because a big customer's negotiating power results in a lower unit price. However, an auction distorts this pattern: there is no negotiating at an auction, so buying power carries no weight. On the contrary, we expect that big buyers must bid higher to maintain their market share. For example, a buyer who has a 20% market share has to put in bids that lead to success in 20% of the cases, whereas a buyer with a 10% market share must put in bids that have only a 10% success probability:

*Hypothesis 1: at sealed-bid auctions, companies with a higher market share pay the same unit price for the same quality of product as companies with a low market share.*

## **2.2 Total Supply and Price**

SCM aims to create customer value in terms of the availability and price of the product. It is therefore important to know why customers buy, continue to buy, or cease buying the product. Although price is usually only one of the factors that customers consider, there may be a narrow price range that is acceptable. When a product is traded through an auction, variations in supply may lead to varying prices. However, customers may not want to worry about buying a product at the wrong time and suppliers may adopt an "everyday low pricing" strategy by offering a product at a constant price. This strategy avoids price hikes, which cause loss of customers - who may take a long time to return. This strategy results in more stable customer demand patterns. We therefore want to determine the effects of total supply per "mussel year" on auction prices; such a mussel year starts toward the end of June and ends in April.

*Hypothesis 2: prices do not vary with total annual supply.*

### **2.3 Seasonality and Price**

Many commodities show seasonal price behavior. Examples are heating oil with low demand in summer and high demand in winter, and agricultural supplies that follow the stages from planting to harvest. Such variations in demand or supply cause volatile prices. If products can be stored for several months, fewer will be purchased when prices are high, thus decreasing the price differences among months (arbitrage).

*Hypothesis 3: prices do not vary with the time of the year.*

### **2.4 Does the Purchase Manager Pay the Right Price?**

Purchase managers are receiving greater attention in the performance improvement plans of firms. However, there is little systematic empirical evidence about their performance. For example, Farmer (1985) states: “Despite the importance of price to the performance evaluation of buyers, to the purchasing process and to company profitability, understanding of pricing issues is often unclear and confused. For example, the difficulty in assessing the buyer’s success in purchase price reduction contributes to the problem of introducing a sound performance-based reward system for buyers.”

We propose the following three-step method to assess performance:

(i) Develop a theoretical price formula (a regression model) for the items the manager purchases. This model should account for all objective characteristics of the item and the circumstances under which it is bought. To obtain reliable estimates of the parameters of this formula, we should use a large number of transactions made by several purchase managers.

(ii) Calculate the “premium” paid at each transaction. This premium is defined as the difference between the price actually paid and the theoretical price. Obviously, this premium can be either positive or negative.

(iii) Compare the premiums paid by a particular purchase manager with the premiums paid by other purchase managers. Again, many observations are needed, for example, to prevent one “lucky buy” distorting a particular manager’s performance assessment.

We calculate a theoretical price by means of a multiple regression model that incorporates all available objective information that affects the price.

*Hypothesis 4: all purchase managers buying the same class of products, show the same performance levels.*

### **3. The Dutch Mussel Industry**

Aquaculture of mussels is thriving all around the world, from Norway to South Africa and from the United States to China. The major producing countries are Spain and China. In the Netherlands, approximately eighty ships are used to harvest and transport mussels cultivated on the sea bed. Mussel “farmers” lease part of the bottom of two North Sea estuaries in the Netherlands, namely the Wadden Sea (or Dutch Shallows) and the Eastern Scheldt (*Oosterschelde*); these two areas are a few hundred kilometers apart.

Mussels come in different *qualities*. On some cultivating plots, mussels gain little weight but grow thick shells; on other plots, the growth rate is high and the mussels quickly reach the minimum acceptable commercial size. Although the latter mussels have a high meat yield, their shells are thin and transparent and they often have a shorter shelf life.

Annually, between 50 and 100 million kilograms of raw mussels are delivered to the port of Yerseke. 100 million kilograms are equal to more than 26 million kilograms of edible weight. Consequently, mussel cultivation is a food source of considerable importance.

These mussels are sold by the farmers at the auction in Yerseke, the only mussel auction in the world. In section 4, we describe the operational characteristics of this auction.



After the mussels have been sold, they are placed in special plots in the Eastern Scheldt. These “re-watering” plots serve as *wet storage* for this highly perishable produce. From these plots, mussels are harvested on demand. There are two types of demand: *live mussels* and *processed mussels*. The main group of buyers trade in live mussels: they buy on average 84% of the mussels landed. These companies clean, grade, and pack mussels. Their purchasing costs amount to approximately 60% of turnover. These mussels require a higher quality than processed mussels.

The mussel processing factories buy the remaining 16%. They process the raw mussels into frozen mussels or mussel preserves. Their purchasing costs amount to approximately 40% of turnover, so more value is added to processed mussels than to live mussels.

These percentages (84% and 16%) vary from year to year according to the quality and quantity of supply. Supply is abundant in some years and large quantities are processed. In 1998, for example, 26% (instead of the usual 16%) of raw mussels were frozen and preserved. In some years, however, mussels are too expensive: in 1992, only 4% of raw mussels were processed. (Fortunately, 1992 was preceded by several years in which a higher percentage of mussels were processed; stocks built up during these years carried the industry through the year 1992.)

Most Dutch live and processed mussels are exported, mainly to Belgium and France. An increasing quantity, however, is sold on the domestic market.

#### **4. The Mussel Auction at Yerseke**

First, we describe how the Yerseke mussel auction is organized (Section 4.1). We then summarize the challenges faced by purchase managers at this auction (Section 4.2).

#### 4.1 Organization of the Yerseke Mussel Auction

In general, auctions create transparent markets by concentrating demand and supply. The auction at Yerseke is a sealed-bid auction, also known as a simultaneous single-shot auction. Compared with an open-bid or ascending English auction, the sealed-bid auction provides bidders much less information on the behavior of other bidders. However, this type of auction is fast and therefore works well if many small lots are offered for sale. At Yerseke, auctioning 30 lots takes less than an hour. Speed is essential because mussels are highly perishable.

The mussel farmers ship the mussels to the auction, and display them in the harbor at the auction house. The auction house supplies a key service: the *quality control* of the product. Before the auction, auction employees inspect the mussels in the ships. Subsequently, the auction house provides information on each lot's quality to the purchase managers.

All purchase managers are physically present at the auction and simultaneously submit their sealed bids by entering a price on individual keyboards linked to a central computer. The auctioneer publicly announces the end of the bidding time, and the computer then displays the price of the highest bid and the name of the buying company. (However, details of the lower bids are not revealed.) In the case of a draw, the winner is the buyer who entered the price first.

Milgrom and Weber (1982) show that sealed-bid auctions generally yield lower revenues than open-bid ascending auctions. At Yerseke, there is a *minimum price* per "mussel ton" that is fixed for one year; one mussel ton is 100 kilograms. For example, in 1999 the fixed price was 16 euro (EUR 1 = approximately USD 0.9). If no purchase manager bids above the minimum price, then the auction house buys the lot at that price. At the end of the mussel year, the auction house auctions these mussels in the usual way.

All mussels supplied by a farmer in one ship are usually auctioned as one lot. However, the auctioneer may decide to auction each of the two or three holds of the ship as separate lots. In times of great price volatility, this practice might spread the risk for the farmer. Indeed, lots appear at the auction in a random sequence and there may be a drift in price setting during the auction session (for example, in case of a buying frenzy). The anomaly of different prices for identical lots has been widely investigated. In a study of wine auctions, Ginsburgh (1998) argues that it is unlikely that a bidder's valuation would differ for identical lots of wine, saying that "a rosé is a rosé is a rosé". Van den Berg et al. (1999) investigate a flower auction, and assume that "a rose is a rose is a rose".

All eighty Dutch mussel farmers sell all their produce through the auction. Occasionally, the auction sells the produce of German mussel farmers. The number of buyers varies slightly over the years: companies close down, start up, or merge. There are on average twenty live mussel buyers and four processed mussel buyers. Sellers and buyers pay a percentage of their sales and an amount per mussel ton as a fee to the auction house.

Lot sizes are measured in mussel tons. However, it is not practical to measure the weight of an individual lot directly. It is assumed that seven tons go into one cubic meter. The cubic capacity of a ship was carefully measured when the ship was built. Hence, the content of a particular lot is determined as a percentage of the ship's full cubic capacity. The weight estimated in this manner is the "gross" tonnage. However, the buyer pays only the "net" tonnage, which is gross tonnage minus "impurity". Impurity consists of loose shells, starfish, dead or damaged mussels, seed mussels (mussels shorter than 30 millimeter), and other shellfish and crustaceans such as crabs. This impurity is measured as a percentage of gross tonnage.

## 4.2 Challenges for Mussel Purchase Managers

Purchasing management at the mussel auction is important: a single lot may cost as much as EUR 200,000. Purchasers may spend several million euro's within an hour, so errors can be costly. Purchasers may face the following problems at the auction:

(i) A mussel lot consists of a great diversity of types and sizes. The consumer, however, is supplied with five sizes of mussels sorted in the factory according to shell width.

(ii) Each lot has a different mix: some consist largely of small mussels and others of large mussels. So there are never lots of only one size.

(iii) Lots are auctioned sequentially, so the buyer cannot optimize the combination of lots to be bought (at least not simply, for example, by linear programming). The buyer must wait to see whether the bid price is the highest resulting in the lot being bought (and the desired market share being gained).

## 5. Regression Model for Mussel Prices

We use regression analysis to explain the price of mussels at the sealed-bid auction in Yerseke. In this analysis, we include elements from the hedonic price literature. There is much literature on the hedonic prices of agricultural commodities, including cotton (Brown et al. 1995), wheat (Espinosa and Goodwin 1991), Christmas trees (Davis 1993), and tuna fish (McConnell and Strand 2000).

To determine the hedonic price, Rosen (1974) also proposes *linear regression* analysis with a set of independent variables that affect this price. We specify our regression model in Section 5.1. In Section 5.2, we describe the independent variables of this model (the four variables of the four hypotheses of Section 2, and eight control or concomitant variables).

## 5.1 Specification of the Regression Model

We specify a linear multiple-regression model:

$$y = \beta_0 + \sum_j \beta_j x_j + e. \quad (1)$$

The dependent, explained variable is the price per mussel ton,  $p$ . In model (1), we use the natural *logarithm* of that price,  $y = \ln(p)$ , for two reasons:

(i) The marginal effect  $\partial y = \partial \ln(p) = \partial p/p$  is the *relative* price change, so we remove the *scale effects* caused by choosing a particular currency such as euro's or guilders.

(ii) When we also use the logarithm of the original independent variable of  $z$  so  $x = \ln(z)$  and that variable is a real number, its regression parameter  $\beta$  denotes the *elasticity coefficient*,  $\beta = (\partial p/p) / (\partial z/z)$ , which is popular in economic theory.

Table 1 provides definitions and the predicted signs of variables. We distinguish between the *original* variable  $z$  in Table 1 and the *regression* variable  $x$  in model (1). Though some original variables are real numbers, we are not interested in their elasticity coefficient. For example, for barnacles ( $z_8$ ), we wish to estimate the relative price change as that variable changes by an absolute value:

$$\ln(p) = \dots + \beta_8 z_8 + \dots \text{ or } (\partial p/p) / (\partial z_8) = \beta_8 \text{ or } (\partial p/p) = \beta_8 \partial z_8.$$

There may be zero barnacles in a lot, so the logarithmic transformation does not then apply. Moreover, we study various scatter plots to decide whether logarithmic transformations provide a better-fitting regression model.

Table 1 also shows that three independent variables are not real numbers, but are *binary* variables:  $z_4$ ,  $z_{10}$ , and  $z_{11}$ . For example,  $z_{11} = 1$  if the mussels originate in the Wadden Sea (hereafter Wadden) and  $z_{11} = 0$  if the mussels originate in the Eastern Scheldt (hereafter Scheldt). However, mathematically,  $\ln(0)$  is undefined; economically, an elasticity coefficient for origin is nonsense. The coefficient of a binary variable can therefore be interpreted as the estimated percentage change in price when the lot has the characteristic described by the

binary variable and all other characteristics are constant. For example, Wadden mussels are  $\beta_{11}$  percent more expensive than Scheldt mussels.

In summary, we specify a combined regression model (1) that has three types of independent variables:

(i) For some independent variables (market share, supply, season, meat yield, size count, and impurity) we estimate elasticity coefficients (double-log transform):

$$\mathbf{b}_j = \frac{\partial p / p}{\partial z_j / z_j} \quad \text{if } y = \ln p, x_j = \ln z_j, \quad z_j \in \mathfrak{R}^+. \quad (2)$$

(ii) For some other variables (barnacles, slippers, trend), we estimate relative price changes when these variables change by an absolute amount (single-log transform):

$$\mathbf{b}_j = \frac{\partial p / p}{\partial z_j} \quad \text{if } y = \ln p, x_j = z_j, \quad z_j \in \mathfrak{R}. \quad (3)$$

(iii) We define three binary variables (specific buyer, use as live mussel, origin). For example,  $z_{11}$  implies: if  $z_{11} = 1$  then (1) gives  $\ln(p) = \beta_0 + \beta_{11} + \dots$  or  $p = \exp(\beta_0 + \beta_{11} + \dots)$ ; if  $z_{11} = 0$  then  $\ln(p) = \beta_0 + \dots$  or  $p = \exp(\beta_0 + \dots)$  so the price ratio (say)  $p_1/p_0$  is  $\exp(\beta_{11})$ , that is, the relative price increase is

$$\partial p / p = e^{b_j} - 1 \quad \text{if } x_j = z_j, z_j \in \{0, 1\}. \quad (4)$$

Finally, the term  $e$  in model (1) represents the *noise* or *disturbance* caused by our exclusion of some relevant explanatory variables. For example, the auction does not measure the mussels' color, taste, or texture. We assume that this disturbance is either *white noise* or *autocorrelated noise*. White noise means that  $e$  is normally, independently, and identically distributed (NIID); autocorrelated noise means that the independence assumption does not hold (see Section 7).

## 5.2 Independent Regression Variables

In model (1), we include most of the information that in the real world is provided by the auction house to the buyers before the auction starts. We presume that the auction house provides this information based on the assumption that it may affect prices. Nevertheless, we exclude some of the auction's information because of parsimony: It is well known that reducing the number of variables increases prediction performance. For example, we use size count, not shell width and length. Yet the latter two variables are displayed in the information sheet that the auction house distributes to sellers and buyers.

### 5.2.1 Independent Variables for Hypotheses 1 through 4

In Section 2, we discussed the following four hypotheses.

*Market share of the buying company ( $z_1$ ):* Hypothesis 1 requires testing whether big buyers tend to pay a higher than average price for mussels of the same quality.

*Supply ( $z_2$ ):* Hypothesis 2 tests to what extent aggregate annual supply affects prices. Supply considerably fluctuates from year to year (for example, storms may sweep mussels away from cultivation plots). In years of low production, mussels are imported, mostly from the German Wadden Sea. For a mussel processing factory, this supply variability leads to tremendous profit fluctuations because purchasing costs are higher and coverage of fixed costs is smaller. This supply variability is less problematic for mussel farmers because small supply volumes are partly compensated by high prices.

*Season ( $z_3$ ):* Hypothesis 3 tests whether there is any seasonal movement in prices. Supply and demand result in much higher prices in June, July, and August. The variable "meat yield" ( $z_5$ ) is also higher in these three months, so collinearity between these two variables will be accounted for in our analysis.

*Purchase manager's performance* ( $z_4$ ): To test Hypothesis 4, we include a binary variable. If the coefficient of this variable is significantly positive, then we conclude that this manager outperforms the competition. However, we first estimate our model without this binary variable, because we wish to validate our model before we apply it to evaluate managerial performance.

### **5.2.2 Independent Variables: Control or Concomitant Variables**

We discuss four types of control variables, labeled (i) through (iv).

(i) The following five variables control *quality*, so they affect the hedonic price.

*Meat yield* ( $z_5$ ): The consumer is interested in the amount of mussel meat. The auction's personnel estimates this percentage from a sample from each lot.

*Size count* ( $z_6$ ): The size count is determined by counting the number of mussels per 2.5 kilograms (net). As smaller mussels are cheaper, it is expected that a higher size count will reduce the price.

*Impurity* ( $z_7$ ): We discussed impurity in Section 4.1.

*Barnacles* ( $z_8$ ): Barnacles do not always grow on mussel shells, so this variable may be zero. Barnacles cause extra wear on the machines, and make mussels less attractive to consumers. The buyers' sorting machines categorize mussels according to shell width, so the machines may erroneously categorize small mussels with barnacle growth as large mussels.

*Slippers* ( $z_9$ ): Slippers are animals that grow on mussels, like barnacles do. Slippers create the same problems as barnacles.

(ii) The next control variable is *product usage* ( $z_{10}$ ). All lots are listed by the auction in the order of the ship's arrival at the harbor. As we mentioned in Section 4.1, these lots are traded in a random order, so mussels intended for live mussel production and for making into preserves are auctioned in a mixed order.



(iii) The third control variable is *origin* ( $z_{11}$ ). Soil characteristics can affect the flavor of mussels (like wine). In practice, the average price of Wadden mussels is higher. However, these mussels also tend to be heavier ( $z_6$ ) and meatier ( $z_5$ ), and this causes a collinearity problem. Our variable *origin* measures whether Wadden mussels generate a premium, even if we control for characteristics such as meat yield and size count.

(iv) Finally we discuss the *trend* variable ( $z_{12}$ ). For example, the value 86 denotes the mussel year from June 1986 through April 1987. Apart from seasonal price movements (see  $z_3$ ), there has been an increasing price trend over the years. Trend elements are inflation in general and a considerable rise in the demand for mussels without a noticeable increase in supply. This price increase has mostly benefited the mussel farmers: the bottleneck in the supply chain is the areas where mussel farmers cultivate mussels; live mussel traders and mussel processing factories have excess capacity.

## **6. Data Source and Sample Selection**

We obtained our data from the mussel auction house at Yerseke. Since 1986, its auctioning process has been *computerized*, so extensive data is available for most variables. Before each auction session starts, the auction house compiles an information sheet about the lots. This sheet displays the lot's quantity, farmer, origin, and various quality indicators. After each auction session, the auction house completes this sheet by adding the price per lot and the name of the highest bidder. This sheet is immediately distributed to sellers and buyers. We obtained data about all the 30,303 lots that were traded at the auction during the years 1986/1987 through 1999/2000.

However, we removed a number of lots from our data because they are not representative: all mussels caught in the Netherlands are traded at the auction, but some fishing and

purchasing companies belong to the same group and trade produce at the auction at pre-arranged prices. This reduces the number of lots to 28,017.

The variables  $z_4$  through  $z_{11}$  are measured for each lot. These variables (with the exception of  $z_4$ ) determine the hedonic price.

However, the variables *supply* ( $z_2$ ) and *trend* ( $z_{12}$ ) are measured per year, resulting in only fourteen measurements. Market share  $z_1$  is measured per year and per buyer, so its number of observations is approximately fourteen times twenty-four.

The variable *season* ( $z_3$ ) also has fewer observations: we denote the first day of a specific season by the integer 1, the next day by 2, and so on.

## 7. Regression Results

We use SPSS version 9.0 for our regression analysis. The first column of figures in Table 2 shows the estimates of the regression coefficients  $\beta_j$  in model (1) when using *ordinary least squares* (OLS). These estimates are “best” if the white noise assumption holds ; “best” means that the linear estimator is unbiased and has minimum variance.

We do not show the estimated correlations between pairs of estimated coefficients. Obviously, the correlations between certain independent variables imply that these correlations are not zero. However, we do indirectly show the estimated variances as follows.

Table 2 shows Student’s *t statistic* per regression coefficient (see the ‘*t Stat.*’ column). This statistic is the ratio of the estimate for the regression coefficient and its standard error. All these statistics are significant at any reasonable  $\alpha$  value, even at 0.001. One explanation for this is that the number of observations for variables measured per lot is extremely high (28,017).

However, these *t statistics* assume white noise. (OLS gives unbiased estimators even when this assumption does not hold; only the expected value of the noise must be zero.) But the

table (line –3) shows a Durbin-Watson statistic of 0.954, which indicates positive autocorrelation in our model.

We therefore use SPSS's *Prais-Winsten* method, which uses generalized least squares (GLS) assuming the noise  $e$  follows a first-order autoregressive process. (SPSS claims that this method is superior to the Cochrane-Orcutt method, which is used in the hedonic price analysis for the apple industry by Tronstad et al. 1992). The autocorrelation coefficient, denoted  $\lambda$ , is estimated to be 0.5826 with a standard error of 0.0049. This method gives an acceptable Durbin-Watson statistic of 2.290. Its point estimates of the regression coefficients are close to the (unbiased) OLS estimates (compare the two appropriate columns in Table 2). Comparing the GLS and the OLS  $t$ -values shows that the GLS values are smaller for some coefficients, but certainly not for all.

When we wish to compare the *relative* effects of the independent variables, we can use the *standardized* regression coefficients displayed in the last column of Table 2. These coefficients are the unstandardized regression coefficients multiplied by the standard deviation of the independent variable and divided by the (common) standard deviation of the independent variable. These coefficients suggest that the most important variables are supply, size count, season, trend, and meat weight; the least important variables are barnacles, origin, and slippers.

The overall explanatory power of the model is reasonably good: the Adjusted  $R^2$  is 66% for OLS and 56% for GLS (see last line of table 2). Other regression models for hedonic prices give 37% for Christmas trees, 64% for tuna fish, 89% for wheat, and 93% for cotton; see the references in Section 5. For a discussion of the Adjusted  $R^2$ , we refer to Sutton (1990).

## **7.1 Testing the Four Hypotheses of Section 2**

*Market share* ( $z_1$ ) turns out to have a significant positive effect on price (Table 2). Big buyers tend to bid high and Hypothesis 1 is therefore rejected at the 0.001 level.

*Supply* ( $z_2$ ) has a significant negative effect. This confirms the demand curve usually postulated in economic theory. The size of this effect, however, is surprising: the elasticity coefficient is  $-0.8$ .

*Season* ( $z_3$ ) strongly affects the mussel industry: Hypothesis 3 is rejected. Our explanation is that buying companies start the season without any raw mussels in stock. So, at the start they quickly build stocks up to normal working levels. Apparently, in that short period of time (approximately six weeks) supply cannot keep up with demand.

*Purchase manager's performance* ( $z_4$ ) can be included as a binary variable denoting whether a particular manager buys a specific lot (Table 1). We can then test whether its regression coefficient is significantly different from zero. Indeed, we reject Hypothesis 4 at the 0.001 level (not displayed in Table 2).

## **7.2 New Tool for Performance Measurement of Purchase Managers**

To assess the performance of a specific purchase manager, we have developed the tool illustrated in Table 3. Why did this manager pay 6.12% (see bottom right-hand corner of box) more than the predicted price, accounting for the characteristics of his company, his mussel quality, and his timing? For example, the average market share gives  $\ln(z_1) = 1.8475$ , whereas his company has a relatively high market share,  $\ln(z_1 | z_4 = 1) = 2.2161$ . The price effect of this difference is  $(2.2161 - 1.8475) \times 0.0343 = 0.0127$  where 0.0343 is the GLS estimate of the  $\ln(z_1)$  effect displayed in Table 2. This 0.0127 gives a price increase of  $\exp(0.0127) - 1 = 1.0127 - 1 = 0.0127 = 1.27\%$ . So, this manager pays 1.27% more because he works for a large company. This explains the first row of figures in Table 3.

Similarly, his working for a company that uses live mussels instead of processed mussels could explain that he pays 1.48% more than average. He buys mussels of good quality and therefore pays 13.62% more than average (six quality characteristics, from meat yield to origin).

Furthermore, he bought when there was a good supply of mussels and therefore paid 2.27% less than average. However, he started not when the auction started its automated process in 1986; instead, he started when the trend had already increased prices: 10.95% price effect. Finally, he bought early in the season when prices were 2.56% higher (live mussel buyers cannot wait as long as mussel processing factories can).

All in all, this manager is expected to pay 29.86% more, whereas he actually paid 37.81% more: he should explain why he paid 6.12% more. This 6.12% is significant: if we add the independent variable  $x_4$  to the GLS model in Table 2, we find a regression coefficient of 0.0939, which is significantly different from zero at the 0.001 level ( $t = 10.94$ ).

However, this conclusion is only tentative. For example, this buyer obtains high-quality mussels and this costs him 13.62%. This quality is justified if his company actually needs this quality to keep its customers satisfied; otherwise, this premium is not well spent. It might mean that his company is shipping excellent mussels but its customers are only willing to pay the price for average-quality mussels. Indeed, for mussels (and other natural products) customers do not always get exactly the quality they ordered. In this type of business, the ability to deliver the exact quality ordered by customers is probably a critical success factor.

We can refine the analysis in Table 3, which compares the performance of a specific purchase manager with the *mean* performance of purchase managers at the auction. However, it might be more appropriate to compare a particular manager who buys, for example, live mussels, with the average live mussel manager. In that case, we would estimate the regression coefficients for the more homogeneous subsample consisting of all live mussel

buyers excluding this particular manager. Similarly, we might compare the performance of a manager of a large firm with a subsample consisting only of large firms.

Whichever model we use, a particular purchase manager might argue that he (or she) pays more than his competitors because he buys mussels that score better on characteristics not included in our model, such as color, taste, and texture. Nevertheless, he would then have to explain why he is willing to pay more for these characteristics and why he thinks his customers are willing to pay for these characteristics while his competitors' customers are not. Ultimately, this manager's justification would have to be judged by professionals.

### 7.3 Control Variables

In Table 2, the various control variables all show the expected signs except for origin: see the five quality indicators  $z_5$ ,  $z_6$ ,  $z_7$ ,  $z_8$ , and  $z_9$ . The *use as live mussels* ( $z_{10}$ ) indicator also has a positive effect.

Surprisingly, the regression coefficient for *origin* ( $x_{11}$ ) has a significantly negative sign (see Table 2). In practice, Wadden mussels tend to be more expensive than Scheldt mussels. Our model, however, controls for quality and season; Wadden mussels turn out to be less expensive. Specifically, this quality is measured by *meat yield* ( $z_5$ ) and *size count* ( $z_6$ ), on which Wadden mussels generally outperform Scheldt mussels. Indeed, after the period of reproduction (May and June), Wadden mussels reach the minimum quality requirements earlier. So, at the beginning of the mussel year - when demand is high because companies want to build up stocks - most mussels sold are Wadden mussels. However, buyers do not pay a higher price simply because mussels originate from the Wadden: they pay a higher price for Wadden mussels because they are of a better quality and many Wadden mussels are sold at the very beginning of the mussel year when demand is high. Wadden prices may actually be *lower* because of the distance between the Wadden and the auction. It may take a

ship up to eighteen hours to travel this distance and this shortens shelf life considerably. In hot weather, the journey may kill up to 5% of the mussels on board the ship. We conclude that origin is important, but in a way that violates our a priori expectation.

Finally, there is a long-term increase in the price of mussels: see  $x_{12}$  in Table 2.

We have also investigated the “robustness” of the preceding regression estimates. We estimated a regression model for each of the fourteen years. Comparing the estimates for each variable, we conclude that the model *is* robust. Furthermore, we find that market share does significantly increase prices.

## **8. Predictive Power of the Regression Model**

We subsequently eliminated the most recent year (1999/2000) and estimate model (1) from the subsample covering the remaining thirteen years. We used this re-estimated model to predict the eliminated year, that is, the price of the 2,199 lots auctioned during 1999/2000.

We obtained descriptive statistics for these 2,199 lots, both actual and predicted. The standard deviation of the predicted values is lower and the range of values is narrower (a lower maximum and higher minimum, the latter being slightly higher than the auction house’s minimum price described in Section 4.1). An explanation is that model (1) does not account for all variations that occur in practice: its  $R^2$  is smaller than one.

When we predict the price of an individual lot, we should account for *autocorrelation*: When the preceding lot turned out to have an actual price that exceeded the estimated price, then we increase our prediction for the current lot, (say) lot  $t$ :

$$\ln(\hat{p}_t) = \hat{\mathbf{b}}_0 + \sum_j \hat{\mathbf{b}}_j x_{t,j} +$$

$$+ [\hat{\mathbf{I}} \ln(p_{t-1} / \hat{p}_{t-1}) + \hat{\mathbf{I}}^2 \ln(p_{t-2} / \hat{p}_{t-2}) + \hat{\mathbf{I}}^3 \ln(p_{t-3} / \hat{p}_{t-3}) + \dots \hat{\mathbf{I}}^{t-1} \ln(p_1 / \hat{p}_1)] / c$$

with  $t = 1, 2, \dots, 2199$  and  $c = \sum_{i=1}^{t-1} \hat{\mathbf{I}}^i$

where the first two terms follow from (1) through (4) and the remaining terms make the weights of older price prediction errors decrease geometrically; factor  $c$  makes the sum of the geometric weights equal to one. To explain factor  $c$ , we suppose that past lots with important weights all show the same relative prediction error of (say) 10%. We then increase our prediction for the current lot by the same percentage. Notice that the independent variables  $x_{t,j}$  are specified per lot, per season, or per year.

We use the first two terms combined with (1) through (4) and the GLS estimates in Table 2 to derive the formula for the absolute price. The mean and median of the predicted prices turn out to be higher than the actual values (remember  $E[\ln(p)] \neq \ln[E(p)]$ ). The predicted prices  $\hat{p}$  versus the actual prices  $p$  gives the following regression line:

$\ln(\hat{p}) = 1.559 + 0.675 \ln(p)$  with  $R^2 = 0.54$  (computed from 2,199 lots). This positive intercept and slope smaller than one are to be expected if the model is correct (see Kleijnen et al. 1998). For the non-transformed variables, the expected non-linear relationship is

$$\hat{p} = \exp(1.559) p^{0.675} = 4.75 p^{0.675}.$$

We show time plots in Figure 2. Figure 2 (a) displays the week averages of the actual prices and their OLS predictions, which do not account for autocorrelation. Figure 2 (b) shows the analogous picture for the GLS prediction with autocorrelation. A comparison of Figures 2 (a) and 2 (b) shows that the performance of our predictor improves considerably if autocorrelation is accounted for.

Finally, we investigate whether our model is suitable for computer-assisted buying. An example would be: buy 20% of all lots to be auctioned in 1999/2000 (without intentional bias



for any characteristic, that is, the program is not told to purchase, say, meaty mussels). In the period 1986 through 1998, the estimated 20% quantile of the differences between actual prices and their predictions is -23.64. We therefore enter a bid equal to the model's predicted value minus 23.64. Our program turns out to buy 385 lots – or 18% - of the 2,199 auctioned during 1999/2000, whereas a normally distributed and unbiased estimator has a 50% chance of underestimating the true value.

So, our model (1) needs only minor calibration to make it suitable as a decision support system for computer-assisted buying. However, we ignore the influence our program would have on its competitors' bidding behavior. (Our approach resembles the use of Black-Scholes's option pricing model. However, Black and Scholes (1973) developed their pricing formula by means of stochastic differential equations, whereas we apply linear regression. The practical applications are nevertheless quite similar.)

## **9. Conclusions and Future Research**

We have presented an empirical investigation of the sealed-bid auction for mussels at Yerseke, the Netherlands. We rejected four hypotheses:

- (i) large buyers pay higher prices;
- (ii) the price/supply elasticity coefficient is  $-0.8$ ;
- (iii) season is important; and
- (iv) purchase managers perform significantly differently from each other.

Moreover, Wadden mussels fetch higher prices in practice, but – surprisingly - our model suggests that these higher prices are not caused by the origin *per se*, but by the concomitant quality characteristics and the season.

To arrive at these conclusions, we used regression model (1) that

(i) extracts information from a database of 28,017 mussel lots and we could therefore reject the hypotheses mentioned above;

(ii) has correct signs for all explanatory variables; and

(iii) provides a novel tool for the objective performance evaluation of purchase managers.

(This tool allows us to conclude that a specific manager may underperform: in his effort to get hold of the lots that he thinks his company needs, he overshoots his target.)

Our investigation has some limitations.

(i) Only successful bids are included in our database which does not contain offers outbid by other parties. However, this limitation is typical of sealed-bid auctions.

(ii) Our conclusion that big companies are at a disadvantage when making sealed bids in the Dutch mussel industry, may not be valid for other industries. Actually, all lots offered at the Yerseke auction are so small that any bidder can afford to buy any single lot. However, in (say) the building industry, not all companies are large enough to carry out every single building project.

Our model does incorporate actual measurements of characteristics that are shown on the auction's information sheet used by the purchasing managers. However, it is arguable that future research of food products should also consider color, taste, and texture.

Future research might also consider the requirements for successful introduction of *futures* in mussels in addition to spot markets. Martínez-Garmendia and Anderson (1999) studied shrimp futures contracts traded at the Minneapolis Grain Exchange, the world's only seafood futures trading facility. These contracts are designed to control price volatility and volume. They conclude that product homogeneity is an important requirement for a successful futures contract. Our analysis of the relationship between hedonic factors and price might enable meeting this homogeneity requirement for a futures exchange in mussels.

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**Table 1. Variables, expected signs, and definitions**

Variable (number)	Expected sign	Definition
Price		Price in guilders per mussel ton (= 100 kg) of net tonnage (i.e., gross tonnage minus impurity).
Market share (1)	+	Quantity bought by a particular buyer at the auction in a mussel year, divided by the total quantity traded at the auction in the same period.
Supply (2)	–	Total quantity of mussel raw material offered for sale at the auction during one mussel year.
Season (3)	+	Variable indicating the number of the day starting at 1 for lots offered for sale at the first day of the mussel year.
Purchase manager's performance (4)		Binary variable is 1 for lots bought by the purchase manager whose performance is assessed; it is otherwise 0.
Meat yield (5)	+	Percentage mussel meat in mussel raw material.
Size count (6)	–	Number of mussels contained in 2.5 kg raw material.
Impurity (7)	–	Everything that is not the mussel (shells, etc.), as a percentage of gross tonnage.
Barnacles (8)	–	Weight of barnacles attached to mussel shells; in grams per 2.5 kg raw material.
Slippers (9)	–	Weight of slippers attached to mussel shells; in grams per 2.5 kg raw material.
Use as live mussels (10)	+	Binary variable is 1 for mussels bought by a live mussel trader; 0 otherwise (i.e., mussels bought by a mussel processing factory).
Origin (11)	+	Binary variable is 1 for mussels from the Wadden; it is otherwise 0 (i.e., from the Scheldt).
Trend (12)	+	Integer variable indicating the year in which a lot was offered for sale.

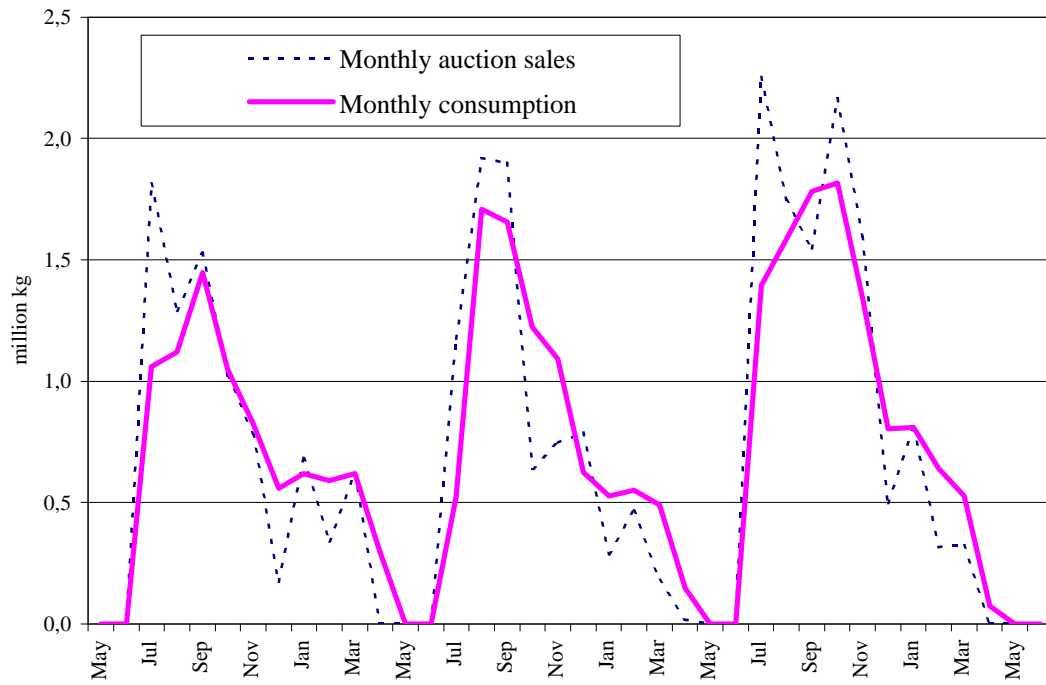
**Table 2. Results of Regression Analysis**

	<i>OLS</i>		<i>GLS (autoregressive)</i>		
	Unstand. coeff.	<i>t</i> Stat.	Unstand. coeff.	<i>t</i> Stat.	Stand. coeff.
Constant ( $x_0$ )	6.9806	78.85	7.0785	59.08	
Market share ( $x_1$ )	0.0421	17.81	0.0343	19.57	0.0795
Supply ( $x_2$ )	-0.8396	-91.93	-0.8473	-49.65	-0.2127
Season ( $x_3$ )	-0.1586	-78.56	-0.1474	-40.81	-0.1666
Meat yield ( $x_5$ )	0.8147	55.39	1.1046	76.07	0.3659
Size count ( $x_6$ )	-0.8748	-85.92	-1.0526	-107.12	-0.4533
Impurity ( $x_7$ )	-0.1412	-27.89	-0.1728	-43.08	-0.1784
Barnacles ( $x_8$ )	-0.0005	-9.02	-0.0011	-24.66	-0.1063
Slippers ( $x_9$ )	-0.0007	-6.31	-0.0003	-3.83	-0.0164
Use as live mussels ( $x_{10}$ )	0.1975	32.41	0.0916	19.19	0.0835
Origin ( $x_{11}$ )	-0.0339	-6.16	-0.0581	-10.21	-0.0511
Trend ( $x_{12}$ )	0.0414	75.22	0.0418	40.19	0.1708
Durbin-Watson statistic	0.954		2.290		
Sample size $n$	28,017		28,017		
Adjusted $R^2$	0.66		0.56		

**Table 3. Performance assessment tool**

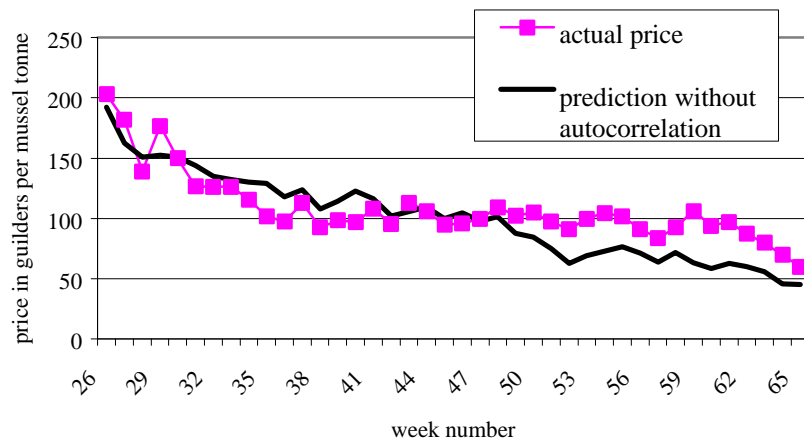
coefficients (1)	mean all (2)	mean this manager (3)	price Difference (4)=(1)x[(3)-(2)]		% costs this manager compared to benchmark
0.0343	1.8475	2.2161	0.0127	market share ( $x_1$ )	1.27%
0.0916	0.8396	1.0000	0.0147	use as live mussels ( $x_{10}$ )	1.48%
				<b>buying company characteristics</b>	<b>2.77%</b>
1.1046	3.2621	3.3183	0.0620	meat yield ( $x_5$ )	6.39%
-1.0526	4.9288	4.8902	0.0407	size count ( $x_6$ )	4.16%
-0.1728	2.9815	2.8584	0.0213	impurity ( $x_7$ )	2.15%
-0.0011	17.5835	15.6651	0.0020	barnacles ( $x_8$ )	0.20%
-0.0003	6.7544	4.0686	0.0008	slippers ( $x_9$ )	0.08%
-0.0581	0.4963	0.4808	0.0009	origin ( $x_{11}$ )	0.09%
				<b>quality of mussels</b>	<b>13.62%</b>
-0.8473	4.4098	4.4369	-0.0230	supply ( $x_2$ )	-2.27%
0.0418	92.6692	95.1552	0.1039	trend ( $x_{12}$ )	10.95%
-0.1474	4.1373	3.9660	0.0253	season ( $x_3$ )	2.56%
				<b>Timing</b>	<b>11.21%</b>
				Theoretical price of manager compared to benchmark	<b>29.86%</b>
				Actual price manager compared to benchmark	<b>37.81%</b>
				Unexplained (i.e., premium paid)	<b>6.12%</b>

**Figure 1. Bullwhip effect in a live mussel supply chain**





**Figure 2(a) Prediction without autocorrelation (week average)**



**Figure 2(b) Prediction with autocorrelation (week average)**

