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. Quite surprisingly, companies buying large quantities of mussels turn out to pay higher unit prices. Further, auction prices react sharply to changes in annual supply. Seasonality causes a bullwhip effect. Purchase managers perform significantly differently from each other. The paper quantifies the importance of factors that objectively measure product characteristics (so-called hedonic price factors). To derive these results, this paper uses a linear regression model that: (i) extracts information from a large database (including 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.

1. Introduction

In this paper we present the results of our investigation into the role of auctions in *supply chains* (SCs). By definition, a SC is a flow of goods, services, and information in a single organization or between organizations. Organizations may 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 a *purchase manager* can 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. A 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 (the classic reference is Milgrom and Weber 1982; recent references are given by Ribbers et al. 2002). 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; in our case study, however, mussels are sold at an auction.)

(ii) The relationship between *supply quantities* and *auction prices* implies that abundant supply lowers auction prices (unless the supply curve would be completely inelastic), or that high auction prices prompt sellers to increase supply (shift of supply curve). 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, which shows data for 'live' mussels, which are to be distinguished from 'processed' mussels (see Section 3).

(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 use a regression model to calculate a "hedonic" price; that is, the implicit price of objectively measured characteristics of a differentiated product (the classic reference is Rosen 1974). Obviously, a purchase manager is expected to pay higher prices for 'better' products.

Our *main conclusions* will turn out to be: (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 may perform significantly differently from each other (all other things being equal).

We derive these conclusions from our linear regression model. This model extracts information from a huge database of 28,017 mussel lots (these data concern the trade in Yerseke during the years 1986/1987 through 1999/2000). Our model 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 its purchase managers. 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. In Section 9, we present our final conclusions and topics for future research. More details about this study can be found in Van Schaik and Kleijnen (2001).

2. Four Hypotheses on SCM issues

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; i.e., the type I error probability is only α, for example, 5%. We do not explicitly formulate the alternative hypotheses, since they simply negate the corresponding null-hypotheses (for example, the alternative hypothesis 2 is that mussel prices *do* vary with the total annual supply; see Section 2.2).

2.1 Market Share and Price

Common sense suggests that the buyer who purchases larger quantities pays a lower price because a big customer's negotiating power results in a lower unit price. However, a sealed-bid auction distorts this pattern: there is no bilateral negotiating at such 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. This leads to the following null-hypothesis.

Hypothesis 1: in sealed-bid auctions, companies with a higher market share pay the same unit price for the same quality of mussels 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, customers may accept only a narrow price range. 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, so 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 next April.

Hypothesis 2: mussel 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.

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

2.4 Purchase Manager and Price

Purchase managers are receiving increasing attention in firms' performance improvement plans. 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 purchase manager's 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 most of the available objective information that affects the price (see Section 5.2).

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 seabed. Mussel "farmers" rent part of the bottom of two North Sea estuaries in the Netherlands, namely the Wadden Sea (or Dutch Shallows, from now on called Wadden) and the Eastern Scheldt (from now on called Scheldt); 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 shell is 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. These 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 auctioned 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 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 trades in live mussels: these buyers purchase on average 84% of the mussels landed. These companies clean, grade, and pack mussels. Their purchasing costs amount to approximately 60% of the turnover. These mussels are required to have a higher quality than do the processed mussels.

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

Actually, these percentages of live versus processed mussels (84% versus 16%) vary from year to year—according to the quality and quantity of supply. Supply is abundant in some years; large quantities are then 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 for processing: 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 facing 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 (further described below). 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, sealed-bid auctions are fast so they work 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. Another fast auction type is the Dutch auction, which is applied in the Dutch flower trade; see Ribbers et al. (2002). Flower lots, however, are much less expensive than mussel lots: a single mussel lot may cost as much as € 200,000 (€ 1 is approximately $ 0.9).

The mussel farmers ship the mussels to the auction, and display them in the harbor at the auction house. The auction house supplies a crucial service, namely *quality control*. So—before the auction—employees of the auction house 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 (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 or reservation price* per "mussel ton" that is fixed for one year; one mussel ton is 100 kilograms. For example, in 1999 this price was fixed at € 16. 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 as well 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 buyers for live mussels, and four buyers for processed mussels. Sellers and buyers pay a fee to the auction house, namely a percentage of their sales and an amount per mussel ton.

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 in the mussel auction is important: purchasers may spend several million euros within an hour, so errors can be costly. Purchasers face the following problems in the auction.

(i) A mussel lot consists of a great diversity of types and sizes: some lots consist largely of small mussels, other lots consist of large mussels, etc. So there are never lots of only one mussel size. The consumer, however, is supplied with only five sizes of mussels—sorted in the factory according to shell width. (The purchasing

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manager knows about this mix: the auction house provides information on each lot's quality; see Section 4.1 above.)

(ii) 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 his bid price is the highest price so he does purchase that lot (and realizes his desired market share).

5. Regression Model for Mussel Prices

We use regression analysis to explain the price of mussels in the sealed-bid auction in Yerseke. In this analysis, we cover elements from the literature on the hedonic prices of agricultural commodities, which includes 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

Table 1 provides the definitions and the predicted signs of our regression variables. In general, a *linear multiple-regression model* may be written as

$$y = \beta_0 + \Sigma_j \beta_j x_j + e. \tag{1}$$

In our case study, the variable to be explained is the price per mussel ton, p. In model (1) we use the dependent variable $y = \ln(p)$ with the natural *logarithm*, 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 dollars.

(ii) Some original independent variables z_j are real numbers and for a subset of these variables (see next paragraph) we use their logarithm so the independent variable becomes $x_j = \ln(z_j)$. For these independent variables the regression parameter β_j denotes the *elasticity coefficient* $(\partial p / p)/(\partial z_j / z_j)$, which is popular in economic theory.

Some original variables are real numbers; nevertheless, we are not interested in their elasticity coefficients. For example, for barnacles (z_8) we wish to estimate the relative price change as that variable changes by an absolute value:

$\ln(p) = \ldots + \beta_8 z_8 + \ldots$ or $(\partial p/p)/(\partial z_8) == \beta_8$ or $(\partial p/p) = \beta_8 \, \partial z_8$.

Notice that there may be zero barnacles in a lot, so the logarithmic transformation would not apply anyhow. Actually, we study various scatter plots to decide whether logarithmic transformations provide a better-fitting regression model.

Some other variables—namely, z_4, z_{10}, and z_{11}—are not real numbers but *binary* variables. For example, $z_{11} = 1$ if the mussels originate in the Wadden: $z_{11} = 0$ if the mussels originate in the Scheldt. (Mathematically, $\ln(0)$ is undefined; economically, an elasticity coefficient for origin is nonsense.) The coefficient of a binary variable is the estimated percentage change in price when the lot has the characteristic described by the binary variable while all other characteristics are constant. For example, Wadden mussels are β_{11} percent more expensive than Scheldt mussels.

In summary, we specify a regression model (1) with three types of explanatory variables:

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

$$\beta_j = \frac{\partial p / p}{\partial z_j / z_j} \quad if \ y = \ln p, \ x_j = \ln z_j, \quad z_j \in \Re^+. \tag{2}$$

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

$$\beta_j = \frac{\partial p / p}{\partial z_j} \quad if \ y = \ln p, \ x_j = z_j, \quad z_j \in \Re. \tag{3}$$

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

$$\partial p / p \ = \ e^{\beta_j} - 1 \quad if \ x_j = z_j, z_j \in \{0, 1\}. \tag{4}$$

Finally, the term e in model (1) represents the *noise* or *disturbance* caused by our exclusion of some explanatory variables. For example, the auction does not measure the mussels' color, taste, or texture; neither does the auction measure the potential buyers' utility functions. 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 the auction house gives to the buyers before the auction starts. We presume that the auction house provides this information because 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 independent variables increases prediction performance (also see the Adjusted R^2 in Section 7). For example, we use size count but 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 do not tend to pay a higher than average price for mussels of the same quality.

Supply (z_2): hypothesis 2 concerns the effect of aggregate annual supply on 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 seasonal movement in prices. Supply and demand result in much higher prices in June, July, and August. However, 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 have already 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 processing machines. The buyers' sorting machines categorize mussels according to shell width, so the machines may erroneously categorize small mussels with barnacle growth as large mussels. Barnacles also make mussels look less attractive to consumers

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}): live versus processed mussels. All lots are listed by the auction in the order of the ship's arrival at the harbor. As we have already mentioned (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): 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.

This concludes our discussion of the variables in Table 1.

6. Data Source and Sample Selection

The Yerseke auctioning process has been computerized since 1986, 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 on 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 (some fishing and purchasing companies belong to the same group and trade produce at the auction at pre-arranged prices). This correction reduces the number of lots to 28,017.

Not all variables have the same sample size. 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 compute our regression results through SPSS version 9.0. Table 2's first column of figures shows the estimates of the regression coefficients β_j in model (1) when using *ordinary least squares* (OLS). These estimates are "best" if the white noise assumption holds ; "best" means it is the minimum-variance unbiased linear estimator.

We do not show the estimated correlation coefficients for pairs of estimated regression coefficients. Obviously, these correlations are not zero as some independent variables are correlated. We do show the estimated variances indirectly—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 turn out to be significant at any reasonable α value, even at 0.001. One explanation for this significance is that the number of observations for variables measured per lot is extremely high (namely, 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 switch to 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 by λ, is estimated to be 0.5826 with a standard error of 0.0049. This method gives an acceptable Durbin-Watson statistic of 2.290 (see Table 2, line -3). These GLS 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. The standardized coefficients equal the unstandardized regression coefficients β_j multiplied by the standard deviation of the independent variable $s(x_j)$ and divided by the (common) standard deviation of the independent variable $s(y)$. These standardized 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 acceptable: the Adjusted R^2 is 66% for OLS and 56% for GLS (see last line of table 2), whereas other regression models for hedonic prices give only 37% for Christmas trees and 64% for tuna fish—but 89% for wheat, and 93% for cotton; see the references in Section 5. Switching for OLS to GLS decreases our R^2; nevertheless, GLS gives better predictions (see Section 8, especially Figure 2). Indeed, R^2 is a popular but possibly misleading statistic; see Kleijnen and Deflandre (2002). For a discussion of the Adjusted R^2, we also 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; see again Table 2. Big buyers tend to bid high, so Hypothesis 1 is rejected at the 0.001 level.

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

Season (z_3) strongly affects the mussel industry: hypothesis 3 is rejected. Our explanation is that the 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 (see again 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? The first row of figures in Table 3 shows that the average market share gives $\ln(z_1) = 1.8475$, whereas his company has a relatively high market share, $\ln(z_1 \mid z_4 = 1) = 2.2161$. 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.

Similarly, his working for a company that uses live mussels instead of processed mussels could explain that he pays 1.48% more than average. Further, 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 ($t = 10.94$). Nevertheless, this conclusion is only tentative, for at least the following two reasons.

(i) The GLS model has an R^2 of no more than 56%, whereas the statistical significance of x_4 holds only

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under the assumption of a perfectly valid regression model.

(ii) The buyer may obtain high-quality mussels, which 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 might 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. 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 the model is only an approximation of reality. For example, he may pay 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}) also has a positive effect.

We were surprised to find that the regression coefficient for *origin* (z_{11}) has a significantly negative sign. 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 place (Yerseke). It may take a ship up to eighteen hours to travel this distance, which 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, as follows. We estimated a new regression model for each of the fourteen years. We find that for each variable the regression estimates do not change much over these fourteen years. (This robustness study is analogous to cross-validation, which is getting popular in regression modeling; also see the next section.) Furthermore, we find that market share significantly increases prices.

8. Predictive Power of the Regression Model

Subsequently, we 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 the following descriptive statistics for the prices of these 2,199 lots, both actual and predicted. The standard deviation of the predicted prices is lower and the range 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*, as follows. 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*:

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

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

$$with \; t = 1, \; 2, ..., 2199 \quad and \; c = \sum_{i=1}^{t-1} \hat{\lambda}^i$$

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, let us 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.

To derive the formula for the absolute price, we use the first two terms combined with (1) through (4) and the GLS estimates in Table 2. 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 $\hat{p} = \exp(1.559) \, p^{0.675} = 4.75 \, p^{0.675}$.

Figure 2 shows time plots. 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 these two figures demonstrates 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.

In conclusion, 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 might 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, and concluded:

(i) large buyers pay higher prices (to maintain their market share?);

(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 large database (with 28,017 mussel lots), so we could 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: it does not contain offers by other parties that were outbid. This limitation, however, 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 (for example) the building industry, not all companies are large enough to carry out every single building project.

Our model does incorporate most 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 characteristics such as color, taste, and texture.

It is well-known that game theory might provide a different methodology to study auctions with their buyers and sellers. Whether game theory provides a better method for the mussel trade remains to be investigated; see Rothkopf and Hardstad (1994).

Future research might also consider the requirements for the 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.

Finally, our model for the purchasing manager's performance may be extended through a Data Envelop Analysis (DEA), distinguishing between live and processed mussels, and between small and large 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 day of the mussel year (this variable starts at 1 for lots auctioned at day 1 of that year).
Purchase manager's performance (4)		Binary variable is 1 for lots bought by the purchase manager whose performance is assessed; otherwise it is 0; this variable is not used in the initial analysis (see Section 5.2.1).
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; 0 otherwise (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

	OLS		GLS (autoregressive)		
	Unstand. coeff.	t Stat.	Unstand. coeff.	t 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

coeffi-cients (1)	mean all (2)	mean this manager (3)	price Difference (4)=(1)x[(3)-(2)]	Performance Report	% 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%
				buying company characteristics	**2.77%**
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%
				quality of mussels	**13.62%**
-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%
				timing	**11.21%**
				Theoretical price of manager compared to benchmark	**29.86%**
				Actual price manager compared to benchmark	**37.81%**
				Unexplained (i.e., premium paid)	**6.12%**

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)

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