Sources of Market Making Profits:
Man Does Not Live by Spread Alone

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Abstract

This paper employs a highly detailed data set to analyze the trading profits of futures market makers by decomposing profits into two components, one due to the sale of liquidity and the other due to the impact of price movements. Because our data reports trade direction (buy or sell) we are able to discover several empirical regularities that have not been observable to researchers who must infer trade direction from less extensive data.

We find empirical support for standard microstructure theories which maintain that increased asymmetric information is associated with greater customer liquidity costs. However, our data show that the market makers, not the customers, have the information advantage. Finally, our investigations reveal that market makers receive (customers pay) less for trade execution when they make a well-timed (poorly-timed) trade. These observations demonstrate that market makers have both an execution advantage and a timing advantage relative to other market participants, and the data show that they are willing to reduce or eliminate the execution advantage to exploit the information advantage.

1. Introduction and Summary

This paper studies the interactions of trade execution costs and market timing for trading on the Chicago Mercantile Exchange (CME). Trade execution cost is the price of immediacy or liquidity; this cost is closely associated with the bid/ask spread. Market timing measures the post-trade price movement. For example, an individual who buys at the ask price prior to a price increase will exhibit poor trade execution (paying the ask) but good timing (buying before the price goes up).

Standard microstructure theories [for example Glosten and Milgrom (1985), Kyle (1985), or Admati and Pfleiderer (1989)] make very strong predictions about execution and timing. These theories predict that market makers profit from trade execution but accept losses due to market timing. The customer net revenues are the market maker's expenses. The models predict that, on average, customers profit from market timing and pay a liquidity or trade execution cost.

Although there are many published papers that accept this standard theory (or some close variation of it), empirical support is weak and highly inferential. The empirical support is inferential because many studies of equity markets use incomplete data. For example, data sets that report only price, quantity, time of trade, and prevailing bid/ask quotes are typically employed. But these data do not report trade direction, thus for each transaction, who is the buyer and who is the seller is not directly observed but must be inferred.

Previous methods of inferring trade direction fail to properly distinguish between *trade-aggression* and *trade-direction.* Trade aggression identifies which side, buy or sell, initiated a trade. Trade direction identifies which participant, customer or market maker, was buyer or seller. This is an important point. For example, previous research methods which fail to account for potential differences between trade aggression and trade direction cannot identify circumstances when a market maker anticipates a price increase and buys from a customer at the ask price. Yet our data, with direct observation of trade direction, reveals this is a fairly common occurrence.

The most common techniques for inferring trade direction are based on a paper by Lee and Ready (1991) (LR). The LR technique compares a transaction price to the prevailing bid/ask quote to assign trade aggression(buyer initiated or seller initiated). The LR technique is designed to identify a passive and an active side to a trade. However, following classical microstructure theory, many researchers using the LR technique assume that customers initiate each trade, and assign trade direction (whether customers or market makers bought or sold) on the basis of trade aggression. Thus, researchers using LR methods identify all trades at the ask as customer-aggressive buys and market maker-passive sells; and all trades at the bid as customer-aggressive sells and market maker-passive buys. We refer to this method of estimating trade direction as aggression-based inference.

Even allowing that this technique correctly identifies trade aggression, the technique was not designed to be used to identify trade direction. Furthermore our data show that employing the aggression-based trade techniques to identify both trade aggression and trade direction (as is common in the literature) can lead to inaccurate conclusions regarding market maker behavior and customer trading costs.

In this paper we exploit detailed data provided by the Commodity Futures Trading

Commission (CFTC) to analyze the trading profits of futures market makers. The data identify trade direction (buy or sell) and contra parties for each transaction. This level of detail in the data facilitates a decomposition of trading profits into execution profits and timing profits. Our empirical results show that observing trade direction is very important. Many researchers (for example, Bessembinder (1997), Easley, Kiefer, and O'Hara (1997), Huang and Stoll (1996), Madhavan, Richardson, and Roomans (1997) and Harris and Schultz (1997)) infer trade direction from less comprehensive data using aggression-based methods. We use the precise identification of trade contra parties to provide results that contrast sharply with previous research. Our empirical examination leads to four principal findings:

1. *Direct observation of trade direction is very important.*

Using *inferred* trade direction it appears that outside customers trading on the Chicago Mercantile Exchange incurred net trading costs of $358 million in the first half of 1992. Based on inferred trade direction, customers appeared to have earned $9 million in profits from good timing but spent $367 million in trade execution costs. However, these conclusions are seriously flawed.

Using *directly observed* trade direction we find that customers' total trading costs were only $100 million: $38 million in execution costs and $62 million in timing losses.

2. *Market Makers are the Informed Traders*

Contrary to most theoretical predictions, we find that market makers profit both from timing and execution. This finding is consistent and conclusive across all pits in our sample and for nearly every individual trader. For the first six months of 1992 our data show that Chicago Mercantile Exchange market makers' trading revenues totaled $130 million. Of the total revenue, only $45 million (34 percent) was due to execution profits. These execution profits occurred within one minute of trade execution. The remaining $85 million was due to favorable timing. From this evidence we conclude that market makers have better information regarding short term price movements than other market participants.[1]

3. Increased asymmetric information is associated with greater customer liquidity costs.

This is consistent with prevailing theory, which maintains that liquidity is more expensive when information asymmetries are larger. In the standard models a portion of the outside customers are endowed with superior information. However, our data show that the market makers, not the customers, have information advantages (see point 2 above). We find that when some market makers have better information, customers pay greater average execution costs.

4. Market makers engage in tradeoffs between timing and execution

On average a market maker receives less for trade execution when he or she is making a well-timed trade. Stated differently, customers pay less for trade execution when making a poorly timed trade. This is true for all levels of asymmetric information but becomes more pronounced when the market maker's information is more valuable. One can easily imagine the following good-news, bad-news story told by a customer, "The bad news is that the bid-ask spread was large. The good news is that I got fantastic trade execution - I bought at the bid. The worst news is that right after I bought the price fell."

[1]Although contrary to classical theory [for example, Glosten and Milgrom(1985)], the idea of informed market makers is getting some attention in both the empirical literature [Manaster and Mann (1996), Mahavan and Sofianos (1998), Ito, Lyons, and Melvin (1998),Ready (1999)] and with developing theoretical models (Brown and Zhang (1997), Cao and Lyons (1998)].

These four empirical observations demonstrate that futures market floor traders can have *both* an execution advantage and a timing advantage relative to other market participants. The data show that they are willing to reduce, or eliminate, the execution advantage to exploit the information advantage.[2] As a consequence, studies that use aggression-based trade direction to examine trading cost are unlikely to provide a complete understanding of customer trading costs.

The discovery that the empirical results are so highly sensitive to correct identification of trade direction in an important contribution of this research. Researchers using the aggression-based techniques to identify trade direction may find support for standard market microstructure theory even if it is not true. Moreover, empirical observations (2), (3) and (4) show that results based on directly observed trade direction suggest a more complicated role for market makers than many previous theoretical and empirical studies have acknowledged.[3]

We structure the paper in the following sequence. Section 2 provides a brief description of the data. Section 3 explains our methodology and the decomposition of trading profits into the execution and timing components. Section 4 provides empirical results. Section 5 provides a brief summary and conclusions.

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[2]These findings are consistent with the evidence provided by Ready (1999), who shows that specialists make price improvements (reducing execution costs for the contra party) in order to participate in trades that are ex-post profitable for the market maker.

[3]Although our findings are based on futures trading data from the Chicago Mercantile Exchange, there is no reason to suppose that the results are not applicable to other markets, including equity trading. If so, then our results may help reconcile paradoxical findings such as those of Christie and Schultz (1996) and Chan and Lakonishak (1997). In comparing NASDAQ and NYSE trading, Christie and Schultz find that customer trade execution as measured by the spread is decidedly higher on the NASDAQ. Chan and Lakonishak, however, find that when trade costs are measured against a subsequent or prior day benchmark the NYSE advantage is less clear. Our results may help to reconcile these findings available through the NYSE: lower NYSE customer execution costs may be partially offset by inferior customer timing. Our results are based entirely on futures market data, so at this stage their applicability to stock market behavior remains to be examined. Nonetheless, based on our empirical findings the issues we raise should be of concern to students of microstructure in all venues.

2. Data

The data employed in this study consist of the transaction records of all futures trades (over 12 million) on the Chicago Mercantile Exchange (CME) during the first six months of 1992. These data were obtained from the Commodity Futures Trading Commission (CFTC). The transaction records are released directly from the CFTC's audit trail records, which are maintained for investigation into possible trading abuses and as documentary evidence to support enforcement actions as well as for purposes of economic analysis. The audit trail data allow the CFTC to analyze the precise transactions of individual traders.[4]

Each trade is recorded twice, once by the buyer and once by the seller. Both sides of the trade identify the executing traders and the *trade direction* (whether the trade was a purchase or a sale by a given trader). The record details the commodity and delivery month, the quantity, the price, and the date and time of the transaction. The trader identification also classifies the trade as one of four customer types via a Customer Type Indicator (CTI), which ranges from 1 to 4 as follows:

Customer Type Indicator	Description
CTI 1	Floor trader personal account trades (local trades)
CTI 2	Clearing member's house account trades (commercial trades)
CTI 3	Another member present on the exchange floor (floor hedger trades)
CTI 4	executed on behalf of outside customers (customer trades)

[4] The data are coded by the CFTC to conceal identities of individual market participants. The CFTC mapped each trader's audit trail identification (exchange badge number) to a randomly selected number unique to each trader. Therefore the data provide a complete six month trading history for each trader, but leave the trader's identity confidential.

CTI 2 trades are typically trades by employees of large commercial members. CTI 3 trades are often delta hedging trades done on behalf of options market makers.

The CTI indicators enable the identification of trade direction. Trade direction (whether a transaction is a customer buy, customer sell, both a customer buy and a customer sell or neither) is the key element in estimating trading costs. The trade direction identification provided by the audit trail data allows us to examine trading costs without the bias that could be introduced by a trade classification procedure in which the direction of trade would only be inferred. In addition to identifying trade direction, the data provide another level of detail, identifying the CTI type of the trade contra party (the opposite side of the trade). The contra party identification is missing for trades representing 0.6% of contract volume, and we eliminate those trades whenever our analysis requires contra party identification.

3. Methodology

3.1 A decomposition of trade profitability

Consider a market maker's round-trip trade, buying for price B_0 during period 0 and selling during period t for price S_t. Market makers hope to earn income from liquidity provision by buying at lower prices and selling at higher prices than customers. If we designate the average price for all trades during time t as μ_t , then we can identify the liquidity revenue attributed to the buy trade as μ_0 - B_0 and the liquidity revenue attributed to the sell as S_t - μ_t. The total profit from these transactions is S_t -B_0, and the profit can be apportioned into execution profits and timing profits as:

$$
\begin{array}{rll}
 & S_t - \mu_t & \textit{Sell execution} \\
+ & \mu_t - \mu_0 & \textit{Price movement} \\
+ & \mu_0 - B_0 & \textit{Buy execution} \\
= & S_t - B_0 & \textit{Round trip trade profit.}
\end{array}
\qquad \textbf{(1)}
$$

Under this scheme, profit comes from two sources. We designate *execution* as the ability to buy at lower than average prices and sell at higher than average prices. Execution is the revenue associated with selling immediacy. However, when average prices change between period 0 and period t, then total revenue includes another component due to price movement, $\mu_t - \mu_0$. We designate the profit component due to price movements as *timing*.

Consider a market maker who buys prior to a price increase, then subsequently sells. In this case, $\mu_t - \mu_0 > 0$ and the long trade had "good" timing. Alternatively, if the long trader sells subsequent to a price decrease, then $\mu_t - \mu_0 < 0$ and the trade was poorly timed.[5] Given the decomposition of profit for each trade, we can allocate market maker daily trading profits and aggregate customer trading costs between profits due to execution and profits due to the impact of price movements on market maker positions, which we designate timing.[6]

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5 Logic is symmetric for a market maker sale followed by a market maker purchase.

6 Profits are gross trading profits, not net. We do not take into account transaction and clearing fees, or any other charges such as seat lease or the opportunity cost of the investment in the seat.

3.2 Measuring execution and timing.

Daily Trading Profit

Following Fishman and Longstaff (1992), we calculate a trader's profit as the total selling revenues less total purchase expenses for positions that are open and closed during the trading day, with any remaining open positions (typically small) marked to market using the closing price μ_C.[7] Thus trader i's profit (daily by contract) is defined as:

$$Profit = \sum_{t=0}^{C} Q^{s}_{ti} S_{ti} - \sum_{t=0}^{C} Q^{b}_{ti} B_{ti} + \left(\sum_{t=0}^{C} Q^{b}_{ti} - \sum_{t=0}^{C} Q^{s}_{ti}\right) \mu_C , \qquad \textbf{(2)}$$

where Q^{b}_{ti} is trader i's buy volume at during period t, Q^{s}_{ti} is trader i's sell volume during period t and μ_C is the closing price for the contract.[8]

[7] Positions remaining at the end of the trading day are typically quite small relative to daily trade volume. See Fishman and Longstaff (1992), Manaster and Mann (1996), and Kuserk and Locke (1993).

[8] For the closing price we use the volume-weighted mean trade price during the last minute of trade, unless the contract failed to trade at the close; then we use the mean price for the last minute that it did trade.

Next we decompose profit into components due to execution and timing. Trader daily profit as represented in (2) can be rewritten as:

$$
\begin{aligned}
& \sum_{t=0}^{C} Q^{s}{}_{ti}(S_{ti} - \mu_t) \qquad (\textit{total sell execution}) \\
+ \quad & \sum_{t=0}^{C} Q^{b}{}_{ti}(\mu_t - B_{ti}) \qquad (\textit{total buy execution}) \\
+ \quad & \sum_{t=0}^{C} Q^{b}{}_{ti}(\mu_C - \mu_t) \qquad (\textit{total buy timing}) \\
+ \quad & \sum_{t=0}^{C} Q^{s}{}_{ti}(\mu_t - \mu_C) \qquad (\textit{total sell timing}) \\
= \quad & \textit{total daily profit for trader } i.
\end{aligned}
\qquad \textbf{(3)}
$$

The profit decomposition (3) illustrates that each trade makes two contributions to profit, one from timing and one from execution. For example, when a trader buys, the trader's buy execution $\mu - B$) captures the edge a trader gains from buying at a lower price than the average purchase price. The buy trade will have positive timing ($_C -\ _t$) as well, if the mean price at the time of the purchase is lower than the price at the end of the day.

The first is based on one-minute execution; the second is based on five-minute execution. For one-minute execution the mean price μ in equation (3) is calculated as μ_{1t} , the volume-weighted

the trading day. For five-minute execution, the estimate of μ_τ is $\ _5$, the volume weighted mean trade price for the five-minute bracket τ.[9] None of our major conclusions are sensitive to the use of one-minute versus five-minute execution measures. The total trading profits under either calculation are the same. With the five-minute execution, a larger proportion of profits and/or losses are attributable to execution and a smaller proportion to timing.[10] In most of the tables that follow we report results for both one-minute and five-minute execution. In the text, however, we focus almost exclusively on the one-minute results.

The closing price μ_C is the same for both the one-minute and five-minute calculations. Daily settlement, as well as trader reluctance to carry overnight positions, motivates the use of the end of day price μ_C instead of an alternative benchmark.[11]

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[9] The CTR data originate with trader's cards, which indicate time by a 15-minute bracket code. The CME uses Time and Sales data in conjunction with card trade sequences and trade contra party identification to impute a trade time (the ctr-time) to the nearest minute. We choose five-minute periods so that the original 15-minute bracket is divided into three consecutive five-minute periods.

[10] Measured five-minute execution profits should be larger for two reasons. First, benchmarking trades against mean prices for longer time periods will result in any intra-period timing profits being allocated as execution profits. Our one-minute execution profits likely include much intra-minute timing as well, particularly for volatile pits such as the S&P500, where 82% of volume occurs in minutes with at least 5 different prices. The second reason is that if offsetting customer transactions occur at different sides of a spread in different minutes, our method would allocate the spread earned entirely to timing, rather than execution. We report results using both one-minute and five-minute execution benchmarks, recognizing that the longer five-minute intervals will mitigate the second problem but exacerbate the first problem.

[11] Other researchers use varied terminal benchmarks. Bessembinder (1997) uses the midpoint of the first quoted prices of the next trading day. Huang and Stoll (1994), Madhavan and Cheng (1996), Bessembinder and Kaufman (1996), LaPlante and Muscarella (1997), and Chan and Lakonishak (1997) use various pre and post trade benchmarks with general consensus that their results are robust to the choice of benchmark.

4. Empirical Results

4.1 Inferred trade direction versus actual trade direction.

Previous researchers have not had the luxury of data that provided unambiguous trade direction. Early work such as Glosten and Harris (1988), Stoll (1989), and George, Kaul, and Nimalendran (1991) focused on the bid/ask spread as an indication of trade execution costs. Building on ideas introduced by Roll(1984), the underlying assumption implicit in this vein of research is that price reversals are exclusively due to bid/ask bounce. Observed serial correlations in transactions prices are used to estimate bid/ask spreads. For this method to produce plausible results serial price correlation is required to be negative. Frequently, however, asset prices exhibit non-negative serial correlation.

A second vein of research uses bid/ask quotes to estimate market maker execution and timing revenues. This approach does not require negative serial correlation of prices, but it still maintains an implicit assumption that market makers gain on execution and lose on timing. Bessembinder (1997), Bessembinder and Kaufman (1997), Easley, Kiefer, and O'Hara (1997), and Huang and Stoll (1996) all use aggression-based trade classification schemes such as Lee and Ready (1991) to assign trades as either customer buys from market makers or customer sells to market makers. Lee and Ready (LR) compare trade prices to quote midpoints and prior quote changes to identify trade aggression (buy-initiated versus sell-initiated). Relying on traditional theory (uninformed market makers), it is standard for researchers to assign trade direction (market maker buy versus customer buy) by assuming the customer is the more aggressive trader.

Summarizing, aggression based techniques to infer trade direction attributes trade direction to customers and market makers according to rules similar to what is provided below:[12]

1. If the trade is above the midpoint of the ex ante bid/ask quote it is a customer buy and a market maker sell. If it is below the midpoint, it is a customer sell.

2. If the trade is at the midpoint and is an uptick (downtick), it is a customer buy (sell).

3. If the trade is at the midpoint and it is not a change, go to the prior quote revision. If the prior is an uptick (downtick) then the trade is a customer buy (sell).

Our measures can be contrasted with the Huang and Stoll (1996) (HS) measures, developed using the aggression-based methods, which they refer to as "effective half spread" and "price-impact." These correspond closely to our measures of "execution" and "timing." Unlike HS our data does not include bid/ask quotes, but does specify trade direction. Therefore, we measure execution as the difference between the transaction prices and the mean price for the corresponding minute, while HS measure effective half spread as the difference between the transaction price and the mid-point of the most recent bid/ask spread. Thus, *setting aside issues of trade direction*, the difference between the HS effective half spread and our trade execution is the difference between the mean price for the subject minute and the mid-point of the bid/ask spread.

We believe this difference is too small to account for the differences between our conclusions and the conclusions of earlier authors.[13] Unfortunately our futures market data has no

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[12]The rules as presented are those of Lee and Ready. Empirical usage varies. Some researchers (e.g. Huang and Stoll 1997) eliminate trades at quote midpoints, using only trades at the bid or ask.

[13]We have performed some sensitivity analysis that supports our belief. We have replicated all of the results presented in the paper using the alternative benchmark m_t (the midpoint of the mean customer buy and sell prices), instead of the mean price $\mu_{t.}$ Our conclusions were not affected. For example, we report that timing accounts for 66% of local income, using the μ_{1t} benchmark. If we instead we use m_t, timing accounts for 61% of local income.

equivalent of spread midpoint, as futures quotes are not recorded in the audit trail, thus we cannot use the aggression-based techniques in exactly the same form as that implemented by equity market researchers.[14]

The critical difference between our methods and the HS approach is that HS and other equity researchers must guess at trade direction. The critical point is that the aggression-based methods assumes customer aggression for every trade. Thus aggression-based methods, like LR, assign positive market maker execution to each trade *by definition*, so that positive execution is used to define the trade as a trade by a market maker. For example, if a market maker buys against a limit customer sell, the aggression-based methods would mistakenly classify the trade as a customer buy from a market maker. Market maker trades motivated by information that sacrifice execution in order to profit from price movement are subject to misclassification by the aggression-based scheme.

The aggression-based procedures also fail to account for customer-to-customer trades. When customer limit orders compete with the market maker, the limit order typically has good execution but is likely to have poor timing (Handa and Schwartz (1996), Harris and Hasbrouck (1996)). Aggression-based techniques assign the limit order trades to market makers, thus upwardly biasing market maker execution and negatively biasing market maker timing.[15]

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[14]Futures quotes are generally not binding, other than in a reputational sense; trader quotes are good instantaneously, but are honored after a time lag at the discretion of the quoter.

[15]Demsetz (1997) makes this point, noting that the NYSE has more limit order activity than NASDAQ.

4.2 Results: Observed Contra parties

i) Customers don't always trade with market makers.

Table 1 provides total contract volume broken down by customer type combinations. Panel A reports "double counted volume." Recall that in our data each trade is reported twice; once for each party to the trade. If each data entry accurately recorded the correct contra party then there would be no "missing" contra party information, and the matrix in panel A would be perfectly symmetric. In practice 0.6% of the contra party information is missing, and departures from perfect symmetry must be attributable to data errors. For example, it is tautological that the volume of CTI 1 trading with CTI 4 (18,304,061 contracts in panel A) equals the volume of CTI 4 trading with CTI 1 (18,426,174 contracts in panel A), but the data show a small difference. Nonetheless, the error rate is acceptably low, and with no known bias.

Panels B and C of Table 1 show the same percentage participation rate for each CTI type by volume. The two panels are nearly identical and differ only in treatment of missing data. The conclusions from either table are the same. Customers participate on at least one side of more than 65% of all volume. Locals participate on at least one side of nearly 70% of all trading volume.

Panel D provides percentage volume by contra party trade combination. The "missing" contra party data are omitted from the calculations. By far the most common trading is between a local and a customer (40.7% of volume), but significant volume exists in all combinations. Note that customers trading against other customers account for 11% of all volume and locals crossing trades with other locals account for 9%.

Panel D has implications for methods of inferring trade direction. As commonly used, the aggression-based technique assumes that 100% of trade volume is customers trading with market makers. In our data less than 41% of the trades match this assumption. Notably, Madhavan and Sofianos (1998) find that the median specialist participation rate for the 2,751 NYSE issues in their 1993 sample was 23.3%, and that 17% of the stocks had specialist participation rates below 10%.

ii) Even when customers do trade with market makers, they don't always get bad execution.

Table 2 provides percentages of positive and negative execution for customer trades with non-zero execution, against all contra parties (columns 4 and 5) and then against exclusively market makers (columns 1 and 2). For the entire sample, 31.5% of customer volume has zero execution (recall that zero execution occurs for trades at prices equal to the average price during the execution interval). Excluding the trades with zero execution, in 41.68% of customer volume versus market makers, the customer has positive execution.

The evidence in Tables 1 and 2 shows that customers don't always trade against market makers, and that even when they do, they frequently have positive execution. Yet the aggression-based technique classifies essentially all trades as having inferior execution for customers and positive execution for market makers. We examine the consequences of the aggression-based assumptions by comparing actual execution and timing costs for customers to those that we would estimate if we did not know the trade direction, and instead inferred it from the LR based perceived aggression.

We perform an experiment by applying the LR techniques to evaluate the data as if we were not provided with trade direction information. Following the logic of the aggression-based procedures, we assign all trades with negative execution to customers. We then compute total execution and timing costs for our hypothetical customers and compare the results to the actual costs measured with identified trade direction in Table 3. Table 3 shows that total customer trading costs are substantially overestimated when trade direction is only inferred. Actual customer costs are about $100 million. The costs calculated by inferred trade direction are over $350 million.

The inferred trade direction technique introduces a sizable positive bias to customer execution costs and negative bias to customer timing costs. Note that customers actually lost $62 million in timing, but the inferred trade direction technique suggests that customers gained $8 million in timing.

The aggression-based technique does not allow for the case of a market maker who sacrifices execution for timing. Consider an example. If a floor trader correctly anticipates a price rise and buys at the ask from a customer limit order, the market maker will have poor execution but good timing; the customer will have good execution but poor timing. Our data suggest that this behavior is fairly common. Yet a trade classification scheme based on trade aggression will assign the good execution to the market maker and the good timing to the customer. Due to data limitations a similar experiment has not been performed for an equity market, but we suspect that the problems exposed in Table 3 for the CME also may be relevant for equity markets.[16]

[16]Madhavan and Sofianos (1998, page 197) provide the following warning for equity markets which is remarkably similar to our concerns for the CME: "Thus, the NYSE has attributes of both auction and dealer markets. This fact suggests caution when applying models of specialist trading (Glosten and Milgrom, 1985) in which the specialist is assumed to provide liquidity for all externally initiated transactions to make inferences about the size and components of the bid-ask spread."

4.3 Are market makers the informed traders?

Theoretical models of trading under circumstances of asymmetric information generally assume that market makers are completely uninformed, and that market makers will therefore have negative timing (some exceptions are Madhavan and Smidt (1993), and Spiegel and Subrahmanyam (1996)). Our evidence shows that this assumption is incorrect. Market makers in our sample earn a substantial portion of their income from timing; customers lose more on timing than they do on execution. On average then, who are the informed traders? Our results suggest that the market makers are the predominant informed traders.

To investigate this matter, we begin by identifying who gains from whom. Table 4 is a "pecking order" table, based on timing and execution measured against a one-minute benchmark. We break down all trades in the sample by contra party combinations. In each panel of Table 4, the columns report total gains by each trader type against each contra party type. The rows therefore report total losses by each trader type against each contra party type. The diagonals represent total trader type gains against their own trader type. If the data were error free, the diagonals would be exactly zero.[17] Panels A and B report total execution and timing, respectively. Panels C and D show mean (per contract) execution and timing.

Panels A and C of Table 4 show that market makers (CTI 1) have the best execution, while customers have the worst execution. Panel A reports that on average customers (CTI 4) lose to all other trader types on execution, losing a total of $38 million. Panel C shows that customer execution costs are highest against local traders, losing $1.89 per contract to CTI 1 contra parties,

[17] A primary source of the error is the 0.6% of trade volume with missing contra party identification.

but only about 50 cents per contract to CTI 2 and CTI 3 trades. Locals (CTI 1) have positive execution against all contra parties. Locals have better execution against customers than against CTI 2 and 3 trades. The execution pecking order could be described as “locals beat everybody, CTI 2 and 3 beat customers, and customers lose to everybody.”

Panels B and D show that market makers earn almost two thirds of their income from timing, rather than execution. Locals are timing winners against all contra parties, doing the best against customers and CTI 2 (commercial house account) trades. Locals are the clear timing winners. The battle for second place among customers and the other trader types is unclear; CTI 3 loses to CTI 2 but has positive timing against customers.

Tables 5 and 6 provide detailed breakdowns by contract of the results highlighted in Table 4. There is some variation across commodities, but the points are clear: locals have positive timing; timing is a large component of their income; and negative timing is a large component of customer costs.

Panel B of Tables 5 and 6 reports timing and execution measured against a five-minute execution benchmark. There are no surprises. Qualitatively, the results are identical with Panel A. Only the apportionment of market maker profits between timing and execution is altered with five-minute execution. Predictably, more market maker profits are attributed to execution with five-minute as opposed to one-minute execution benchmarks (see footnote 10).

4.4. Individual market maker timing and execution.

Microstructure theory has consistently treated market makers as uninformed traders that lose on price movements. Our results are at variance with the basic paradigm. One possible explanation for our results could be that some subsample of local traders may be responsible for the timing gains, and that other, uninformed locals fulfill the role of "uninformed market makers." We investigate the pervasiveness of positive timing among the market makers, through a cross-sectional examination of timing and execution across individual trader volume quartiles. We use volume as the discriminant, following the logic that traders who trade the most provide the most liquidity to the market. We rank all traders in each commodity by total contracts traded for the sample period. After dropping all traders with less than 100 trades for the six-month sample period, we split the traders into volume quartiles and examine the mean execution and timing for the median trader within each commodity volume quartile. Table 7 reports the median trader's mean timing and execution for each quartile, as well as the percentage of traders within each volume quartile with positive timing and positive execution.

Table 7 shows that among the volume quartiles, market makers generally have both positive execution and positive timing - with this general rule becoming more pervasive at higher volume quartiles. Clearly, most market makers have positive timing, and the more they trade, the more likely they are to have positive timing.

4.5. Information and customer execution costs.

An implication of adverse selection models of trading is that increased information asymmetry increases customer trading costs. Our data corroborate this intuition. We find that when asymmetric information, as measured by market maker timing, is high, customer execution costs are also high. These findings are reported in Table 8.

The entries in Table 8 in the column labeled “Low (High) 63 days of local timing” provide mean customer execution per contract for the half of the days (for each pit) with the lowest (highest) total local timing income. For example, consider the S&P 500 contract. The first entry in the first column shows that for the days with the poorest timing results by locals, customers pay an average of $2.25 per contract as an execution cost. However, for the days with higher total local timing, the customer execution costs increase to $2.57 per contract (the second column). The difference, an increase of $0.32, is reliably different from zero at classical significance levels. In fact, for nine of sixteen pits customer execution costs are larger when locals have their highest timing days compared with the lower local timing days. The relevant t-statistics can be found in the last column.

We interpret this finding as consistent with the received theory which maintains that execution costs increase when there is greater asymmetric information. However, in one important aspect our findings conflict with the standard theoretical construct. In traditional microstructure theory the external customers have a net information advantage. Our data strongly suggest that the information advantage resides with the market makers.

4.6. Tradeoffs between execution and timing.

Table 8 shows that customer execution costs are greater when the asymmetry of information is greater. In Table 9 we report results of our investigation whether, for any level of asymmetric information, there is a trade-off between timing and execution, in the sense that traders may sacrifice execution in order to complete the trade. The results for locals (CTI 1) are very strong and consistent. When market makers have information regarding the direction of a price movement they will give up some of their execution advantage in order to make a favorable trade.

Table 9 is closely related to the execution portions of Table 6. From the first entry in Table 6 we see that on average locals (CTI 1 traders) earned \$2.63 per contract in execution for trades in the S&P 500 contract. This \$2.63 is the local's execution "edge", which corresponds conceptually to the "effective half spread" of Huang and Stoll (1996). The first entry in Table 9 shows that when locals make well timed S&P 500 trades (trades with positive timing), their "edge" is reduced by \$0.31 per contract compared to poorly timed (negative timing) trades. All of the negative entries (43 of 48 entries in Panel A) in columns 1, 3, and 5 of Table 9 are evidence that market makers will give up part of their execution "edge" in order to make well timed trades.

When locals trade with each other they must give up more of an "edge" to obtain trades with good timing than when customers are the contra party.[18] For example, against all contra parties combined, S&P 500 locals give up an average of \$0.31 to execute favorably timed trades (column 1). But against other locals, the execution difference is \$1.33 (column 3). However, against outside customers the difference in execution is nearly zero (column 5).

Columns 7, 9, and 11 report the same information as 1,3, and 5, but for customer trades rather than local trades. Some of the information is conceptually redundant. Except for data

[18]Note that total execution for local vs. local trades is zero by definition; positive execution for one trader (e.g. buy low) is negative execution for the other trader (e.g. sell low). Total timing for local-local trades is definitionally zero as well. However, specific trades have an execution winner and a timing winner. Often one side wins (implying the other side loses) both on timing and execution. If locals sacrifice execution for timing in intralocal trades, then timing winners lose execution, on average, to timing losers.

errors, column 5 (local trades against customer contra parties) and column 9 (customer trades against local contra parties) should be identical. Column 11 (customers trading with other customers) is particularly revealing. Most of the entries are positive and many are reliably different from zero at classical significance levels. In general, and for the currency contracts in particular, it appears that better informed customers can make well timed trades with other customers and have an execution advantage as well. For example, Swiss franc customers with positive timing against other customers also have better execution, by $0.67 per contract. However, the franc customers lose an incremental $0.22 in execution to a local when executing well timed trades.

The results in Table 9 show that local traders sacrifice execution for timing. Locals trade off execution for timing against each other and against customers. An examination of customer tradeoffs reveals that customers have better execution against locals when the customer's trade is poorly timed. However, when customers trade against each other, the pattern is much less clear, as good timing is also associated with good execution for many commodities.

5. Summary and Conclusions

The foregoing sections lead us to four conclusions. First, CME market makers are informed traders, not merely order fillers who provide liquidity services. This conclusion is based on the evidence in Tables 4 and 5. Our data show that this conclusion is pervasive across pits and holds for nearly every individual market maker (Table 7).

Second, since market makers are informed traders, research methods that infer trade direction by assuming that they are not will lead to errors, and the errors can be very large. The evidence from Table 3 makes this point clear. In our sample, imputing trade direction based on the false assumption that locals are uninformed produces a calculated timing gain to CME customers of about $8.8 million for the first half of 1992. In fact, using actual trade direction, customers actually lost over $61 million. This result from Table 3 makes us skeptical about conclusions regarding trading cost components currently available in the empirical microstructure literature that are based on speculative methods of assigning trade direction.

Third, this study provides empirical support for one of the most fundamental underpinnings of market microstructure. As information asymmetries increase, trade execution costs increase. This is the lesson of Table 8. However, there is an important departure from standard theory: the market makers rather than the outside customers appear to have the information advantage.

Fourth, market makers with valuable information give up an execution "edge" (or reduce the "effective half spread") in order to secure favorable timing. The "edge" they give up is greater when they trade against other market makers than against customers. The evidence supporting this conclusion is found in Table 9.

Finally, we hope that our empirical results will advance the understanding of market behaviors. However, we believe that a more important aspect of this paper is to underscore the dangers of using a theoretical construct (uninformed market makers) to justify an empirical method (aggression-based trade direction inference) which will then be used to verify, or measure the consequences of, that same theoretical construct.

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Table 1: Volume matrix by contra party customer type

Panel A: "Double-counted" contract volume by trader type and contra party type

contra party type	trader type: local	commercial	floor hedger	customer	row total
missing	244,683	77,884	42,901	184,667	550,135
local	8,169,655	6,651,173	2,790,075	18,426,174	36,037,077
commercial	6,576,893	1,854,973	880,442	4,153,477	13,465,785
floor hedger	2,766,054	885,367	653,808	1,961,838	6,267,067
customer	18,304,061	4,160,772	1,955,862	9,971,565	34,392,260
column total	36,061,346	13,630,169	6,323,088	34,697,721	90,712,324

Panel B: Percentage of volume with given trader type on at least one side of the trade

trader type	local	commercial	floor hedger	customer
volume percentage	70.5%	27.8%	13.2%	65.2%

Panel C: Percentage of volume with given trader type on at least one side of the trade

(observations with missing contra party CTI type eliminated)

trader type	local	commercial	floor hedger	customer
volume percentage	70.6%	27.9%	13.2%	65.4%

Panel D: Percentage volume by contra party combination

(observations with missing contra party CTI type eliminated)

trader type	contra party combination: local	commercial	floor hedger	customer
local	9.1%	14.7%	6.2%	40.7%
commercial		2.1%	2.0%	9.2%
floor hedger			0.7%	4.3%
customer				11.1%
			sum:	100.0%

NOTE - Panel A reports total sample contract volume for each CTI type (column) broken down by indicated contra party type (rows). Total volume reported in Panel A is double-counted, as the trade is reported once by each contra party type. Panel B reports the percentage of volume involving a given trader type on at least one side of the trade; Panel C reports the same information but eliminates trades with missing contra party information. Percentages in Panels B and C will not sum to 1 due to double counting. Panel D provides percentage volume by paired CTI types, combining all trades with the same combination of contra parties.

Table 2: Customer trade execution: proportions by sign

Panel A: Execution measured with the one-minute mean price benchmark μ_{1t}

(Column)	(1)	(2)	(3)	(4)	(5)	(6)
	customer trades against locals			customer trades against all contra parties		
	with nonzero execution		customer volume	with nonzero execution		customer volume
	percentage of nonzero execution		with zero execution:	percentage of nonzero execution:		with zero execution:
Pit	negative	positive	against locals only	negative	positive	all contra parties
Equity Index						
S&P 500	54.8%	45.2%	2.2%	53.0%	47.0%	1.7%
S&P Midcap 400	52.6%	47.4%	81.3%	51.8%	48.2%	81.5%
Currency						
Deutsche mark	59.3%	40.7%	5.9%	55.5%	44.5%	5.3%
Swiss franc	60.1%	39.9%	7.6%	56.7%	43.3%	7.2%
Yen	61.5%	38.5%	11.6%	56.2%	43.8%	11.7%
Pound	58.5%	41.5%	13.2%	55.0%	45.0%	12.0%
Canadian Dollar	64.9%	35.1%	48.1%	55.8%	44.2%	47.2%
Australian Dollar	81.9%	18.1%	82.6%	68.7%	31.3%	81.7%
Interest rate						
Eurodollar	58.2%	41.8%	49.6%	54.9%	45.1%	52.1%
T-bill	69.1%	30.9%	82.4%	62.6%	37.4%	83.5%
Libor	68.0%	32.0%	95.6%	59.0%	41.0%	96.0%
Agricultural						
Live Cattle	59.6%	40.4%	28.7%	54.9%	45.1%	26.6%
Pork Bellies	64.1%	35.9%	31.6%	59.8%	40.2%	28.9%
Hogs	63.9%	36.1%	39.9%	57.8%	42.2%	36.6%
Feeder cattle	68.9%	31.1%	60.7%	63.1%	36.9%	59.7%
Lumber	66.8%	33.2%	53.3%	62.5%	37.5%	52.1%
Entire Sample:	**58.32%**	**41.7%**	**31.5%**			

Panel B: Execution measured with the five-minute mean price benchmark μ_{5t}

	customer trades against locals			customer trades against all contra parties		
	with nonzero execution		customer volume	with nonzero execution		customer volume
	percentage of nonzero execution		with zero execution:	percentage of nonzero execution:		with zero execution:
Pit	negative	positive	against locals only	negative	positive	all contra parties
Equity Index						
S&P 500	52.4%	47.6%	0.5%	51.6%	48.4%	0.3%
S&P Midcap 400	55.2%	44.8%	48.8%	51.4%	48.6%	44.8%
Currency						
Deutsche mark	57.9%	42.1%	0.9%	54.4%	45.6%	0.6%
Swiss franc	57.9%	42.1%	1.1%	55.2%	44.8%	0.8%
Yen	58.3%	41.7%	1.5%	54.6%	45.4%	1.1%
Pound	56.8%	43.2%	1.9%	54.2%	45.8%	1.4%
Canadian Dollar	61.6%	38.4%	12.6%	54.5%	45.5%	10.1%
Australian Dollar	68.0%	32.0%	57.0%	61.0%	39.0%	54.9%
Interest rate						
Eurodollar	58.4%	41.6%	20.5%	55.0%	45.0%	22.3%
T-bill	68.1%	31.9%	54.8%	61.3%	38.7%	56.9%
Libor	71.1%	28.9%	84.1%	59.9%	40.1%	84.6%
Agricultural						
Live Cattle	57.7%	42.3%	5.1%	54.1%	45.9%	4.0%
Pork Bellies	60.3%	39.7%	6.4%	57.3%	42.7%	5.6%
Hogs	62.2%	37.8%	8.6%	57.2%	42.8%	7.2%
Feeder cattle	65.7%	34.3%	23.2%	61.0%	39.0%	22.1%
Lumber	62.7%	37.3%	18.2%	59.5%	40.5%	17.1%

The table reports proportions of customer trades with zero execution against all possible contra parties (column 6) and against locals only (column 3). Execution for purchases is the benchmark price less the trade price; execution for sales is the sale price less the benchmark price. Columns 1 & 2 report the proportions of customer trades against locals, with nonzero execution, with positive and negative execution. Columns 4 & 5 report proportions of customer trades against all possible contra parties, with nonzero execution, that have positive and negative execution. Panel A reports proportions for execution measured against a one-minute mean price benchmark, and Panel B reports proportions for execution measured against a five-minute mean price benchmark.

Table 3: Customer trading cost estimates based on *inferred* trade direction.

Panel A: Customer costs measured using execution against the one-minute price benchmarks μ_{1t}

column:	(1)	(2)	(3)	(4)	(5)	(6)
	Actual Customer Gains: overall gain ($000) from:			*Inferred gain* s: estimated using execution to infer trade direction		
Pit	execution	timing	total gain	execution	timing	total gain
Equity Index						
S&P 500	-11,226	-11,537	-22,763	-146,018	-19,544	-165,561
S&P Midcap 400	-8	-980	-988	-101	-91	-193
Currency						0
Deutsche mark	-5,899	-4,663	-10,562	-43,547	-4,637	-48,184
Swiss franc	-3,596	2,453	-1,143	-21,850	3,210	-18,640
Yen	-2,444	2,347	-97	-15,937	1,532	-14,405
Pound	-1,894	-330	-2,224	-13,400	-5,901	-19,302
Canadian Dollar	-179	-365	-544	-1,064	-31	-1,095
Australian Dollar	-11	-224	-235	-23	-82	-105
Interest rate						0
Eurodollar	-10,105	-39,312	-49,417	-110,338	33,141	-77,197
T-bill	-107	-1,645	-1,752	-562	-229	-791
Libor	-17	-1,162	-1,179	-91	-32	-123
Agricultural						0
Live Cattle	-950	-1,768	-2,718	-6,780	2,474	-4,306
Pork Bellies	-806	-1,273	-2,079	-3,054	-840	-3,895
Hogs	-611	-1,624	-2,235	-2,866	409	-2,457
Feeder cattle	-195	-892	-1,087	-579	-246	-825
Lumber	-208	-1,239	-1,447	-687	-300	-988
column totals	-38,257	-62,214	-100,471	-366,899	8,832	-358,067

Panel B: Customer costs measured using execution against the five-minute mean price benchmark μ_{5t}

column:	(1)	(2)	(3)	(4)	(5)	(6)
	Actual Customer Gains: overall gain ($000) from:			*Inferred* gains: estimated using execution to infer trade direction		
Pit	execution	timing	gains	execution	timing	total gain
Equity Index						
S&P 500	-15,078	-7,685	-22,763	-312,260	-16,337	-328,596
S&P Midcap 400	-37	-951	-988	-378	-110	-488
Currency						
Deutsche mark	-10,244	-317	-10,562	-90,752	-3,595	-94,347
Swiss franc	-6,637	5,494	-1,143	-48,609	268	-48,340
Yen	-4,338	4,240	-97	-35,953	-4,062	-40,015
Pound	-4,129	1,905	-2,224	-33,631	-1,294	-34,925
Canadian Dollar	-473	-70	-544	-3,077	-757	-3,834
Australian Dollar	-21	-214	-235	-63	-103	-166
Interest rate						
Eurodollar	-24,673	-24,744	-49,417	-227,661	11,177	-216,484
T-bill	-436	-1,317	-1,752	-1,877	-273	-2,150
Libor	-89	-1,090	-1,179	-404	-210	-614
Agricultural						
Live Cattle	-2,077	-642	-2,718	-16,580	-225	-16,805
Pork Bellies	-1,587	-492	-2,079	-7,488	-364	-7,852
Hogs	-1,454	-780	-2,235	-7,172	-419	-7,591
Feeder cattle	-526	-562	-1,087	-1,738	-275	-2,013
Lumber	-545	-902	-1,447	-2,100	-122	-2,222
column totals	-72,343	-28,127	-100,471	-789,742	-16,700	-806,442

NOTE - The table reports actual customer (CTI 4) trading costs compared to trading costs estimated using inferred trade direction. The first set of columns (1-3) reports actual trading costs for customers, broken down into timing (column 2) and execution (column 1) costs, and the total (column 3). The second set of columns (4-6) report estimated customer costs based on a hypothetical aggresion-based trade-direction allocation: all trades with negative execution are assigned to customers, and the resulting total costs are summed.

Table 4: Pecking order: Contra party gain/loss matrix

Panel A: Total execution by trader type (gains) and contra party type (losses)

contra party *losses*	**total execution *gains* by trader type ($000)** local	commercial	floor hedger	customer	**row total (losses)**
CTI 1 - local		-6,045	-3,871	-34,929	-44,845
CTI 2 - commercial	5,970		108	-2,350	3,728
CTI 3 - floor hedger	3,815	-105		-890	2,820
CTI 4 - customer	34,565	2,375	873		37,813
column total (gains)	44,350	-3,775	-2,890	-38,169	

Panel B: Total timing by trader type (gains) and contra party type (losses)

contra party *losses*	**total timing *gains* by trader type ($000)** local	commercial	floor hedger	customer	**row total (losses)**
CTI 1 - local		-23,840	-722	-62,214	-86,776
CTI 2 - commercial	23,482		-1,054	473	22,901
CTI 3 - floor hedger	803	1391		-1,198	996
CTI 4 - customer	61,970	-364	1,700		63,306
column total (gains)	86,255	-22,813	-76	-62,939	

Panel C: Mean execution per contract, by trader type (gains) and contra party type (losses)

contra party *losses*	**mean execution gain per contract ($), by trader type** local	commercial	floor hedger	customer
CTI 1 - local		-0.91	-1.39	-1.89
CTI 2 - commercial	0.91		0.12	-0.56
CTI 3 - floor hedger	1.38	-0.12		-0.45
CTI 4 - customer	1.89	0.57	0.45	

Panel D: Mean timing per contract, by trader type (gains) and contra party type (losses)

contra party *losses*	**mean timing gain per contract ($), by trader type** local	commercial	floor hedger	customer
CTI 1 - local		-3.58	-0.25	-3.32
CTI 2 - commercial	3.58		-1.20	0.13
CTI 3 - floor hedger	0.29	1.57		-0.62
CTI 4 - customer	3.38	-0.09	0.87	

The Table reports profit decompositions by trader type. Panel A reports *total* sample period execution gains for each trader type (column) broken down by indicated contra party trader type (rows). Each cell represents the total gain by the trader type identified by column, for trades against the contra party trader type identified by row. Alternatively, the cell represents the total loss by the trader types identified by row, for trades against the contra party trader type identified by column. The row totals and column totals do not add exactly due to data errors. Panel B reports *total* timing gains and losses with the same format as Panel A. Panels C and D report *mean* execution and timing in the same layout format as the upper panels.

Table 5. Total local and customer execution and timing gains

Panel A: Execution and timing gains measured with the one minute mean price benchmark μ_{1t}

	Locals (Cti 1)								Customers (Cti 4)							
	Total local income from execution ($000)				Total local income from timing ($000)				Total Customer gains from execution ($000)				Total customer gains from timing ($000)			
		by contra party:				by contra party:				by contra party:				by contra party:		
Pit	overall	Commer. member	floor hedger	customer	overall	Commer. member	floor hedger	customer	overall	local	Commer. member	floor hedger	overall	local	Commer. member	floor hedger
Equity Index																
S&P 500	13,437	1,109	1,262	10,945	12,761	706	-1,840	13,610	-11,226	-11,023	-201	5	-11,537	-13,815	2,193	223
S&P Midcap 400	9	5	0	4	245	-127	15	354	-8	-4	-5	1	-980	-356	-593	-25
Currency																
Deutsche mark	5,408	269	537	4,521	6,549	1,377	298	5,012	-5,899	-4,578	-1,328	5	-4,663	-4,901	-873	1,200
Swiss franc	3,521	111	237	3,122	3,235	2,182	32	1,284	-3,596	-3,150	-460	12	2,453	-1,061	3,151	370
Yen	2,721	235	211	2,206	531	1,715	274	-1,042	-2,444	-2,249	-223	28	2,347	1,416	936	48
Pound	1,742	59	76	1,586	2,073	-479	224	2,383	-1,894	-1,602	-268	-20	-330	-2,307	776	1,086
Canadian Dollar	189	10	18	160	505	-59	103	448	-179	-159	-24	5	-365	-459	-71	165
Australian Dollar	13	1	0	12	216	8	8	198	-11	-12	0	0	-224	-197	-23	-6
Interest rate																
Eurodollar	14,690	4,058	1,254	9,223	50,153	17,468	1,391	30,891	-10,105	-9,363	199	-883	-39,312	-30,956	-4,994	-3,468
T-bill	116	19	6	92	1,621	221	-103	1,489	-107	-91	-5	-9	-1,645	-1,489	97	-264
Libor	21	6	0	15	1,175	261	13	899	-17	-15	-1	-2	-1,162	-900	-157	-110
Agricultural																
Live Cattle	1,122	52	113	933	2,092	300	118	1,770	-950	-940	-10	8	-1,768	-1,581	182	-205
Pork Bellies	799	8	25	761	973	-153	-27	1,127	-806	-760	-21	-20	-1,273	-1,164	-80	-42
Hogs	670	22	54	587	1,704	-3	234	1,459	-611	-583	-3	-17	-1,624	-1,412	-78	-105
Feeder cattle	214	2	17	193	897	-2	47	847	-195	-193	0	-2	-892	-848	4	-46
Lumber	216	6	3	207	1,312	70	16	1,242	-208	-207	0	-1	-1,239	-1,231	3	-19
column totals	44,885	5,970	3,815	34,565	86,043	23,482	803	61,970	-38,257	-34,929	-2,350	-890	-62,214	-61,261	473	-1,198
	total execution =			44,885	total timing =			86,043	total execution =			-38,257	total timing =			-62,214
					total income=			130,928					total income=			-100,471

Panel B: Execution and timing gains measured with the five-minute mean price benchmark μ_{5t}

	Locals (Cti 1)								Customers (Cti 4)							
	Total local income from execution ($000)				Total local income from timing ($000)				Total Customer gains from execution ($000)				Total customer gains from timing ($000)			
		by contra party:				by contra party:				by contra party:				by contra party:		
Pit	overall	Commer. member	floor hedger	customer	overall	Commer. member	floor hedger	customer	overall	local	Commer. member	floor hedger	overall	local	Commer. member	floor hedger
Equity Index																
S&P 500	16,638	695	1,431	14,287	9,560	1,120	-2,009	10,270	-15,078	-14,411	-710	55	-7,685	-10,427	2,702	173
S&P Midcap 400	35	10	0	25	219	-132	15	333	-37	-25	-13	1	-951	-335	-584	-26
Currency																
Deutsche mark	9,690	596	675	8,296	2,268	1,053	160	1,237	-10,244	-8,389	-1,763	-83	-317	-1,089	-438	1,288
Swiss franc	5,875	-128	308	5,616	880	2,421	-38	-1,206	-6,637	-5,661	-980	2	5,494	1,449	3,671	381
Yen	4,077	209	278	3,507	-825	1,741	208	-2,344	-4,338	-3,562	-823	43	4,240	2,729	1,537	32
Pound	3,354	41	87	3,151	461	-462	213	803	-4,129	-3,206	-877	-60	1,905	-703	1,385	1,126
Canadian Dollar	454	15	43	394	239	-65	79	214	-473	-394	-92	14	-70	-224	-4	156
Australian Dollar	26	3	2	21	203	7	7	188	-21	-21	0	0	-214	-188	-23	-7
Interest rate																
Eurodollar	36,458	11,480	2,067	22,561	28,384	10,045	578	17,553	-24,673	-22,796	-162	-1,642	-24,744	-17,522	-4,663	-2,709
T-bill	449	65	14	370	1,288	175	-111	1,211	-436	-369	-10	-52	-1,317	-1,210	102	-22
Libor	97	20	4	73	1,098	248	9	841	-89	-74	-5	-11	-1,090	-841	-153	-100
Agricultural																
Live Cattle	2,439	142	231	2,000	775	210	0	702	-2,077	-2,022	0	-30	-642	-498	171	-168
Pork Bellies	1,578	9	56	1,500	195	-154	-58	388	-1,587	-1,502	-40	-36	-493	-423	-60	-26
Hogs	1,542	52	99	1,376	832	-33	189	671	-1,454	-1,368	-20	-46	-780	-627	-61	-76
Feeder cattle	559	5	36	515	551	-5	28	525	-526	-516	-1	-8	-562	-526	5	-40
Lumber	566	18	4	539	963	57	15	910	-545	-540	2	-5	-902	-897	1	-15
column totals	83,837	13,231	5,336	64,231	47,091	16,224	-719	32,296	-72,343	-64,857	-5,494	-1,857	-28,128	-31,331	3,587	-32
	total execution =			83,837	total timing =			47,091	total execution =			-72,343	total timing =			-28,128
					total income=			130,928					total income=			-100,471

The table reports total ($000) execution gains and timing gains for futures market makers, or locals, and for customers. For each trader type (locals and customers), the table presents total gains for trades against all contra parties (overall), and for trades against each of the three possible other trader types. For locals (CTI 1), the table reports total gains against commercial members (CTI 2), against floor hedgers (CTI 3) and against customers (CTI 4). For customers, the table reports total gains against locals, commercial members, and floor hedgers. Total local gains against customers should, in theory, equal the negative of total customer gains against locals; differences are due to data errors.

Table 6. Mean local and customer execution and timing income.

Panel A: Execution benchmark is one-minute quantity-weighted mean trade price

	Locals (Floor traders)															
	mean execution ($) per contract				mean timing ($)				per contract				mean timing ($) per contract			
						by counterparty:				by counterparty:						
Pit	overall	Comm.	Floor hedger	customer		Comm.	Floor hedger	customer	overall	locals	Comm.	Floor hedger		locals	Comm.	Floor hedger
Equity Index																
S&P 500	2.63	2.92	3.52	3.77	2.50	1.86	-5.14	4.69	-2.42	-3.78	-1.10	0.04	-2.49	-4.73	12.03	1.76
S&P Midcap 400	0.62	1.89	0.40	0.40	17.54	-51.87	52.06	35.69	-0.23	-0.39	-0.51	1.43	-28.11	-35.91	-62.73	-53.76
Currency																
Deutsche mark	1.58	0.63	2.05	2.45	1.92	3.27	1.14	2.71	-1.46	-2.47	-1.89	0.04	-1.15	-2.64	-1.24	9.73
Swiss franc	2.02	0.47	3.11	3.12	1.85	9.34	0.44	1.30	-2.00	-3.14	-1.88	0.37	1.37	-1.06	12.84	11.27
Yen	1.84	1.15	2.48	2.46	0.36	8.39	3.21	-1.16	-1.26	-2.49	-0.74	0.66	1.21	1.57	3.12	1.15
Pound	1.80	0.52	1.88	2.61	2.14	-4.21	5.53	3.91	-1.51	-2.62	-1.81	-0.60	-0.26	-3.78	5.24	32.16
Canadian Dollar	0.78	0.39	1.02	0.93	2.09	-2.36	5.74	2.62	-0.33	-0.92	-0.40	0.28	-0.68	-2.67	-1.17	9.20
Australian Dollar	1.17	0.92	1.21	1.38	19.64	10.46	21.97	23.76	-0.85	-1.36	0.13	0.59	-16.85	-23.24	-37.10	-27.83
Interest rate																
Eurodollar	0.73	0.81	0.72	1.03	2.49	3.50	0.80	3.47	-0.60	-1.04	0.09	-0.63	-2.33	-3.44	-2.14	-2.47
T-bill	0.37	0.23	0.42	0.57	5.19	2.69	-7.12	9.21	-0.31	-0.56	-0.10	-0.27	-4.75	-9.18	1.86	-7.90
Libor	0.15	0.19	-0.06	0.15	8.34	8.43	3.51	9.24	-0.07	-0.15	-0.02	-0.08	-4.40	-9.26	-3.73	-5.68
Agricultural																
Live Cattle	0.84	1.00	1.20	1.06	1.56	5.74	1.25	2.02	-0.58	-1.07	-0.21	0.11	-1.07	-1.79	3.74	-2.86
Pork Bellies	2.24	0.92	1.58	3.13	2.73	-18.61	-1.69	4.64	-2.28	-3.13	-2.38	-1.78	-3.60	-4.79	-9.13	-3.78
Hogs	1.19	1.01	1.14	1.51	3.03	-0.14	4.92	3.75	-0.90	-1.50	-0.17	-0.46	-2.40	-3.63	-4.88	-2.88
Feeder cattle	1.39	0.83	1.54	1.57	5.83	-0.84	4.19	6.87	-1.11	-1.56	0.06	-0.21	-5.08	-6.87	4.33	-6.08
Lumber	2.82	3.99	2.12	3.41	17.12	49.40	11.32	20.52	-2.59	-3.41	0.59	-2.06	-15.41	-20.29	9.59	-27.20

Panel B: Execution benchmark is five-minute quantity-weighted mean trade price

	Locals (Floor traders)								**Customers**							
	mean execution ($) per contract				mean timing ($) per contract				mean execution ($) per contract				mean timing ($) per contract			
		by counterparty:				by counterparty:				by counterparty:				by counterparty:		
Pit	overall	Comm.	Floor hedger	customer	overall	Comm.	Floor hedger	customer		locals	Comm.	Floor hedger	overall	locals	Comm.	Floor hedger
Equity Index																
S&P 500	3.26	1.83	4.00	4.92	1.87	2.95	-5.61	3.54	-3.25	-4.94	-3.89	0.44	-1.66	-3.57	14.83	1.36
S&P Midcap 400	2.51	3.93	0.26	2.56	15.61	-53.90	52.20	33.53	-1.07	-2.56	-1.41	2.59	-27.27	-33.75	-61.83	-54.93
Currency																
Deutsche mark	2.83	1.41	2.59	4.49	0.68	2.50	0.61	0.67	-2.53	-4.52	-2.51	-0.67	-0.08	-0.59	-0.62	10.44
Swiss franc	3.37	-0.55	4.05	5.63	0.51	10.36	-0.50	-1.21	-3.71	-5.64	-4.00	0.05	3.07	1.44	14.96	11.59
Yen	2.76	1.02	3.26	3.92	-0.57	8.51	2.43	-2.62	-2.23	-3.95	-2.74	1.04	2.18	3.03	5.12	0.78
Pound	3.47	0.36	2.15	5.19	0.48	-4.06	5.26	1.32	-3.29	-5.25	-5.92	-1.77	1.52	-1.15	9.35	33.33
Canadian Dollar	1.87	0.60	2.39	2.30	1.00	-2.57	4.37	1.25	-0.88	-2.29	-1.51	0.77	-0.13	-1.30	-0.06	8.71
Australian Dollar	2.35	3.35	4.53	2.52	18.38	8.03	18.65	22.64	-1.55	-2.50	0.37	1.64	-16.15	-22.10	-37.34	-28.88
Interest rate																
Eurodollar	1.81	2.30	1.19	2.53	1.41	2.01	0.33	1.97	-1.46	-2.54	-0.07	-1.17	-1.46	-1.95	-1.99	-1.93
T-bill	1.44	0.79	0.95	2.29	4.05	2.13	-7.65	7.49	-1.26	-2.28	-0.18	-1.56	-3.80	-7.47	1.95	-6.61
Libor	0.69	0.63	1.08	0.76	7.83	7.98	2.37	8.66	-0.34	-0.76	-0.12	-0.59	-4.13	-8.66	-3.63	-5.17
Agricultural																
Live Cattle	1.82	2.72	2.44	2.28	0.58	4.03	0.01	0.80	-1.26	-2.30	0.01	-0.41	-0.39	-0.57	3.52	-2.34
Pork Bellies	4.42	1.04	3.51	6.17	0.55	-18.72	-3.63	1.60	-4.49	-6.18	-4.61	-3.21	-1.39	-1.74	-6.90	-2.35
Hogs	2.74	2.36	2.08	3.53	1.48	-1.48	3.97	1.72	-2.15	-3.52	-1.26	-1.27	-1.15	-1.61	-3.79	-2.08
Feeder cattle	3.64	1.98	3.26	4.18	3.65	-1.99	2.46	4.26	-2.99	-4.18	-0.57	-0.99	-3.20	-4.26	4.95	-5.30
Lumber	7.38	13.02	3.15	8.90	12.52	40.37	10.28	15.03	-6.78	-8.90	6.45	-7.97	-11.21	-14.79	3.73	-21.29

table presents mean gains for trades against all contra parties (overall), and for trades against each of the three possible other trader types. For locals (CTI 1), the table reports mean gains against commercial members (CTI 2), against floor hedgers (CTI 3) and against customers (CTI 4). For customers, the table reports mean gains against locals,

data errors.

Table 7. Timing and execution for locals across trade activity quartiles.

Panel A: Execution benchmark is one-minute quantity-weighted mean trade price

		Mean timing and execution for the median local within each volume quartile								**Percentage of locals with positive timing or execution within each volume quartile**							
		median local mean execution volume quartile				median local mean timing volume quartile				percent with positive execution volume quartile				percent with positive timing volume quartile			
Pit	(# of traders)	least	2	3	most	least	2	3	most	least	2	3	most	least	2	3	most
Equity Index																	
S&P 500	(387)	1.17	2.37	2.92	2.64	5.46	3.39	2.18	1.58	60%	73%	81%	87%	59%	66%	73%	69%
S&P Midcap	(9)	-1.13	0.68	1.18	0.45	11.22	3.97	-3.09	25.27	0%	100%	67%	100%	100%	100%	33%	100%
Currency																	
Deutsche mark	(160)	0.32	0.49	1.84	1.77	-2.02	0.44	1.00	1.47	60%	55%	95%	93%	45%	55%	73%	90%
Swiss franc	(27)	0.33	0.88	1.43	2.43	2.85	2.56	2.60	1.40	63%	67%	89%	100%	63%	67%	78%	74%
Yen	(79)	-0.20	1.38	1.91	1.58	-2.55	0.50	1.16	0.96	47%	80%	95%	95%	42%	55%	90%	85%
Pound	(56)	0.51	2.03	2.27	2.26	-2.49	-1.66	1.99	2.24	71%	79%	93%	86%	29%	43%	79%	100%
Canadian Dollar	(23)	0.15	0.66	0.74	0.79	5.06	-0.12	2.88	2.33	80%	83%	100%	100%	60%	50%	100%	100%
Australian Dollar	(2)	0.52	nm	nm	1.72	17.96	nm	nm	24.52	100%	-	-	100%	100%	-	-	100%
Interest rate																	
Eurodollar	(348)	0.21	0.65	0.77	0.64	0.59	2.21	1.63	2.10	54%	86%	97%	93%	63%	77%	78%	98%
T-bill	(22)	-0.11	0.12	0.42	0.31	2.79	3.59	3.23	9.73	40%	67%	100%	100%	80%	83%	100%	100%
Libor	(15)	-0.15	0.04	0.17	0.13	-2.09	3.78	7.45	10.28	33%	50%	100%	100%	33%	75%	100%	100%
Agricultural																	
Live Cattle	(128)	0.41	0.40	0.85	0.98	0.11	1.37	0.54	0.92	69%	66%	91%	88%	53%	59%	63%	72%
Pork Bellies	(56)	1.36	1.77	2.18	2.09	3.90	4.04	4.23	3.41	79%	100%	93%	100%	71%	86%	86%	86%
Hogs	(74)	0.68	1.27	0.96	1.24	5.16	1.94	3.66	2.34	67%	89%	89%	100%	67%	68%	89%	100%
Feeder cattle	(24)	0.34	0.36	1.71	1.31	2.53	6.62	4.66	6.05	67%	83%	100%	100%	67%	67%	83%	100%
Lumber	(26)	1.95	3.53	2.97	2.45	7.59	18.59	21.80	12.91	100%	100%	100%	100%	67%	100%	86%	100%

Panel B: Execution benchmark is five-minute quantity-weighted mean trade price

		Mean timing and execution for the median local within each volume quartile								**Percentage of locals with positive timing or execution within each volume quartile**							
		median local mean execution volume quartile				median local mean timing volume quartile				percent with positive execution volume quartile				percent with positive timing volume quartile			
Pit (# of traders)		least	2	3	most	least	2	3	most	least	2	3	most	least	2	3	most
Equity Index																	
S&P 500	(387)	4.38	2.62	3.60	3.42	4.11	2.49	1.85	1.99	63%	70%	81%	84%	64%	65%	72%	64%
S&P Midcap	(9)	-2.69	2.80	1.47	2.11	12.78	1.85	-4.24	23.61	50%	100%	100%	100%	100%	100%	33%	100%
Currency																	
Deutsche mark	(160)	-0.24	1.08	3.02	3.00	-0.90	0.03	0.02	0.04	48%	63%	90%	95%	43%	50%	50%	55%
Swiss franc	(27)	1.70	2.86	2.29	3.56	-1.32	0.88	1.66	0.71	63%	74%	93%	89%	48%	56%	70%	63%
Yen	(79)	1.23	1.84	3.09	2.27	-3.39	-0.83	-0.16	0.06	58%	90%	95%	90%	37%	40%	40%	50%
Pound	(56)	3.02	5.49	5.20	3.30	-5.08	-1.78	-0.02	0.85	71%	79%	100%	93%	29%	36%	50%	64%
Canadian Dollar	(23)	0.59	1.38	2.18	1.67	4.62	-0.38	1.36	1.37	80%	83%	100%	100%	80%	33%	100%	100%
Australian Dollar	(2)	1.50	-	-	3.09	16.98	-	-	23.15	100%	-	-	100%	100%	-	-	100%
Interest rate																	
Eurodollar	(348)	0.63	1.73	1.54	1.64	0.59	1.10	0.83	1.22	62%	89%	97%	97%	55%	68%	70%	91%
T-bill	(22)	0.84	1.00	1.59	1.08	1.13	2.36	2.07	8.94	100%	67%	100%	80%	80%	83%	100%	80%
Libor	(15)	-0.80	0.27	0.84	0.74	-0.61	3.52	6.84	9.67	33%	50%	100%	100%	33%	75%	100%	100%
Agricultural																	
Live Cattle	(128)	0.97	0.88	2.04	1.76	-1.30	1.34	-0.10	-0.25	69%	81%	94%	91%	34%	56%	47%	41%
Pork Bellies	(56)	4.94	3.13	4.47	4.21	4.35	2.25	1.77	1.45	79%	100%	93%	100%	71%	64%	64%	64%
Hogs	(74)	1.67	2.14	2.93	2.84	2.32	0.96	2.18	0.71	67%	95%	89%	100%	61%	63%	84%	67%
Feeder cattle	(24)	1.72	0.64	4.15	3.25	1.80	5.61	2.21	3.24	67%	67%	100%	100%	67%	67%	67%	100%
Lumber	(26)	6.15	9.57	7.65	6.56	2.00	13.56	15.95	9.62	100%	100%	100%	100%	67%	100%	86%	100%

The table reports mean execution and timing for the median local within each of four volume quartiles for each pit. Locals are ranked into volume quartiles on the basis of total contracts traded during the sample period (first six months 1992). Locals with less than 100 trades are dropped.

Table 8. Customer execution compared for low and high information days.

Panel A: One minute execution benchmarks

Pit	mean *customer* execution for: Low 63 days of *local* timing	High 63 days of *local* timing	**difference**	**t-stat**
Equity Index				
S&P 500	-2.25	-2.57	-0.32	**-5.05**
S&P Midcap 400	-0.14	-0.31	-0.17	-0.83
Currency				
Deutsche mark	-1.19	-1.67	-0.48	**-11.95**
Swiss franc	-1.74	-2.23	-0.49	**-9.14**
Yen	-1.28	-1.23	0.05	1.06
Pound	-1.29	-1.70	-0.41	**-5.75**
Canadian Dollar	-0.33	-0.33	0.00	0.04
Australian Dollar	-1.12	-0.61	0.51	**2.74**
Interest rate				
Eurodollar	-0.44	-0.70	-0.26	**-10.81**
T-bill	-0.31	-0.31	0.01	0.14
Libor	-0.08	-0.05	0.03	0.98
Agricultural				
Live Cattle	-0.50	-0.65	-0.15	**-6.83**
Pork Bellies	-2.19	-2.36	-0.17	**-2.50**
Hogs	-0.92	-0.89	0.02	0.79
Feeder cattle	-0.95	-1.24	-0.29	**-5.17**
Lumber	-2.26	-2.84	-0.58	**-3.36**

Panel B: Five minute execution benchmarks

Pit	mean customer execution for: Low 63 days of local timing	High 63 days of local timing	**difference**	**t-stat**
Equity Index				
S&P 500	-2.79	-3.65	-0.86	**-6.26**
S&P Midcap 400	-0.69	-1.38	-0.68	-1.39
Currency				
Deutsche mark	-1.96	-2.99	-1.03	**-11.68**
Swiss franc	-2.91	-4.38	-1.47	**-12.60**
Yen	-2.16	-2.30	-0.14	-1.41
Pound	-2.27	-4.20	-1.93	**-9.68**
Canadian Dollar	-0.79	-0.97	-0.18	**-2.72**
Australian Dollar	-2.02	-1.33	0.89	**2.67**
Interest rate				
Eurodollar	-1.09	-1.70	-0.61	**-14.34**
T-bill	-1.07	-1.41	-0.34	**-3.30**
Libor	-0.31	-0.36	-0.05	-0.82
Agricultural				
Live Cattle	-1.10	-1.41	-0.30	**-6.83**
Pork Bellies	-4.00	-4.94	-0.94	**-6.72**
Hogs	-2.17	-2.13	0.04	0.68
Feeder cattle	-2.45	-3.43	-0.97	**-8.16**
Lumber	-5.83	-7.49	-1.66	**-4.09**

Comparison of customer execution costs for a sample bifurcation based on total local (CTI 1) timing income; for each of the 126 days, local timing income for each pit is totaled. Then, for each pit, the local timing income for each day is ranked. The sample is split, for each pit, into the lower 63 days and upper 63 days for local timing income. The table reports mean customer execution for the upper 63 days of local timing income and the lower 63 days of timing income, reporting also the difference and a *t*-statistic.

Table 9. Execution differences for local trades and customer trades: good timing vs. bad timing.

Panel A: One minute execution benchmarks

(Column)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Differences in mean execution ($) per contract for trades with good (positive) and bad (negative) timing. Differences are mean good timing execution less mean bad timing execution.											
	Local (Cti 1) trades:						**Customer (Cti 4) trades:**					
			by contra party						by contra party			
Pit	**overall**	t-stat	**local**	t-stat	**customer**	t-stat	**overall**	t-stat	**local**	t-stat	**customer**	t-stat
Equity Index												
S&P 500	-0.31	**-6.00**	-1.33	**-16.14**	0.03	0.37	0.20	**3.23**	0.04	0.59	0.39	**2.85**
S&P Midcap 400	-0.14	-0.39	0.40	0.31	-0.12	-0.31	-0.09	-0.40	-0.13	-0.33	-0.48	-1.63
Currency												
Deutsche mark	-0.17	**-4.53**	-0.53	**-8.64**	-0.05	-0.99	0.12	**2.93**	-0.07	-1.27	0.49	**5.79**
Swiss franc	-0.30	**-5.90**	-0.91	**-10.15**	-0.22	**-3.12**	0.15	**2.87**	-0.22	**-3.27**	0.67	**6.19**
Yen	-0.24	**-5.11**	-0.99	**-10.64**	-0.01	-0.15	0.12	**2.71**	-0.03	-0.43	0.24	**2.88**
Pound	-0.25	**-3.54**	-0.80	**-6.50**	-0.20	**-2.04**	-0.11	-1.48	-0.21	**-2.25**	-0.43	**-3.09**
Canadian Dollar	-0.12	**-2.94**	-0.24	-1.78	-0.08	-1.77	0.04	1.54	-0.11	**-2.40**	0.12	**2.81**
Australian Dollar	-0.58	**-2.71**	0.77	1.54	-0.80	**-3.11**	0.09	0.45	-0.77	**-3.19**	1.66	**3.99**
Interest rate												
Eurodollar	-0.14	**-6.66**	-0.29	**-7.57**	-0.13	**-3.83**	0.06	**2.51**	-0.12	**-3.69**	0.41	**8.04**
T-bill	-0.05	-1.11	-0.03	-0.25	-0.07	-1.17	0.00	0.08	-0.07	-1.07	0.04	0.40
Libor	-0.02	-0.38	0.30	1.66	-0.08	-1.16	-0.04	-1.08	-0.08	-1.17	-0.09	-1.32
Agricultural												
Live Cattle	-0.10	**-4.14**	-0.14	**-2.84**	-0.14	**-4.56**	-0.01	-0.42	-0.14	**-4.93**	0.05	1.39
Pork Bellies	-0.14	**-2.09**	0.33	**2.67**	-0.38	**-4.80**	-0.12	-1.80	-0.37	**-4.83**	0.24	1.69
Hogs	-0.14	**-4.00**	-0.07	-0.88	-0.13	**-3.26**	0.03	1.04	-0.14	**-3.60**	0.18	**2.99**
Feeder cattle	-0.20	**-3.24**	-1.08	**-5.31**	-0.13	-1.98	-0.11	-1.84	-0.13	**-2.07**	-0.28	**-2.19**
Lumber	-0.32	-1.86	-0.86	**-2.34**	-0.28	-1.44	-0.30	-1.68	-0.28	-1.49	-1.01	**-2.26**

Panel B: Five minute execution benchmarks

(Column)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Differences in mean local (CTI 1) execution per contract for trades with good (positive) and bad (negative) timing. Differences are mean good timing execution less mean bad timing execution.											
	Local (Cti 1) trades:						**Customer (Cti 4) trades:**					
			by contra party						by contra party			
Pit	**overall**	t-stat	**local**	t-stat	**customer**	t-stat	**overall**	t-stat	**local**	t-stat	**customer**	t-stat
Equity Index												
S&P 500	-0.17	-1.56	-2.27	**-13.99**	0.24	1.48	-0.29	**-2.07**	0.27	1.72	-1.72	**-5.63**
S&P Midcap 400	-0.75	-1.00	2.15	0.86	-0.49	-0.56	-0.08	0.63	-0.50	-0.57	0.10	0.14
Currency												
Deutsche mark	-0.41	**-5.55**	-0.69	**-6.47**	-0.21	-1.80	0.25	**2.85**	-0.22	**-1.99**	0.62	**3.19**
Swiss franc	-0.40	**-3.78**	-1.01	**-5.99**	-0.36	**-2.27**	0.05	0.47	-0.42	**-2.85**	-0.10	-0.45
Yen	-0.81	**-8.23**	-1.49	**-8.55**	-0.78	**-5.59**	0.42	**4.14**	-0.83	**-6.42**	1.79	**9.00**
Pound	-0.22	-1.27	-1.52	**-6.06**	-0.04	-0.14	-0.42	**-2.10**	-0.07	-0.29	-1.93	**-4.56**
Canadian Dollar	-0.34	**-3.95**	-1.69	**-6.38**	-0.10	-0.99	0.13	1.97	-0.14	-1.41	0.26	**2.46**
Australian Dollar	-0.96	**-2.35**	1.50	1.26	-1.27	**-2.71**	-0.47	0.16	-1.28	**-2.88**	2.52	**3.71**
Interest rate												
Eurodollar	-0.26	**-7.17**	-0.77	**-12.53**	-0.33	**-5.47**	0.06	1.43	-0.33	**-5.81**	0.65	**7.28**
T-bill	-0.37	-3.52	0.12	0.61	-0.84	**-5.24**	-0.11	-0.98	-0.83	**-5.47**	0.40	1.94
Libor	-0.12	-1.13	-0.14	-0.36	0.12	0.97	0.00	0.04	0.12	0.98	-0.28	-1.61
Agricultural												
Live Cattle	-0.22	**-4.28**	0.00	-0.04	-0.28	**-4.49**	0.12	**2.74**	-0.29	**-4.90**	0.67	**9.21**
Pork Bellies	0.03	0.18	1.03	**4.14**	-0.47	**-2.73**	-0.32	**-2.27**	-0.47	**-2.91**	-0.32	-1.07
Hogs	-0.10	-1.54	0.72	**4.81**	-0.24	**-2.96**	0.10	1.62	-0.23	**-3.02**	0.68	**6.03**
Feeder cattle	-0.57	**-4.35**	-1.85	**-5.05**	-0.56	**-3.78**	-0.09	-0.74	-0.55	**-3.92**	0.70	**2.79**
Lumber	-0.96	**-2.39**	-0.93	-1.05	-1.23	**-2.65**	-0.43	-1.04	-1.23	**-2.74**	1.17	1.21

The table reports differences between mean execution for trades with positive (good) timing and mean execution for trades with bad (negative) timing. Differences are calculated as mean execution for trades with positive timing less mean execution for trades with negative timing. Column 1 reports the execution difference for all local trades, and column 2 reports the t-statistic for a test of significant difference. Column 3 reports the difference in local execution for trades against other locals, while column 5 reports the difference in execution for local trades against customers. Columns 4 & 6 report t-stats associated with columsn 3 & 5. Each column reports execution differences for trades. Columns 7-12 report similar information for customer trades. Negative differences indicate that trades with positive timing have inferior execution. Mean executions are contract quantity-weighted means.