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Futures Market Depth: Revealed vs. Perceived Price Order Imbalances

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Practitioner's abstract

In this paper we study futures market depth by examining the price path due to order imbalances thereby allowing us to directly gain insight in the execution costs due to a lack of market depth. We propose a two dimensional market depth measure in which the price path due to order imbalances is described by an S-shape function. The proposed market depth measure is applied to transaction specific futures data from Euronext. Subsequently, we examine CBOT traders' perceptions about the price path due to order imbalances and examine the characteristics that are associated with a particular perception. The proposed market depth measure gives guidelines for improving market depth, and can be used to compare competitive futures contracts. It appears that the actual price path due to order imbalances does not match the perceived price path. Traders have various perceptions about the price path due to order imbalances. Dominant perceptions were, S-shape, linear, exponential or zigzag price paths. The differences in traders' perceptions can be traced back to different traders' characteristics among others type of primary futures contract traded, importance of information sources and trading strategy (herd vs. non-herd behavior). The observed disconnect between perceptions and revealed price path due to order imbalances have great implications for market participants who try to minimize execution costs and for the futures exchange management that tries to increase the market depth.

Keywords: Market depth, Execution Costs, Perceptions

Introduction

The lack of sufficient market depth results in relatively high hedging costs, and inhibits the growth of futures contract volume. In this paper the price path due to order imbalances is analyzed and a two-dimensional market depth measure is derived and tested using transaction specific data from Euronext. Subsequently, we compare the results with the perceptions that CBOT traders have about the price path due to order imbalances. Contrasting the revealed versus perceived price path due to order imbalances provides the management of the futures exchange with a framework for improving their market depth and gives hedgers a better understanding of market depth risk.

A key aspect of futures market performance is the degree of liquidity in the market (Cuny, 1993). The relationship between market depth and futures contract success has been thoroughly investigated in the literature (Black, 1986). A futures market is considered liquid if traders and participants can buy or sell futures contracts quickly with little price effect resulting from their transactions. However, in thin markets, the transactions of individual hedgers may have significant price effects and result in substantial 'transaction costs' (Thompson, Waller, and Seibold, 1993).

These transaction costs are the premiums that traders are forced to pay or the discounts they are forced to accept in order to establish or close out futures positions (Ward and Behr, 1993). Although, hedgers can take positions that offset each other, a futures market, if it is to be successful, should normally create more market depth in the form of attracting additional traders.

In the literature, liquidity is often synonymous with the bid-ask spread for a given number of futures. The bid-ask spread as a measure of liquidity has some limitations. Price may change between the moment the market maker buys and sells, and the trader can earn much more or much less than the spread quoted at the time of the first transaction suggests. Hence, the trader faces costs due to changes in the bid-ask spread. Yet these costs are the essence of market liquidity (Grossman and Miller, 1988). The concept of market depth (the number of securities that can be traded at given bid and ask quotas), an aspect of market liquidity, does not suffer from the limitations of the bid-ask spread (Berkman, 1993; Harris, 1990; Kyle, 1985). Therefore, we turn to an examination of market depth as a measure of liquidity.

The objective of our study is two fold. First we want to improve insights into market depth and the effect it may have on the performance of futures contracts and, consequently, on the success of futures exchanges. Second we want to gain insight in how a lack of market depth, and particularly the shape of the price path due to order imbalances, is perceived by futures traders. In the literature, measures of market depth have not explicitly considered the price path produced by temporary order imbalances. Often there is an implicit assumption of linearity which allows only a limited understanding of the costs associated with lack of market depth. Thus the management of the exchange gets only a limited insight into how the problem of a lack of market depth should be dealt with. We propose and parameterize a model that pays explicit attention to the price path caused by temporary order imbalances. With more information about these price paths, we will be able to distinguish two dimensions of market depth that can be related to the toolbox of the futures exchange (the trading system and trading rules). Evaluating different (competing) futures contracts and futures exchanges using these dimensions can shed light on the performance of the futures contract as a price-risk

management instrument. In addition, having insight in the perceptions that traders have about the price path due to order imbalances allows us new insight in market efficiency and how well traders are able to distinguish between price movements due to order balances and fundamental shifts.

This paper is organized as follows. First the measures of liquidity - and in particular the measures of market depth - are examined. Subsequently, we present a hypothesis of the underlying structure of market depth from which a market depth price path model is then derived. Than we presents an analysis of market depth for three selected futures contracts using transaction specific data from Euronext. Subsequently, we investigate traders perceptions about the price path due to order imbalances and examine the characteristics of traders that are associated with a particular perception. Finally the results and main conclusions are summarized.

Measures of Liquidity, Particularly Market Depth

Previous research developed measures of *liquidity* on the basis of indices usually represented by some weighting of trading activity (Working, 1960; Larson, 1961; Powers, 1979; Ward and Behr, 1974; Ward and Dasse, 1977). An important element in these measures is the proportion of hedging to speculative trading volumes. Several researchers (Roll, 1984; Glosten and Milgrom, 1985; Thompson and Waller, 1987; Stoll, 1989; Smith and Whaley, 1994) propose methods for an indirect estimation of liquidity costs. A liquidity cost proxy based on the estimated covariance of prices has been introduced by Roll (1984). Another accepted proxy for the bid-ask spread has been proposed by Thompson and Waller (1988), who argue that the average absolute value of price changes is a direct measure of the average execution cost of trading in a contract. Smith and Whaley (1994) use a method of moments estimator to determine the bid-ask spread. This estimator uses all successive price change data, and assumes that observed futures transaction prices are equally likely to occur at bid and ask.

Market depth measures are rather scarce. Brorsen (1989) uses the standard deviation of the log price changes as a proxy for market depth. Lehmann and Modest (1994) study market depth by examining the adjustment of quotas to trades and the utilization of the chui kehai trading mechanism on the Tokyo Stock Exchange, where the chui kehai are warning quotas when a portion of the trade is executed at different pre-specified prices. Utilizing the chui kehai trading mechanism can give an indication of market depth, but cannot be used to measure it. Other researchers such as Bessembinder and Seguin (1993) use both price volatility and open interest as a proxy for market depth. Common to all these market depth measures is the fact that they are based on transaction price variability (Huang and Stoll, 1994, 1996) and implicitly assume that the price path due to temporary order imbalances is linear (see, for example, Kyle, 1985). However, there is no reason that the price path is linear, particularly when large orders are concerned. Therefore, we propose a non-linear function which relates the futures price to successive trades.

In the literature there are no measures that reflect the shape of the price path due to order imbalances, in sight of the fact that is this shape that provides insight into the underlying structure of market depth and that determines the execution costs that hedgers face.

A Market Depth Model

Conceptual Model

Market depth is usually analyzed by determining the slope $\frac{dPF}{dQ}$, where PF is the futures price and Q is the quantity traded. As discussed in the previous section, current market depth measures are based on transaction price variability and implicitly assume the price path due to order imbalances to be linear. In this section we hypothesize that the price path arising from order imbalances can be characterized by an S-shaped curve. During the occurrence of such an S-curve, the equilibrium price change is assumed to be constant.[1] The price path is downward-sloping in the case of a sell order imbalance and upward-sloping in the case of a buy order imbalance (Working, 1977; Kyle, 1985; Admati and Pfleiderer, 1988; Bessembinder and Seguin, 1993).

Figure 1 about here

The market depth price path is caused by frictions in the market structure which includes the trading system and the rules of the exchange. The quality of the market information generated by the trading system regarding high price, low price, last price, size of last trade etc., is crucial for such frictions and hence, for the market depth price path (see Domowitz, 1993a,b) for a description of trading systems and their impact on market depth).

The S-shaped price path can only be identified ex post. Recognized market efficiency theory would suggest that the price would not adjust in a predictable way (Fama, 1991). However, at the moment the price changes, the participants are not able to identify whether the price movement is due to fundamental economic factors causing a change in the equilibrium price or whether it is due to a lack of market depth generated by market frictions caused by the trading system itself.

A priori we do not assume that the downward-sloping S-shaped price path is exactly the reverse of the upward-sloping price path. It is possible, for example, that there are many stop-loss buy orders and hardly any stop-loss sell ones and vice versa, thus causing an asymmetry between upward-sloping and downward-sloping price paths (Chan and Lakonishok, 1993).

Mathematical Specification of the Model

In the mathematical model showing the conceptual model of market depth, both sell and buy orders (downward- and upward-sloping price paths) are taken into account. An upward-sloping S-shaped path may well be approximated by a Gompertz curve, since this curve has a non-symmetrical S-shape and thus, does not impose restrictions on the length of the different phases. The Gompertz model is a growth curve and can therefore only be used to describe an upward-sloping price path. However, subtracting a downward-sloping price path from an appropriate constant may establish an upward-sloping price path which will cover the four phases. Consequently, after transforming the data, the price path will always be upward-sloping. We can describe the transformed price series using the Gompertz model given by

(1) $TPF_i = \alpha \exp(-\beta \exp(-\delta i))$

where TPF_i is the transformed price of futures contract i ($i = 0,1,2,...,n$) and α, β and δ are positive parameters. Since the price path is restricted to start in the minimum tick size, TPF_0 is equal to the minimum tick size. The parameter β is determined by both α and TPF_0: $\beta = \ln\left(\frac{\alpha}{TPF_0}\right)$. The parameters α and δ of the Gompertz model capture two dimensions of market depth. The first dimension, represented by α minus the minimum tick size, indicates how far the price rises (falls) as a consequence of a lack of market depth. The second dimension, presented by δ, has a one-to-one relation with the rate of adjustment, which, as we will show below, is equal to $[1 - \exp(-\delta)]$, see Chow (1967) and Franses (1994a,b). This rate of adjustment may be translated into costs in terms of price risk; the futures price may change before actual order execution.
Taking natural logarithms of (1) yields

(2) $\ln(TPF_i) = \ln \alpha - \beta \exp(-\delta i)$

A convenient representation of the Gompertz process is obtained by subtracting $\ln(TPF_{i-1})$ from (2) which can be written as:

(3) $D \ln(TPF_i) = [1 - \exp(-\delta)][\ln \alpha - \ln(TPF_{i-1})]$

where D is the first order differencing filter defined by $Dz_i = z_i - z_{i-1}$. Equation (3) is of particular interest because it can be interpreted as a partial price adjustment model. In order to see this, note that $0 < [1 - \exp(-\delta)] < 1$. As a consequence, although α will always exceed TPF_i, $\ln(TPF_i)$ is rising toward $\ln \alpha$ at a constant rate of adjustment $[1 - \exp(-\delta)]$. For instance, if $[1 - \exp(-\delta)] = 0.1$, it will take many more contracts to achieve a particular price rise than in the situation where $[1 - \exp(-\delta)] = 0.5$, *ceteris paribus*. Similarly, if $\ln \alpha$ exceeds $\ln(TPF_i)$ by one per cent of $\ln(TPF_i)$, then $\ln(TPF_i)$ will increase by $[1 - \exp(-\delta)]$ x 100 per cent. In addition, $\exp(-\delta)$ is the elasticity of TPF_i with respect to TPF_{i-1}.

The parameters of the model provide an indication of market depth. An increase (decrease) of both α and δ implies a decrease (increase) of the market depth. When α and δ have opposite signs we have two counter acting forces. If the order is relatively large the first dimension, α, is particularly relevant as far as incurring execution costs are concerned. For relatively small orders the second dimension δ is relevant. Table 1 summarizes the effects of changes in the two dimensions on market depth.

Table 1 about here

The model in (3) may be extended on three fronts. First, Equation (3) is an approximation to the transformed price series. Hence, we add a disturbance term u_i to (3) under the assumption that $u_i \sim \text{IID}(0, \sigma^2 \text{I}_n)$. Second, notice that the transaction-specific price observations cannot be described by a single curve such as the curve depicted in Figure 1, but by a sequence of such curves where an upward-sloping curve is always succeeded by a downward-sloping one and the other way round. As a consequence, the data series on the transformed price consists of a panel (not restricted to being balanced) of upward-sloping curves in chronological order. Third, as discussed in section 3.4.1, to allow upward- and actually downward-sloping curves to have dissimilar shapes, (3) is extended to:

$$\text{(4)} \qquad \text{D ln } (TPF_{ci}) = \pi_s - \tau_s \text{ ln } (TPF_{c,i-1}) + u_{ci}$$
$$\text{s.t. } u \sim \text{IID}(0, \sigma^2 \text{I}_N)$$

where $\pi_s = [1 - \exp(-\delta_s)] \ln \alpha_s$, $\tau_s = [1 - \exp(-\delta_s)]$, $i = 1, \ldots, n_c$ with $c = 1, \ldots, H$ and s is an index for actually upward- ($s = 1$) and downward-sloping ($s = 2$) curves. H denotes the number of curves. Notice that our dataset on TPF_{ci} consists of $N = \sum_{c=1}^{H} n_c$ observations (i.e., traded contracts), where n_c is the number of contracts per curve c. In the next section more details are given on how we obtain these observations.

Estimation of the Model

In our theoretical model we assume that during the occurrence of an S-shaped price path, the equilibrium price is constant and, therefore, the S-shaped price path is attributed solely to temporary order imbalances. However, actual price changes in the futures market result from both temporary order imbalances and from supply and demand factors of the underlying commodity of the futures contract. Consequently, estimation of the model on the basis of real futures market data might invalidate the assumption of a constant equilibrium price during every separate S-shaped price path. However, S-shaped price paths due to temporary imbalances occur in a very short period of time, say within a matter of minutes. Since the effect of fundamental economic factors occurs over a much longer period of time than a few minutes, we might expect that during such a downward-sloping or upward-sloping price path the price change due to fundamental economic factors, i.e. the change of the equilibrium price, is negligible compared to the price change due to order imbalances.

After identifying the individual price paths, we subtract the observations of each downward-sloping price path from the price at which the price path started, such that all curves become upward sloping.[3] In order to eliminate the general price level effect, we shift the curves downward, such that each curve starts at the minimum tick size. Thus, each S-curve, after being transformed to become upward sloping, is shifted downward to the minimum tick size. In doing so we correct for differences in equilibrium price between S-curves. Using the resulting data series, estimates of the dimensions of market depth α and δ are obtained by the following procedure. First, maximum likelihood estimates of π_s and τ_s are obtained by applying ordinary least squares to (4). The

maximum likelihood estimates of the relevant parameters α_s and δ_s are computed by $\alpha_s = \exp(\frac{\pi_s}{\tau_s})$ and $\delta_s = -\ln(1 - \tau_s)$. Second, the standard errors of α_s and δ_s are computed by the square root of the diagonal elements of $\text{var}(\eta) = [\frac{\partial \eta'}{\partial \theta}]\,\text{var}(\theta)[\frac{\partial \eta'}{\partial \theta}]'$ (see Cramer, 1986), where $\eta = (\alpha_1\ \alpha_2\ \delta_1\ \delta_2)'$ and $\theta = (\pi_1\ \pi_2\ \tau_1\ \tau_2)'$ are four-dimensional parameter vectors. Since the maximum likelihood estimators have asymptotic normal distributions, *t*-values may be used to test if the parameters are significantly different from zero. To see whether one single market depth price path for both upward- and downward-sloping curves suffices, i.e. whether or not the upward-sloping price path is exactly the reverse of the downward-sloping price path, we test the hypothesis H_0: $\{\alpha_1 = \alpha_2 = \alpha$ and $\delta_1 = \delta_2 = \delta\}$. In terms of Equation (4) this implies testing H_0: $\{\pi_1 = \pi_2 = \pi$ and $\tau_1 = \tau_2 = \tau\}$. Since the restrictions are linear we use an *F*-test of which the test statistic has an $F(2,\ N - 4)$ distribution, under H_0.

Data

In order to illustrate the contributions of the model presented above, we apply it to data from Euronext. This exchange is one of the largest agricultural futures exchanges in Europe. The trading system employed by the EURONEXT is the open outcry system. There are no scalpers on the trading floor and all orders enter the trading floor via brokers. Brokers are only allowed to trade by order of a customer. There is no central order book on the EURONEXT. The broker only has insight into his/her own order book. The customer (hedger or speculator) has no information on outstanding orders.

Potatoes and hogs are traded on the EURONEXT. The potato futures contract is a relatively successful one in the sense that the volume generated (about 200,000 contracts annually) is large relative to competitive potato contracts elsewhere in Europe (such as the potato futures traded on the London Commodity Exchange and on the Marché à Terme International de France). The annual volume is small, however, when compared with agricultural futures traded in the United States. Hog futures are not successful as far as their volume (about 30,000 contracts annually) is concerned. The minimum tick size for the potato and hog futures contracts equals 0.10 Dutch Guilders and 0.005 Dutch Guilders, respectively.

We use real-time transaction-specific data for three futures contracts: potato contract delivery April 1996, and hog contract deliveries August and September 1995.[4] Descriptive statistics for both the potato and hog futures price and volume series are presented in Table 2. The average number of contracts per trading day is relatively large for the potato market compared with the hog markets. The latter market faces severe problems of market depth which inhibits its contract growth.

Table 2 about here

Empirical Results

In this section we apply ordinary least squares to (4) and express the estimates of π and τ in those of α and δ.

In Table 3 the estimation results for the potato futures contract, delivery April 1996, are displayed.

Table 3 about here

It can easily be seen that all parameter estimates are significantly greater than zero when using a one-sided *t*-test and a 0.05 level of significance. The Durbin-Watson statistic does not indicate any mis-specification. In spite of its low value, the R^2 is significantly greater than zero, as indicated by the $F(3, 46786)$ statistic. The hypothesis H_0: $\{\alpha_1 = \alpha_2 = \alpha$ and $\delta_1 = \delta_2 = \delta\}$ is rejected. Therefore, the market depth for the potato futures contracts, delivery April 1996, significantly differs between periods of price rise and price fall.

Table 4 presents the estimation results for the hog futures contract, delivery August 1995. Since the hypothesis H_0 cannot be rejected, we conclude that the market depth for this contract is characterized by a single Gompertz curve. So, the upward sloping price path is the reverse of the downward sloping price path. Compared with Table 3, the statistics in Table 4 lead to similar conclusions with respect to the performance of the regression.

Table 4 about here

Table 5 shows the estimation results for the hog futures contracts, delivery September 1995. The results are quite similar to those in Table 4. Again, we cannot reject H_0.

Table 5 about here

To gain more insight into the price path due to order imbalances we draw the Gompertz curves for the upward-sloping and downward-sloping potato futures price path (see Figure 2) and for the hog futures price paths (see Figure 3), using the parameter estimates in Tables 3, 4 and 5.

Figure 2 about here

The figure depicts the Gompertz curves for increasing and decreasing price paths. On the vertical axis the futures price per contract traded is given. On the horizontal axis the prices of successive contracts traded are given, where the serial number of the futures contract is denoted by *i*. $i = 1$ is the first contract traded, $i = 2$ is the second contract traded and so on.

In each of the two figures both dimensions of market depth are visualized simultaneously. Note that since the upward-sloping price paths for both deliveries of hog

are the reverse of the downward-sloping price paths, we only depict the upward-sloping price paths for both hog series in Figure 3.

Figure 3 about here

The figure depicts the Gompertz curves for hog delivery August and hog delivery September. No distinction is made between upward- and downward-sloping price paths, because the upward sloping price path is exactly the reverse of the downward sloping price path. On the vertical axis the futures price per contract traded is given. On the horizontal axis the successive contracts traded are given, where the serial number of the futures contract is denoted by i. $i = 1$ is the first contract traded, $i = 2$ is the second contract traded and so on.

The upward- and downward-sloping Gompertz curves for *potato* futures have dissimilar shapes. The first dimension - indicating how far the price falls or rises due to order imbalances - is quite large compared with the general price level. This might be due to the absence of scalpers. In order to improve the absorption capacity, the EURONEXT might consider allowing scalpers on the floor. The second dimension - the rate of price change - is higher for the upward-sloping price path than for the downward-sloping price path. This can be explained by the fact that there are differences between the number of stop-loss buy and stop-loss sell orders. The difference between the numbers of stop-loss buy and stop-loss sell orders can be explained by the fact that participants in the potato futures market consist of relatively large firms (potato processing industry) who are the net buyers of potato futures contracts on the one hand and relatively small firms (potato farmers and small potato traders) who are net sellers of potato futures contracts on the other. The former participants often use stop-loss buy orders especially because they normally make cash forward contracts with retailers regarding potato products (such as chips and French fries). When the price rises we observe a trigger effect: a considerable number of stop-loss buy orders are executed which push the price upwards and thereby reinforce the stop-loss buy order effect which causes an acceleration of the price of futures. The potato farmers and small traders usually do not use stop-loss sell orders, but wait until the price is satisfactory and then enter the futures market.[5]

Since the curves in Figure 2 do not intersect, we may conclude that the futures market is deeper in the case of a sell order imbalance than in the case of a buy order imbalance. The problem of the high rate of (adverse) price changes at the EURONEXT might be solved by implementing a mechanism for slowing down the trade process if order imbalances do occur and to improve market depth by reporting these. Also the order book information can be improved. At the EURONEXT, the order books of the different brokers are not linked and the customer has no information with regard to outstanding orders. An order book mechanism that allows potential participants to view real-time limit orders, displaying the desired prices and quantities at which participants would like to trade, will improve the rate of adjustment and the distance between the lower and upper bounds.

The upward- and downward-sloping price paths are similar for both *hog* deliveries. In the hog futures market we observe a symmetry between stop-loss buy and stop-loss sell orders in contrast to the potato futures market.[6] Tables 4 and 5 show that α is smaller for delivery August than for delivery September indicating that the delivery August performs

better on the first dimension. However, on the second dimension delivery September performs better than delivery August (i.e, δ for delivery September is smaller than for delivery August). Consequently we observe in Figure 3 that the price paths intersect, indicating that for relatively small orders September delivery is deeper than August, whereas for large orders August delivery is deeper (see also Table 1).

What are the Perceptions of Traders? A Preliminary Study

After we have examined the hard transaction data we are interested in the perceptions of traders, since perceptions drive behavior. That is trader behavior, and hence their reactions to price movements, are a function of their perceptions, that is the interpretation of information, not information itself. In the case that the perceived price path due to order imbalances equals the revealed price path due to order imbalances one might argue that the market is efficient, as all information is reflected in the price changes. When there is a disconnect between perceptions and the revealed price path due to order imbalances market efficiency may be compromised and trading might not be optimal. A hedger, who perceives a linear price path during an order imbalance, might be confronted with unexpected execution costs if the actual price path is S-shaped, which might lead the hedger away from participating in the market thereby decreasing market depth. Exchanges instituting changes to promote market depth must be conscious of trader perceptions. If basing their decisions on ex post statistical data, they may find their changes ineffective because it did not change trader perceptions of market depth, hence failing to change behavior.

We wish to examine whether trader perceptions match the true price path during temporary order imbalances. Since we have not completed the research at the Chicago Board of Trade (CBOT), we use that the S-shaped price path found at Euronext as a reference point to examine trader perceptions. Furthermore, we examine whether particular trader characteristics are associated with traders perceptions.

Research Design

To investigate what traders think that the price path due to order imbalances looks like, we conducted a mail survey with traders of the CBOT in August 2003. The addresses of the seat holders at the CBOT were obtained and used to contact the traders. Interviews with five traders helped to develop and test the survey; ensuring recipients would understand the questions.

One problem with the distribution of the survey was CBOT regulations to protect the confidentiality of names and addresses of seat holders. Many seat holders do not actively trade themselves; instead, they lease their seat. We were unable to screen the list to delete or replace these individuals. Only active traders' survey results were utilized.

Survey Instrument

The final survey consisted of 6 parts. In the first part, we obtained demographics like what type of futures they trade and on what system (electronic vs. open outcry). The second part consisted of questions relating to liquidity. Within this part we exposed traders to four possible shapes of the price path due to order imbalances, and asked them which of the four shapes most resembled the price path due to order imbalances. The four

shapes are described as linear, exponential, zigzag or S shaped (see Figure 4). If in the eyes of the traders these shapes did not match their perceptions of imbalances, they were allowed to draw their own price path. Subsequently we asked questions about how the rate of price, bid-ask spread magnitude, order flow and noise level changes when there is an order imbalance. Similar questions were asked for price changes due to fundamental shifts. In the third part of the survey we asked questions about the psychological aspects of the market place, followed by part four in which questions regarding how they perceive electronic trading versus open outcry were asked. The fifth part dealt with the type of information sources they use. The final section addressed concerns facing hedging operations.

Figure 4 about here

Results

Table 6 shows some descriptive statistics of the traders in our sample. Fifty percent of the traders sampled primarily traded agricultural futures, while only 37.2 percent used financial futures. This appears slightly out of balance given that the financial volume is over three times the volume of the agricultural market (www.cbot.com). The traders, who did not respond to this question, however, responded to the other questions in a similar manner to the financial respondents. The survey pool is very highly concentrating in futures traders (76.7%) as opposed to the options (10.5%).

Table 6 about here

Perceived vs. Actual Price Path Due to Order Imbalances

Figure 5 shows the proportion of traders that believe that the price path due to order imbalances can best described by a linear, exponential, S-shaped function or zigzagged. The figure shows that 23.6% believe it is a linear function, 12.7% an exponential function, 25.5% a S-shaped function and 29.1% a zigzag function. The perceptions are statistically different from one another (p <0.05). Assuming that the actual price path due to order imbalances is S-shaped, the difference between perceptions and the actual price path may lead hedgers and traders having unexpectedly higher risks and transaction costs. The mismatch between perceptions and actual price path might imply that traders are not optimizing their activities and the market is not efficient.

Figure 5 visualizes traders' perceptions about the price path due to fundamental shifts. The figure shows that 39.1% beliefs it is a linear function, 26.1% an exponential function, 13.0% an S-shaped function and 15.2% a zigzag function. These estimates are also statistically significant (p< 0.005). Most traders believe fundamental shifts occur linearly.

Figure 5 about here

What Traders' Characteristics are Associated with a Particular Perception?

To further gain insight in the perceptions of traders, we grouped traders according to their perceptions regarding the price path due to order imbalances. Hence, we classified the traders into four groups depending on their perception of the preice path due to order imbalances (the linear, exponential, zigzag and S-shape group) and examined whether there are characteristics of traders that differ across groups using ANOVA and Chi-square tests.

Table 7 about here

Table 7 shows that various trader characteristics are associated with trader perceptions of price path during temporary order imbalances. The first trader characteristic is the market the trader utilizes. 47.4% of agricultural traders perceive S-shaped price path during temporary order imbalances; while 45.0% of financial traders believe it is zigzagged and 41.7% of traders utilizing both markets see linear price paths. These differences are seen more dramatically in Figure 6.

Figure 6 about here

It appears that the majority of surveyed agricultural market participants at the CBOT perceive the price path due to order imbalances as being S-shaped suggesting that for the majority of these agricultural market participants perception correspond with the actual price path due to order imbalances.

The Chicago financial markets participants perceptions, on the other hand, do not match the shape of the price path found in Amsterdam. There are two possibilities for this observation. First, the actual shape is not S-shaped or the traders' perceptions are "wrong" meaning do not mach the actual price path. A possible explanation for this mis match is the much higher volume and capitalization in the financial markets, which might result in fewer order imbalances and/or shorter duration. Subsequently this could cause traders to perceive the market just going back forth or could desensitize them to order imbalances.

Futures traders are pretty evenly split between linear, s-shaped and zigzagged price path groups. Options traders, however, are concentrated in the exponential group (42.9%).

Whether or not the trader was a primary bond trader was associated with different perceptions. 53.8% of bond traders perceived the price path as zigzagged. Since, the bond market has annual volume slightly higher than the entire agricultural market combined and hence having a deeper market might let them believe that the price path due to order imbalances is zigzagged.

It appears that spreaders perceive the price path due to order imbalances more often to be linear than non spreaders.

The majority of traders who indicated to take an opposite strategy in times of herd behavior feel the price path due to order imbalances to zigzagged, which explains their non-herd behavior.

In addition to trader characteristics, we also examined how each of the four groups (linear, exponential, S-shape and zigzag group) valued informational sources. It appears that the traders in the different groups significantly differed regarding the importance they attached to commercial signals/activities and government information resources. Traders who ranked the importance of governmental information the highest were mainly in the exponential group. The S-shaped group valued commercial signals the most.

Table 8 about here

Forty-seven percent of the hedgers surveyed stated they were indifferent to price concession and much more concerned by the quickness of the execution (48.7% ranking quickness very important). Assuming the large corporations hedging attitudes correspond to those surveyed, the corporations are probably the source of many of the order imbalances as the try to quickly hedge large orders. Traders, who find commercial signals very important, should be very sensitive to such order imbalances. Therefore, it is not surprising that they perceive the S-shaped price path.

Traders were asked if they increased (1 on the scale), decreased (5 on the scale), or did not change (3 on the scale) their trading when the noise levels increased, but there was no new information. Table 9 shows that traders who perceive the price path during temporary order imbalances to be S-shaped increased their trading activity during noise.

Table 9 about here

Traders who perceived an exponential price path decreased their trading slightly. This is an intriguing finding when combined with the knowledge that increased noise levels are associated with order imbalances, see Figure 7. An exponential price path penalizes traders the most if they are wrong about what is occurring. It makes sense that if one perceives the price path this way that one hold back and be more reserved during temporary order imbalances.

Conclusions and Future Research

In contrast to the existing market depth measures, we conjecture that the market price depth path has an S-shape. This S-shaped price path may well be approximated by the Gompertz curve, which allows for a non-symmetrical S-shape and hence, does not impose certain restrictions on the length of the different phases. The two parameters of our model represent two dimensions of market depth. The first dimension represents the distance between the upper and lower bounds, i.e. indicates how far the price falls (rises) due to a lack of market depth. The second dimension indicates the rate at which price falls or rises. The market depth measure has convenient characteristics. First, it provides insights into the underlying structure of market depth and gives guidelines for improving market depth. Second, the measure can be used to compare competitive futures contracts. Third, the market depth model is estimated with simple regression techniques.

Furthermore, since our measure can be presented in a graphical way, it is relatively easy to interpret.

When interpreting the results, it is important to be aware of the following points. First, as we have indicated, our model requires transaction-specific data. Transaction-specific data enable us to identify individual downward-sloping price paths and individual upward-sloping price paths by assuming that each of these price paths ends when the traders expect that price will not change by more than the minimum tick size, and that during each price path, which takes place over the space of a few minutes, price change due to fundamental economic factors will be negligible compared to the price change due to order imbalances, i.e. we may expect that over such a short period of time the equilibrium price does not change. Clearly this is not a conceptually perfect method to distangle price changes due to order imbalances and price changes due to fundamental shifts. A potential solution would be to complement the transaction specific data with data on when new information arrived in the market and the content of that information. Doing so would allow us to relate price changes to fundamental shifts more clearly. Efforts are underway to construct such a data set.

Second, and this a major limitation of our study, we did not test the S-shape model against other models describing different shapes. The relatively low R^2 of our model might hint that the S-shape curve might not be the optimal. Furthermore we assume that the price path due to order imbalances is the same across futures contracts and across trading systems. One could hypothesize that there might be heterogeneity in the shapes of the price path due to order imbalances where the heterogeneity is driven by commodity type and trading system. Future research should address these two important issues.

In this paper we investigated the revealed price path due to order imbalances with futures contracts traded at Euronext, whereas the perceptions were measured with traders who trade at the CBOT. Comparing and contrasting perceived and revealed price path due to order imbalances is not that compelling. Future research should measures perceptions and examining actual price paths due to order imbalances for the same contracts traded at the same exchange.

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Table 1. Effects of changes in the two dimensions on market depth

	α increases	δ increases	α increases and δ decreases	α increases and δ decreases
Lack of market depth (in terms of execution costs)	increases	increases	depending on magnitude order flow	depending on magnitude order flow

Table 2. Descriptive statistics of the real-time transaction-specific futures prices

	Futures Contracts		
	Potato delivery April 1996	Hog delivery August 1995	Hog delivery September 1995
Number of observations (i.e. contracts traded)	46791 (April '95 - August '95)	2742 (February '95 - August '95)	2317 (February '95 - August '95)
Average number of contracts per trading day	503	24	22
Average price per contract*	43.4	2.330	2.276
Standard deviation of the price	18.0	0.150	0.120
Minimum price	21.7	2.065	2.060
Maximum price	79.0	2.655	2.650

* The futures price for potatoes is quoted in Dutch Guilders per 100 kilogram whereas the hogs are quoted in Dutch Guilders per kilogram live weight.

Table 3. Estimates of the parameters describing the underlying dimensions of market depth of the potato futures contract, delivery April 1996

Contract			Parameter estimates Gompertz curve*	
			α	δ
Potatoes futures contracts, delivery April 1996		downward sloping upward sloping	1.374 (0.057) 1.013 (0.053)	0.053 (0.002) 0.060 (0.002)
Number of observations	46790			
R^2	0.099	Probability of $F(3, 46786)$		< 0.001
$F(3, 46786)$	638	Durbin - Watson statistic		1.914
$F(2, 46786)$ for H_0: $\{\alpha_1 = \alpha_2 = \alpha$ and $\delta_1 = \delta_2 = \delta\}$			7.760	
Probability of $F(2, 46786)$			< 0.001	

* standard errors in parentheses.

Table 4. Estimates of the parameters describing the underlying dimensions of market depth of the hog futures contract, delivery August 1995

Contract			Parameter estimates Gompertz curve*	
			α	δ
Hog futures contracts, delivery August 1995			0.039 (0.016)	0.159 (0.009)
Number of observations	2741			
R^2	0.249	Probability of $F(1, 2739)$		< 0.001
$F(1, 2739)$	348	Durbin – Watson statistic		1.811
$F(2, 2739)$ for H_0: $\{\alpha_1 = \alpha_2 = \alpha$ and $\delta_1 = \delta_2 = \delta\}$			0.217	
Probability of $F(2, 2739)$			0.805	

* standard errors in parentheses.

Table 5. Estimates of the parameters describing the underlying dimensions of market depth of the hog futures contract, delivery September 1995

Contract			Parameter estimates Gompertz curve*	
			α	δ
Hog futures contracts, delivery September 1995			0.044 (0.022)	0.115 (0.008)
Number of observations	2314			
R^2	0.200	Probability of $F(1, 2312)$		< 0.001
$F(1, 2312)$	348	Durbin – Watson statistic		1.855
$F(2, 2312)$ for H_0: $\{\alpha_1 = \alpha_2 = \alpha$ and $\delta_1 = \delta_2 = \delta\}$			0.136	
Probability of $F(2, 2312)$			0.873	

* standard errors in parentheses.

Table 6. Characteristics of traders in sample

	Frequency	Percent		Frequency	Percent
Primary Commodity Traded			*Primary Type of Derivative*		
Agriculture	43	50.0%	Futures	66	76.7%
Finance	32	37.2%	Options	9	10.5%
Other	3	3.5%	Other	0	0.0%
No response	8	9.3%	No response	11	12.8%

Table 7. Characteristics affecting traders' perceptions of order imbalances

		Trade groups based on perceived order imbalances			
Characteristic		Linear	Expon.	S-shape	Zigzag
Is the trader in the agriculture or financial markets?	Ag	21.1%	15.8%	47.4%	15.8%
	Fin	15.0%	15.0%	15.0%	45.0%
	Com	41.7%	0.0%	16.7%	25.0%
Does the trader trade futures or options?	Fut.	25.0%	6.8%	29.5%	29.5%
	Opt.	14.3%	42.9%	14.3%	28.6%
Is the trader primarily a bond trader?	No	28.9%	13.2%	31.6%	21.1%
	Yes	7.7%	7.7%	15.4%	53.8%
Is the trader a spreader?	No	14.6%	14.6%	23.8%	34.1%
	Yes	53.8%	0.0%	23.1%	15.4%
Does the trader take opposite positions in herd behavior (scalper behavior)?	No	22.2%	13.9%	33.3%	19.4%
	Yes	18.2%	9.1%	9.1%	63.6%

*The hypothesis that the mean of these variables is equal was rejected at the 10% level using Chi-Square.

Table 8. Importance of information source for the different four different groups of traders

Information Source (1 = least important, 5 most important)	Trade groups based on perceived order imbalances			
	Linear	Expon.	S-shape	Zigzag
Commercial signals	3.818	2.600	4.231	4.000
Government information	3.546	4.333	3.400	3.5385

*The hypothesis that the mean of these variables is equal was rejected at the 10% level using ANOVA.

Table 9. Affects of noise in the absence of information to trader's market activity for the different four different groups of traders

Increase in Noise Level (1 = increases, 5 = decreases)	**Trade groups based on perceived order imbalances**			
	Linear	Expon.	S-shape	Zigzag
Level of trading	1.917	3.500	1.69	2.14

*The hypothesis that the mean of these variables is equal was rejected at the 5% level using ANOVA.

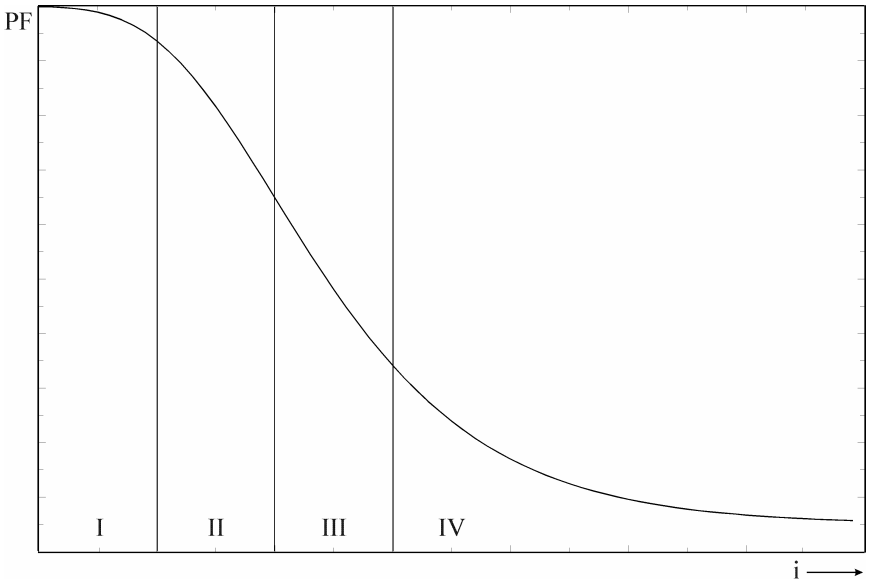

Figure 1. Price pattern of a sell order in a thin market

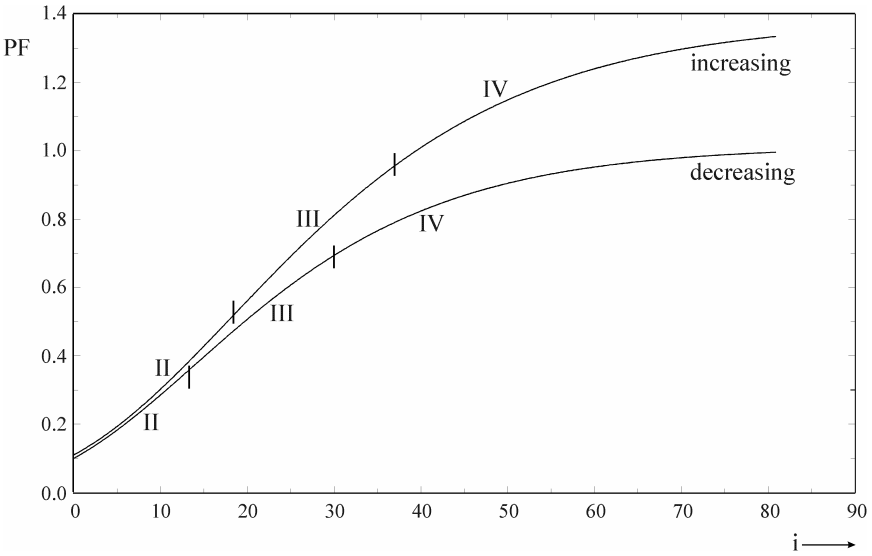

Figure 2. The Gompertz curves for the potato futures contract delivery April

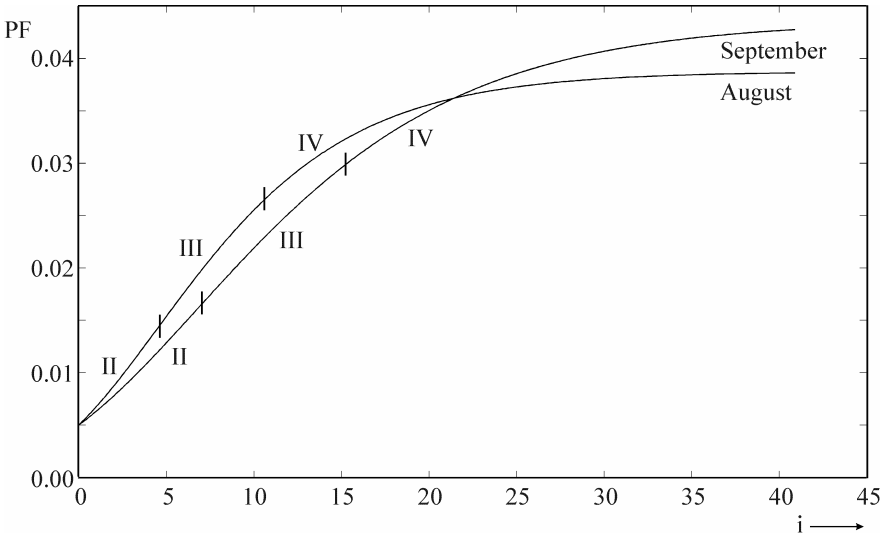

Figure 3. The Gompertz curves for hog futures contracts deliveries August and September

FIGURE 4 TO BE INCLUDED

Shape	Percent	Percent
	Order Imbalance	*Fundamental Shift*
Linear	23.6%	39.1%
Exponential	12.7%	26.1%
S-shape	25.5%	13.0%
Zigzag	29.1%	15.2%
Other	9.1%	6.5%

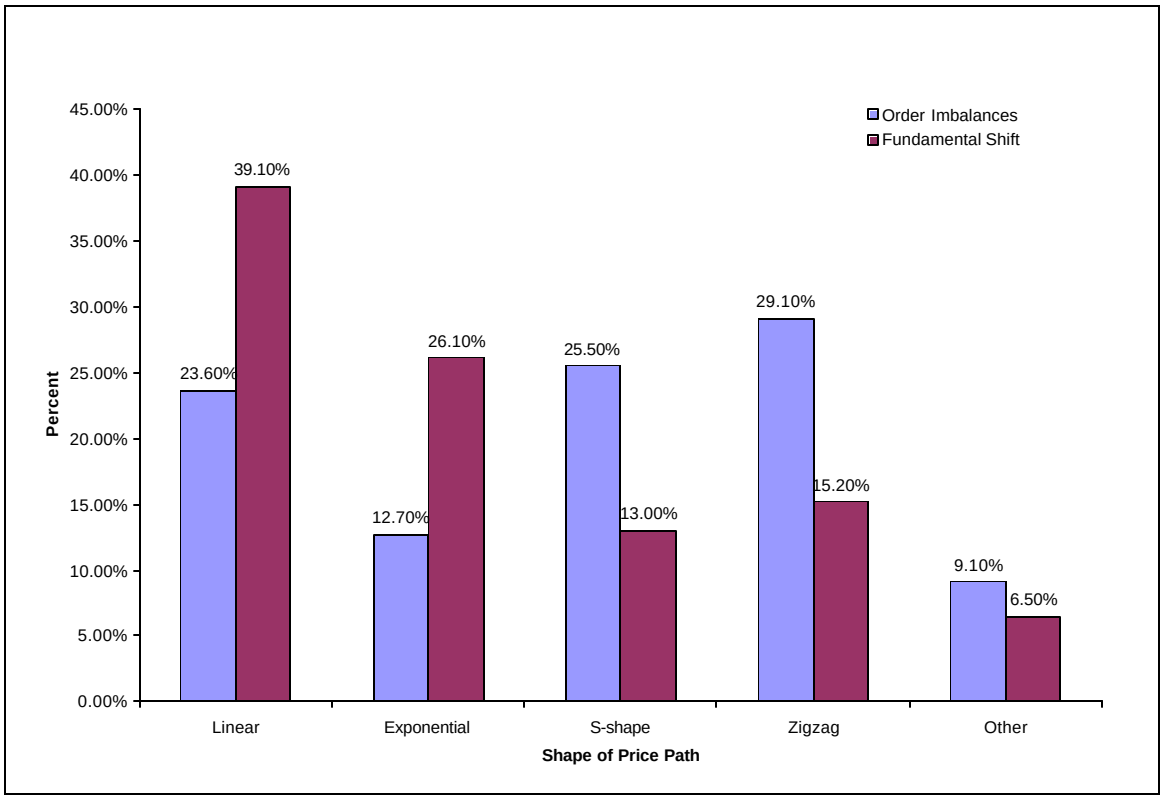

Figure 5. Perceptions of the price path due to order Imbalances vs. perceptions of the price path during fundamental shifts

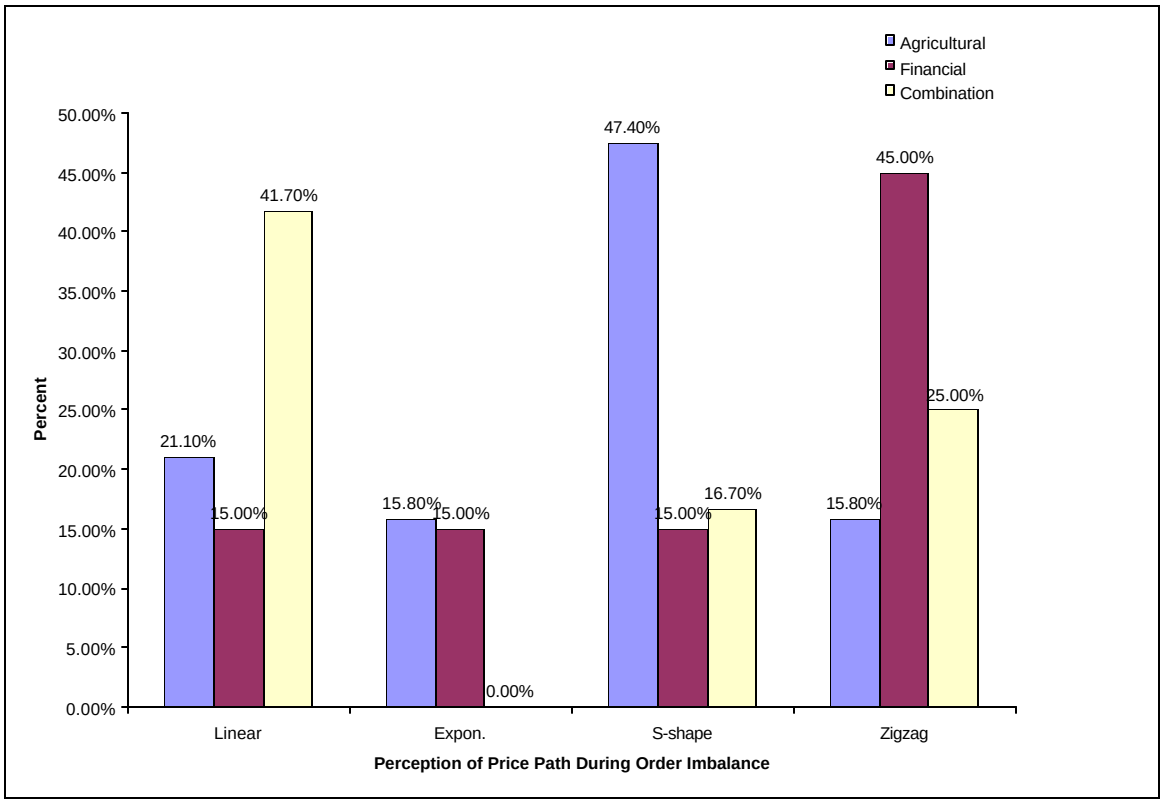

Figure 6. Characteristics associated with traders' perceptions about price path due to order imbalnces

FOOTNOTES

[1] There is a large volume of research (for example, French and Roll, 1986; Fama, 1991; Stein, 1991; Foster and Viswanathan, 1993; Holden and Subrahmanyam, 1994; Oliver and Verrechia, 1994; Hiraki, Maberly, and Takezawa, 1995) on information, market efficiency and market liquidity. In these articles, information refers to changes in the fundamental economic factors (supply and demand factors of the underlying 'commodity' of the futures contract traded). Conceptually, we can split price changes into changes due to fundamental economic factors and changes due to the fact that there is a temporary order imbalance. In this study, we concentrate on the latter.

[2] The resistance price level marks the upper and lower boundary between which the price fluctuates according to the participants if the equilibrium price is constant. The equilibrium price is determined by fundamental economic factors.

[3] From the data it is not clear where the exact split between an increasing and decreasing price path should be imposed when two or more contracts in between are traded at the same price. Therefore, to determine the split we apply the following procedure: for an odd number of contracts traded at the same price we use the middle contract, and for an even number of constant contracts we employ a random assignment with equal probabilities.

[4] The reason that we investigate these three futures contracts is a practical one. In order to estimate the model we had to obtain transaction-specific data. These data were gathered by the exchange on our request. Normally the exchange only saves the daily close price, high price, low price and traded volume. We were able to receive transaction-specific prices only for the three futures contracts investigated in the paper.

[5] We acknowledge the information we received on this subject from the brokers at the Amsterdam Agricultural Futures Exchange.

[6] We acknowledge the information we received on this subject from the brokers at the Amsterdam Agricultural Futures Exchange.