# EXECUTION QUALITY IN OPEN-OUTCRY FUTURES MARKETS

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This study examines the composition of customer order flow and the execution quality for different types of customer orders in six futures pits of the Chicago Mercantile Exchange (CME). It is shown that off-exchange customers frequently provide liquidity to other traders by submitting limit orders. The determinants of customers' choice between limit and market orders are examined, and it is found that higher bid–ask spreads increase the limit-order submission frequency, and increased price volatility makes limit-order submission less likely. Effective spreads, trading revenues, and turnaround times for customer liquidity-demanding and limit orders are also documented. Consistent with evidence from equity markets, the results show that limit-order traders receive better executions than traders using liquidity-demanding orders, but incur adverse selection costs.  Jrl Fut Mark 25:1067–1092, 2005

## INTRODUCTION

Execution costs affect the returns of portfolio investors and profitability of trading strategies employed by active traders. Therefore, it is important for traders to be able to compare execution costs in alternative market

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venues. The market regulators also need to know what the execution costs are in order to evaluate relative benefits of different trading protocols and to examine the effects of rule changes on market liquidity. Although execution costs in equity markets have been extensively studied, execution costs in open-outcry futures markets remain a relatively unexplored area because of the limited availability of appropriate trade and quote data.

Common time-series estimators of effective bid–ask spreads, such as those developed by Roll (1984) and Smith and Whaley (1994a), do not account for intercustomer trades and other microstructure effects in futures markets. Therefore, Locke and Venkatesh (1997) and Ferguson and Mann (2001) advocate estimating effective execution costs by using trade data and aggregating across all customer trades for each interval. Specifically, the effective bid–ask spread can be calculated as the average customer buy price minus the average customer sell price. This approach provides a measurement of the aggregate customer execution costs.

Ferguson and Mann (2001) show that, surprisingly, the effective spreads in futures markets are negative in many intraday intervals, although they are positive on average. They argue that this finding may suggest that exchange locals, who tend to behave as market makers in the futures pits, often employ more complex strategies than simply buying at the bid and selling at the offer. Specifically, the locals offer customers price improvements in order to take positions ahead of anticipated price changes. Manaster and Mann (1999) use a similar argument to explain why off-exchange customers are frequently able to buy low and sell high.

This study extends the prior literature by analyzing execution costs separately for liquidity-demanding and limit orders submitted by off-exchange customers in six futures pits of the Chicago Mercantile Exchange (CME). It is shown that, although off-floor customers tend to use liquidity-demanding orders, limit orders account for a substantial proportion of the customer order flow.

Customers using limit orders compete with market makers to provide liquidity to incoming market orders or to market makers. To minimize execution costs, traders make order submission decisions strategically. Determinants of the order choice in futures markets are examined, and it is found that higher bid–ask spreads increase the frequency of limit-order submissions by off-floor customers. At the same time, higher price volatility seems to reduce the probability of limit-order submissions. Although traders strategically choose the order type depending on market conditions, other factors also affect the order choice. In particular, different traders have different needs, which are best served by different types of orders. Therefore, in addition to the analysis of the aggregate customer trading costs, it is important to separately examine execution costs for different types of customer orders.[1]

The results of the analysis of customer execution costs show that, not surprisingly, the effective spreads for customer market orders and other liquidity-demanding orders are almost always positive. At the same time, effective spreads for customer limit orders tend to be negative, suggesting that limit-order traders earn the liquidity premium. Periods when executed customer limit orders outnumber executed customer market orders are likely to produce negative aggregate effective spreads, documented by Ferguson and Mann (2001).

Further analysis examines the notion suggested by Manaster and Mann (1999) and Ferguson and Mann (2001) that exchange locals offer customers better execution to take positions ahead of favorable price movements. In other words, customer limit orders may be "picked off" by market makers. Returns around customer limit-order trades with market makers and trading revenues for such trades are examined. The results are generally consistent with the notion that floor traders may be able to pick off limit orders submitted by off-exchange customers, although the adverse selection costs imposed on the customers appear to be small.

The article is presented as follows. The next section reviews the relevant literature. The Data section describes the data used in this study, examines distribution of customer trading volume by order type and type of counterparty, and documents turnaround times for different types of customer orders. An Empirical Results section examines the determinants of customer order choice, estimates effective spreads and trading revenues for different types of customer orders, and examines whether market makers are able to pick off customer limit orders. Finally, a summary and conclusions are presented.

## LITERATURE ON EXECUTION-COST MEASUREMENT

Analysis of trading costs and market frictions is central to market microstructure research. Most of the literature concerning trading costs was originally in equity markets. Roll (1984) derived a frequently used

[1]Studies of execution costs and execution quality in equity markets (e.g., Bacidore, Ross, & Sofianos, 2003; Battalio, Hatch, & Jennings, 2003; Harris & Hasbrouck, 1996; Werner, 2003) separately examine market and limit orders, with most studies focusing on execution quality for market orders.

estimator of the effective bid–ask spread. It is calculated based on the serial covariance of trade prices as $S_R = 2\sqrt{-Cov(\Delta P_t, \Delta P_{t-1})}$. The implicit assumption of this estimator is that all trades occur between customers and market makers. In this framework market makers act as sole liquidity suppliers, and customers initiate all trades and pay the bid–ask spread on a round trip. This approach is consistent with the definition of the bid–ask spread proposed by Demsetz (1968) as the price paid for immediacy.

Subsequent literature on equity market spreads examined effective and realized spreads under similar assumptions. For example, the effective half-spread is commonly defined as $D_t(P_t - M_t)$, where $P_t$ is the trade price, $M_t$ is the spread midpoint at the time of the trade, and $D_t$ is an indicator variable equal to 1 for customer buy orders and $-1$ for customer sell orders. Because commonly available data sets (such as NYSE's TAQ database) do not identify customer buy and sell trades, this information must be inferred. For example, based on the widely used Lee and Ready (1991) trade-classification algorithm, all trades above the spread midpoint are classified as customer buys and all trades below the midpoint are classified as customer sells. This leads to positive effective spreads for all customer trades. Again, the underlying assumption is that all trades are initiated by customers, with the resulting effective spread estimates being the effective spreads for customer market orders.

Perhaps the main reason for the restrictive assumptions about trading in most existing studies is that the commonly available data sets do not include trade direction (buy or sell), order type, or trader type (market maker or outside customer). However, in markets where customers frequently use limit orders (which can be expected to have *negative* effective spreads) this approach produces an incomplete picture of customer execution costs. Several equity market studies (e.g., Harris & Hasbrouck, 1996, Werner, 2003) use data on customer orders to estimate execution costs for liquidity-demanding and limit orders.

The literature on execution costs in futures markets is relatively limited. In contrast to market makers in equity markets, exchange locals in futures pits have no obligation to make a market. Quoted bid–ask spreads arguably do not exist in open-outcry futures markets because bid–ask quotes are good "only for as long as the breath is warm." Furthermore, the bid–ask quotes are not recorded systematically. Consequently, most studies of execution costs in futures markets estimate the effective spreads using time and sales data that contain execution times and prices of trades that result in price changes. Effective spread estimators commonly applied to time and sales data include Roll's (1984) serial covariance estimator,[2] the mean absolute price change estimator suggested by Thompson and Waller (1988), and the method-of-moments estimator of Smith and Whaley (1994a).

The effective spread estimator suggested by Thompson and Waller (1988) is calculated simply as the average absolute value of price changes during an interval. A potential drawback of this estimator is that fundamental price changes are treated as fluctuations between the bid–ask quotes, leading to a possible bias. The method-of-moments estimator proposed by Smith and Whaley (1994a) is designed to purge the effects of fundamental price changes on the estimated effective spread. Assuming normal distribution for the fundamental price changes, Smith and Whaley (1994a) show that the effective spread can be estimated with the use of the first two moments of the empirical distribution of absolute price changes. The unique microstructure of futures markets makes them very different from the equity markets. At the same time, following the approach of many equity market studies, common time-series effective spread estimators implicitly assume that all trades are between customers and market makers and that customers initiate all trades.

The debate about dual trading triggered a renewed interest in measurement of execution costs in futures markets. In particular, Smith and Whaley (1994b) use the method-of-moments estimator to examine the effects on liquidity of the "top step" rule, which restricted dual trading in the S&P 500 futures. On the other hand, Chang and Locke (1996) examine the effects of dual trading restrictions by estimating effective spreads for off-floor customers with the use of trade reconstruction data by aggregating across all customer orders. Locke and Venkatesh (1997) argue that this "social cost" (i.e., the cash flow from customers to market makers) is the relevant measure of transaction costs when analyzing the effects of market rules changes.

Locke and Venkatesh (1997) point out that frequent intercustomer trades in futures markets reduce the aggregate customer execution costs, which is not captured by the common effective spread estimators. Furthermore, Locke and Venkatesh (1997) maintain that the common spread estimators do not adequately account for other features of the futures market microstructure. In particular, the Smith and Whaley (1994a), Thompson and Waller (1988), and other estimators that use the absolute value of a price change impose a lower bound on the estimated effective spread equal to the minimum price change. In addition to discreteness issues, this can be a binding constraint, because

[2]Because prices in the time and sales date are recorded only after a price change, in estimation of effective bid–ask spreads in futures markets the Roll's estimator must be divided by 2.

the theoretical effective spread is unbounded. Studies of futures trading beginning with Silber (1984) show that profits of scalpers (floor traders acting as voluntary market makers in futures pits) tend to be less than the minimum price change on a round trip. Locke and Venkatesh (1997) examine the relationship between the effective spread for all customer orders and some of the common time-series estimators of effective spreads including the Roll (1984) serial covariance estimator and the Smith and Whaley (1994a) method-of-moments estimator. The study finds no relationship between the aggregate customer execution costs in futures markets and the common effective spread estimators.

This article extends the prior literature by analyzing execution quality for different types of customer orders in futures markets. Off-floor customers choose order types strategically in an effort to minimize execution costs. However, as Harris (2003) notes, different traders have different needs. Some traders need to trade without delay, whereas other traders are more patient. Some traders have to trade, and others are not committed to trading. Trading objectives influence the decisions concerning order choice and ultimately affect market liquidity. Therefore, it is important to examine trading costs and execution speed for different types of customer orders.

## DATA AND DESCRIPTIVE STATISTICS

### Data

The data are time and sales and computerized trade reconstruction (CTR) data for six futures contracts traded on the floor of the Chicago Mercantile Exchange (CME). These contracts include two index futures (S&P 500 and Nasdaq-100), two currency futures (Euro and Japanese Yen) and two agricultural futures (live cattle and lean hogs). The data are obtained from the Commodity Futures Trading Commission (CFTC). CTR data contain separate records for both sides of each trade. Available CTR data include the contract ticker symbol, trade date, trade time to the nearest second, the contract month, buy/sell code, number of contracts traded, trade price, customer-type indicator (CTI), CTI of the opposite side of the trade, trade type (regular or spread trade), order type,[3] and order arrival time stamp (when the order is received on the floor).[4]

[3]The order type is available for customer trades but it is not available for local trades.

[4]The exact execution time is not recorded by the traders and is estimated by the CTR algorithm based on time and sales data, 15-minute time brackets, trade sequence on trader cards, order arrival time stamps, and other available data. Although execution times are not error-free, they are used by the exchange for enforcement purposes.

CTI is assigned to four different types of traders as follows: CTI1 are trades executed for the personal account of the executing floor trader (local trade), CTI2 are trades executed for an account of a clearing firm, CTI3 are trades executed for a personal account of another floor trader, CTI4 are trades executed for an account of an off-exchange customer. All trades are executed by floor traders (exchange members or leaseholders). The one-year period from July 1, 2000 to June 30, 2001 is examined. Days with more than 1 hour of data missing, such as shortened pre-holiday days, were removed from the sample. For every trading day, only the most actively traded contract is considered in each market.

## Distribution of Customer Trading Volume by Order Type and Type of Counterparty

The traders' choice between market and limit orders remains an important issue in the market microstructure literature.[5] Market orders and marketable limit orders are thought of as liquidity-demanding order types (e.g., Harris, 2003, Werner, 2003). Market orders offer certain execution but the execution price is uncertain. Furthermore, market-order traders are likely to pay a liquidity premium by buying at the offer and selling at the bid. On the other hand, limit-order submitters are patient traders willing to accept the risk of not getting a fill to get their orders executed at a better price. Standing limit orders provide liquidity by creating trading opportunities for market-order traders. Limit-order traders tend to buy at the bid and sell at the offer, leading to negative effective spreads for limit orders.

The composition of customer order flow in open-outcry futures markets, and particularly the role of limit orders, remains unexplored in the market microstructure literature.[6] Therefore, the distribution of customer trading volume by type of order and type of counterparty is examined first. This allows two goals to be met. First, the relative prevalence of liquidity-demanding and limit orders submitted by customers can be documented. Second, the degree to which market makers provide liquidity to market-order traders or consume liquidity supplied by customers using limit orders can be examined. The distribution of customer trading volume by order type is shown in Table I.

[5]See, for example, Harris and Hasbrouck (1996); Handa and Schwartz (1996); and Bae, Jang, and Park (2003).

[6]Locke and Sarkar (2001) provide indirect evidence on this issue by analyzing trading between customers in futures markets.

**TABLE I**
Distribution of Customer Trading Volume by Type of Order

| | *Liquidity-demanding orders* | | | | | | |
|---|---|---|---|---|---|---|---|
| | *Market* | *Discretionary* | *Stop* | *Market on close* | *Marketable limit* | *Limit* | *Other* |
| S&P 500 | | | | | | | |
| Mean size | 3.72 | 9.22 | 2.75 | 5.46 | 6.10 | 5.25 | 3.24 |
| Percent of total volume | 29.9% | 14.8% | 4.0% | 1.1% | 14.9% | 31.0% | 4.2% |
| Nasdaq-100 | | | | | | | |
| Mean size | 3.33 | 5.86 | 2.48 | 2.83 | 4.27 | 3.64 | 2.63 |
| Percent of total volume | 29.3% | 11.3% | 3.0% | 0.4% | 14.4% | 26.2% | 15.6% |
| Euro | | | | | | | |
| Mean size | 3.53 | 7.65 | 3.11 | 5.60 | 7.03 | 5.07 | 8.45 |
| Percent of total volume | 30.6% | 1.2% | 5.1% | 2.1% | 23.1% | 28.3% | 9.6% |
| Yen | | | | | | | |
| Mean size | 3.41 | 10.50 | 3.30 | 4.96 | 6.86 | 5.58 | 5.94 |
| Percent of total volume | 28.3% | 2.5% | 7.5% | 2.7% | 23.3% | 27.8% | 7.7% |
| Lean hogs | | | | | | | |
| Mean size | 2.43 | 5.48 | 2.24 | 3.88 | 4.15 | 3.00 | 3.06 |
| Percent of total volume | 32.6% | 15.8% | 7.8% | 3.0% | 11.8% | 25.0% | 4.0% |
| Live cattle | | | | | | | |
| Mean size | 3.43 | 7.55 | 3.01 | 5.15 | 6.34 | 4.31 | 4.19 |
| Percent of total volume | 29.0% | 18.8% | 5.8% | 2.1% | 14.3% | 26.1% | 3.9% |

*Note.* Orders are classified as marketable limit orders if the order price is equal to or exceeds estimated ask price for buy orders or if the order price is equal to or below the estimated bid price for sell orders. Bid and ask prices at the time of order arrival are estimated from the time and sales data as follows. The prices of up-tick trades are classified as ask prices and prices of down-tick trades are classified as bid prices. Then the last available estimated bid and ask prices are used to classify limit orders. Limit orders submitted before the market opening, as well as orders with missing arrival time, are classified using estimated bid and ask prices at time of execution. Trades for which the order arrival time exceeds the reported execution time are removed.

For five order types, including market, discretionary, stop, market-on-close, and marketable limit orders, brokers acting on behalf of customers trade against the bids or offers of other traders.[7] Therefore, all of these order types are classified as liquidity demanding. In contrast, customer limit orders provide liquidity to other traders, because brokers bid or offer customer limit orders when the limit price represents the best quote. Table I shows that in all six pits liquidity-demanding orders account for approximately 60% to 70% of the customer trading volume. This finding is consistent with the notion that off-floor traders tend to act as liquidity demanders in futures markets. In the liquidity-demanding category, market orders are the most prevalent in terms of the trading volume.

[7]A stop order becomes a market order after being triggered. Discretionary orders allow the broker to use his expertise to get the best possible fill. As shown in the next section, filling these orders tends to take significant time.

Table I also shows that traders often submit marketable limit orders rather than market orders. Marketable limit orders are priced so that they can be executed immediately. The limit price of such orders is set at the current ask price or higher for buy orders or at the current bid price or lower for sell orders. An advantage of marketable limit orders is that they allow traders to control slippage, that is, the difference between the market price at the time of order submission and the execution price.

To classify limit orders as marketable or nonmarketable, estimated bid and ask prices at the time of order arrival are used.[8] Because the present data do not include bid–ask quotes, bid and ask prices are estimated by using the time and sales data. Prices of up-tick trades are classified as ask prices and prices of down-tick trades are classified as bid prices. Then the last available estimated bid and ask prices are used to classify limit orders.[9] Limit orders submitted before the market opening, as well as orders with missing arrival time, are classified by using estimated bid and ask prices at the time of execution.[10] Given that many off-floor traders use the time and sales sequence disseminated by the exchange to make trading decisions, using time and sales data to estimate benchmark quotes appears reasonable. Some errors in the order classification based on the estimated quotes are unavoidable, but such errors are likely to be random.

Limit orders account for at least 25% of the customer trading volume in all six markets, suggesting that off-exchange customers provide liquidity to other traders in a significant proportion of their trades.[11] Given that many limit orders may remain unexecuted, it is likely that limit orders account for a larger proportion of customer order flow arriving into the trading pit. This finding does not necessarily imply that some off-exchange traders act as market makers by submitting limit orders on both sides on the market. Instead, it suggests that off-floor traders may be able to use limit orders to reduce their execution costs and supply liquidity to other traders in the process.

Table I also shows that discretionary orders, as well as both marketable and nonmarketable limit orders, tend to be larger than customer

[8]Harris and Hasbrouck (1996) use the quotes at the time of order submission to classify aggressiveness of limit orders. Bessembinder (2003) and Bacidore et al. (2003) discuss the issue of choosing the time of the reference quote.

[9]An alternative approach to identifying liquidity-demanding orders is a modified Lee and Ready (1991) classification algorithm employed by Locke and Sarajoti (2004), with the mean trade price during an interval used as a proxy for the midquote.

[10]Werner (2003) uses the quotes at the time of execution to classify limit orders, because the order submission times are not available in her data set.

[11]Werner (2003) reports a similar proportion of limit orders for downstairs trades in NYSE stocks.

market orders.[12] Orders marked as "other" in the CTR data also account for a substantial proportion of the customer trading volume. These may be market-if-touched, fill-or-kill, opening only, or other infrequently used order types.

Table II shows distribution of customer trading volume by type of counterparty. Consistent with the prior literature, trades with exchange locals account for between 36.7% and 67.6% of customer trading volume. Customers trade from 26.3% to 44.0% of their volume with other customers. Trades with clearing members account for a substantial proportion of the customer trading volume in both currency pits. The proportions are similar for all customer orders, liquidity-demanding orders, and limit orders. It is interesting that off-floor limit order traders frequently trade with exchange locals. In these trades the market makers demand liquidity by effectively acting as market-order traders. Overall, the statistics reported in Tables I and II are consistent with the notion from Ferguson and Mann (2001) that the strategies of dealers and outside customers in open-outcry futures markets may overlap.

## Turnaround Time for Different Types of Customer Orders

An important dimension of order execution quality is execution speed. Although a number of articles examine execution speed in equity markets (e.g., Bacidore, Ross, & Sofianos, 2003; Battalio, Hatch, & Jennings, 2003), the author knows of no study that has looked at the order turnaround time in open-outcry futures markets. It is interesting to examine execution speed in open-outcry futures markets, because the microstructure of these markets differs substantially from microstructure of equity markets. Order arrival time stamps and execution times reported in the CTR data allow examination of turnaround time for different types of customer orders. Table III reports turnaround time statistics.

As expected, market orders are filled faster than other types of orders. The median time between order arrival and the reported execution time ranges from 11 seconds for the S&P 500 futures to 41 seconds for the live cattle futures. Trading appears to be slower in the agricultural pits. For example, although in the index and currency futures markets more than 40% of all customer market orders are executed in less than

[12]Average order sizes reported in Table I are likely to underestimate the actual order sizes because the reported averages are based on trades and larger orders are often filled in several trades.

**TABLE II**
Distribution of Customer Trading Volume by Type of Counterparty

| | Customers with | | | |
|---|---|---|---|---|
| | *Locals* | *Clearing members* | *Other floor traders* | *Other customers* |
| Panel A. All orders | | | | |
| Index | | | | |
| S&P 500 | 67.6% | 2.4% | 3.7% | 26.3% |
| Nasdaq-100 | 55.1% | 4.7% | 7.2% | 33.0% |
| Currency | | | | |
| Euro | 36.7% | 34.2% | 0.7% | 28.4% |
| Yen | 44.9% | 18.8% | 1.4% | 34.9% |
| Agriculturals | | | | |
| Lean hogs | 58.1% | 2.0% | 2.2% | 37.8% |
| Live cattle | 49.6% | 1.9% | 4.4% | 44.0% |
| Panel B. Liquidity-demanding orders | | | | |
| Index | | | | |
| S&P 500 | 68.4% | 2.4% | 3.8% | 25.5% |
| Nasdaq-100 | 56.7% | 5.1% | 7.7% | 30.4% |
| Currency | | | | |
| Euro | 40.9% | 35.5% | 0.6% | 23.0% |
| Yen | 48.4% | 19.6% | 1.2% | 30.8% |
| Agriculturals | | | | |
| Lean hogs | 60.1% | 1.9% | 2.2% | 35.8% |
| Live cattle | 51.3% | 1.7% | 4.4% | 42.5% |
| Panel C. Non-marketable limit orders | | | | |
| Index | | | | |
| S&P 500 | 67.9% | 2.3% | 3.4% | 26.3% |
| Nasdaq-100 | 61.3% | 3.4% | 5.8% | 29.5% |
| Currency | | | | |
| Euro | 33.5% | 39.0% | 0.6% | 26.9% |
| Yen | 37.8% | 18.6% | 1.8% | 41.8% |
| Agriculturals | | | | |
| Lean hogs | 53.2% | 2.6% | 2.2% | 42.0% |
| Live cattle | 45.3% | 2.7% | 4.3% | 47.7% |
| Panel D. Marketable limit orders | | | | |
| Index | | | | |
| S&P 500 | 68.8% | 2.4% | 3.9% | 24.9% |
| Nasdaq-100 | 57.2% | 5.3% | 7.2% | 30.3% |
| Currency | | | | |
| Euro | 29.4% | 41.4% | 0.7% | 28.5% |
| Yen | 35.7% | 22.1% | 2.5% | 39.6% |
| Agriculturals | | | | |
| Lean hogs | 58.4% | 2.4% | 2.4% | 36.7% |
| Live cattle | 49.7% | 2.5% | 3.8% | 44.0% |

*Note.* Market, discretionary, marketable limit, stop, and market-on-close orders are classified as liquidity demanding. Orders are classified as marketable limit orders by using estimated bid and ask prices at the time of order submission. Limit orders submitted before the market opening, as well as orders with missing submission time, are classified by using estimated bid and ask prices at the time of execution.

**TABLE III**
Turnaround Time Statistics for Customer Orders

| *Order Type* | *Mean sec.* | *Median sec.* | *Between 0 and 10 sec.* | *Between 11 and 30 sec.* | *Between 31 and 60 sec.* | *Between 61 sec. and 5 min.* | *More than 5 min.* |
|---|---|---|---|---|---|---|---|
| S&P 500 | | | | | | | |
| Market | 111.8 | 11 | 48.8% | 28.5% | 9.6% | 8.8% | 4.3% |
| Discretionary | 655.1 | 83 | 16.5% | 11.4% | 15.3% | 31.0% | 25.8% |
| Marketable limit | 343.6 | 15 | 44.3% | 19.8% | 10.3% | 12.5% | 13.0% |
| Limit | 549.6 | 31 | 32.2% | 17.5% | 10.2% | 18.0% | 22.1% |
| Nasdaq-100 | | | | | | | |
| Market | 89.1 | 14 | 41.7% | 30.9% | 12.3% | 11.3% | 3.8% |
| Discretionary | 570.0 | 99 | 13.3% | 11.3% | 14.8% | 36.5% | 24.2% |
| Marketable limit | 276.9 | 18 | 40.4% | 20.4% | 12.0% | 15.4% | 11.9% |
| Limit | 617.2 | 38 | 28.1% | 18.2% | 11.7% | 19.5% | 22.5% |
| Euro | | | | | | | |
| Market | 87.0 | 13 | 43.6% | 29.6% | 13.5% | 10.5% | 2.8% |
| Discretionary | 646.2 | 99 | 13.6% | 9.1% | 15.6% | 38.4% | 23.3% |
| Marketable limit | 402.9 | 16 | 43.5% | 18.2% | 10.8% | 14.5% | 13.0% |
| Limit | 1116.6 | 127 | 18.8% | 12.8% | 9.2% | 20.5% | 38.7% |
| Yen | | | | | | | |
| Market | 94.8 | 13 | 43.6% | 30.8% | 11.8% | 10.9% | 2.8% |
| Discretionary | 656.5 | 88 | 15.8% | 9.1% | 13.9% | 38.5% | 22.7% |
| Marketable limit | 382.7 | 19 | 41.6% | 16.7% | 13.3% | 15.6% | 12.7% |
| Limit | 1044.6 | 84 | 20.9% | 13.0% | 10.9% | 20.7% | 34.5% |
| Lean hogs | | | | | | | |
| Market | 98.3 | 38 | 21.1% | 21.8% | 25.7% | 28.1% | 3.3% |
| Discretionary | 720.2 | 129 | 6.8% | 8.4% | 13.9% | 38.2% | 32.7% |
| Marketable limit | 605.9 | 67 | 20.1% | 12.5% | 15.0% | 27.3% | 25.1% |
| Limit | 1455.9 | 349 | 8.9% | 7.3% | 8.5% | 23.2% | 52.1% |
| Live cattle | | | | | | | |
| Market | 113.1 | 41 | 13.7% | 25.1% | 25.9% | 31.9% | 3.4% |
| Discretionary | 824.2 | 145 | 4.4% | 10.3% | 14.1% | 35.2% | 36.0% |
| Marketable limit | 700.7 | 69 | 11.9% | 18.3% | 17.0% | 25.3% | 27.4% |
| Limit | 1558.7 | 377 | 5.4% | 9.5% | 9.5% | 22.2% | 53.3% |

*Note.* Times shown represent the time from the order arrival time stamp to the reported execution time. Orders are classified as marketable limit orders by using estimated bid and ask prices at time of order submission. Orders submitted before the market opening, as well as orders for which the arrival time exceeds the reported execution time, are removed.

10 seconds, this proportion is much lower in the agricultural pits. Marketable limit orders follow the market orders, with the median turnaround time ranging from 15 to 69 seconds. The median turnaround time for limit orders far exceeds that for marketable limit orders. Furthermore, many limit orders remain unexecuted for more than 5 minutes. Discretionary orders also tend to take a long time to execute. The median turnaround time for this order type ranges from 83 seconds in the S&P 500 futures to 145 seconds in the live cattle futures. Between 23% and 36% of discretionary orders remain unexecuted for at least

5 minutes. For all order types the means of the turnaround times are much larger than the medians.

Estimates of the turnaround times are likely to be downward biased for several reasons. First, because the order arrival time is one of the data items used by the CTR algorithm to determine the execution time, it is possible that for some trades the reported execution time is the same as the order arrival time, whereas in reality the order was not executed instantaneously. Second, when the execution times are estimated by the CTR algorithm, multiple trades are usually assigned to the same tick in the time and sales sequence. Most of those trades actually occurred during the interval between the tick to which they are matched and the next tick. Given that the average time interval between ticks ranges from about 8 seconds in the S&P 500 futures to about 42 seconds in the lean hog futures, the impact of this feature of the CTR data on estimates of order turnaround times is likely to be limited. Finally, these estimates of the order turnaround times may be affected by the common occurrence of larger orders being filled in multiple trades. For a large order, the time it takes to fill the entire order is likely to exceed the estimate of the average turnaround time.

The CME offers side-by-side electronic and open-outcry trading in the futures contracts considered here. The execution times for the different types of orders documented will be useful to traders who are considering the choice between the open-outcry and electronic trading venues. The execution speed statistics may also be used by the CME in the analysis of execution quality in the CME's trading pits.

## EMPIRICAL RESULTS

### Determinants of Order Choice

When do customers demand liquidity by using market orders and when do they supply liquidity by submitting limit orders? Griffiths, Smith, Turnbull, and White (2000); Bae, Jang, and Park (2003); and Ranaldo (2004) analyze traders' choice of order type in equity markets. It is interesting to examine the determinants of this choice in open-outcry futures markets, which have a very different microstructure. Variables that are likely to affect traders' choice of order type, including the estimated bid–ask spread and price volatility, are now examined.

The trade-off between market and limit orders is the trade-off between higher execution costs for market orders and uncertainty of execution for limit orders. Limit-order traders also face the adverse selection risk, because a limit order is more likely to be executed before the price moves against the newly established position. The bid–ask spread represents the cost of immediacy paid by market-order traders. High bid–ask spreads increase the incentive to submit limit orders and lead to an increase in their usage. Foucault (1999) shows that higher volatility increases the risk of adverse selection faced by limit-order traders, leading them to price their orders less aggressively. As the bid–ask spreads increase, market–order strategies become more costly and more traders choose to submit limit orders. Although Foucault (1999) models a pure limit-order market, an open-outcry futures market is examined here, where liquidity is supplied primarily by exchange locals. Furthermore, the locals have an advantage over off-exchange customers. This advantage is derived from direct access of locals to the trading floor and their ability to observe the customer order flow. This advantage may allow exchange locals to "pick off" customer limit orders. Therefore, it is possible that the increased risk of adverse selection in periods of high volatility results in more off-floor traders optimally choosing market orders.

Measures of the bid–ask spread and price volatility need to be based on information available to off-floor traders in real time, because traders can condition their choice of order type only by variables they observe. Only the time and sales record, which contains prices of trades that result in price changes, is disseminated to off-floor traders. Therefore, a proxy is used for the bid–ask spread at the time of order submission based on the estimated bid and ask quotes obtained by time and sales data and a tick rule. The standard deviation of the last 15 continuously compounded returns based on the estimated ask prices is used as a proxy for volatility.

Following Griffiths et al. (2000) and Ranaldo (2004), the determinants of order choice are examined with the use of probit analysis.[13] The probit results are presented in Table IV. As expected, off-floor traders are more likely to submit limit orders when the spreads are wide. This result is consistent with evidence from equity markets documented by Griffiths et al. (2000) and Ranaldo (2004), despite the very different microstructure of futures markets. Given the dynamic equilibrium nature of the market, customer order submission strategies are likely to affect the execution costs paid by other traders. It would be interesting to examine whether competition between market makers and customer limit orders

[13]One caveat is in order. Although many limit orders are canceled or simply remain unexecuted, this data set allows only executed orders to be examined. Therefore, the probit results need to be interpreted with caution.

**TABLE IV**
Probit Analysis of Determinants of Customer Order Choice

| | *Coefficient of spread* | *Coefficient of volatility* |
|---|---|---|
| Index | | |
| S&P 500 | 0.7340 (807.03)** | −4.1437 (494.31)** |
| Nasdaq-100 | 0.0922 (29.89)** | −0.7293 (54.70)** |
| Currency | | |
| Euro | 0.3385 (9.95)** | −0.4820 (4.47)* |
| Yen | 2.5563 (214.31)** | 0.6378 (2.23) |
| Agriculturals | | |
| Lean hogs | 0.4125 (96.17)** | −0.2799 (5.12)* |
| Live cattle | 0.5290 (56.48)** | −0.9274 (12.81)** |

*Note.* The reported coefficients are obtained by estimation the following probit regression: prob(Order Type = 1) = $g(\alpha_0 + \alpha_1 \text{Spread}_t + \alpha_2 \text{Volatility}_t + \text{Interval Dummies})$, where Order Type is 1 for customer limit order and 0 for customer market order, $g(.)$ is the probit function, Spread is the estimated effective bid–ask spread (in percent of the contract value) at the time of order submission based on time and sales data, Volatility is the standard deviation of the last 15 tick returns calculated based on estimated ask prices, and Interval Dummies are dummy variables for 15-min intraday intervals. Orders classified as marketable limit orders, orders submitted before the market opening, and orders with missing arrival time are removed. To reduce the impact of outliers, the estimated spreads are winsorized at the 1st and 99th percentile. Chi-square statistics are given in parentheses.

*Chi-square statistic significant at 5%.

**Chi-square statistic significant at 1%.

leads to lower execution costs for customers who demand liquidity. This analysis is left to further study.

The coefficient of volatility is negative for almost all futures contracts examined, suggesting that off-exchange customers are less likely to submit limit orders in periods of high volatility. This result contrasts with findings for equity markets, where greater volatility appears to increase the usage of limit orders, as documented by Bae et al. (2003) and Ranaldo (2004). This finding indicates that the increased adverse selection risk in periods of high volatility plays an important role in order submission decisions of off-exchange customers.

## Execution Costs for Different Types of Customer Orders

Traders choose the order type depending on market conditions but also based on their different trading objectives. The choice of order type has a direct impact on customer execution costs. Therefore, it is important to be able to estimate execution costs for liquidity-demanding and limit customer orders. Similar to Ferguson and Mann (2001), the effective spread for customers is calculated as the average customer buy price minus the average customer sell price, with prices weighted by trade size,

**TABLE V**
Effective Spreads for Different Types of Customer Orders

| | *All trades* | | | *Liquidity-demanding orders* | | | *Limit orders* | | |
|---|---|---|---|---|---|---|---|---|---|
| | *Mean (basis points)* | *Number of spreads* | *Percent negative* | *Mean (basis points)* | *Number of spreads* | *Percent negative* | *Mean (basis points)* | *Number of spreads* | *Percent negative* |
| Index | | | | | | | | | |
| S&P 500 | 0.71 | 20,149 | 31.8% | 3.13 | 20,140 | 8.9% | −4.48 | 19,492 | 87.5% |
| Nasdaq-100 | 1.56 | 20,072 | 37.9% | 7.87 | 19,358 | 17.8% | −10.90 | 15,864 | 81.5% |
| Currency | | | | | | | | | |
| Euro | 0.67 | 16,869 | 31.4% | 1.94 | 14,591 | 14.3% | −2.06 | 7,285 | 75.7% |
| Yen | 0.74 | 14,840 | 25.8% | 1.99 | 11,622 | 10.6% | −1.80 | 4,752 | 75.0% |
| Agriculturals | | | | | | | | | |
| Lean hogs | 2.28 | 10,015 | 28.3% | 5.71 | 8,777 | 14.0% | −9.94 | 2,756 | 82.9% |
| Live cattle | 0.86 | 11,091 | 30.2% | 2.59 | 10,290 | 14.3% | −5.03 | 4,150 | 84.5% |

*Note.* Effective spread is calculated as the mean customer buy price minus the mean customer sell price, with prices weighted by trade size, over a 5-min interval. Market, marketable limit, discretionary, stop, and market-on-close orders are classified as liquidity demanding. Orders are classified as marketable limit orders by using estimated bid and ask prices at the time of order submission. Limit orders submitted before the market opening, as well as orders with missing submission time, are classified by using estimated bid and ask prices at the time of execution. Trades for which the order arrival time exceeds the reported execution time are removed.

over a 5-minute interval. Table V shows effective spreads calculated for all customer orders, as well as for customer liquidity-demanding and limit orders. Unsurprisingly, effective spreads are very different for different types of orders. For example, the all-trade effective spread in the S&P 500 futures market is about 0.7 basis points. At the same time, the effective spread is about 3.1 basis points for liquidity-demanding orders and about −4.5 basis points for limit orders. This finding is consistent with the notion that traders using liquidity-demanding orders tend to pay the bid–ask spread, whereas customers using limit orders are able to earn the liquidity premium.

In the S&P 500 market, about 31.8% of the 5-minute spread estimates for all customer orders are negative. The corresponding proportion is only 8.9% for liquidity-demanding orders and 87.5% for limit orders. The proportions are qualitatively similar in the other pits. These results suggest that negative effective spreads observed by Ferguson and Mann (2001) are likely to be explained by frequent executions of customer limit orders. In essence, the aggregate effective spread is a weighted average of the effective spreads for liquidity-demanding and limit orders. As shown in the previous section, customers tend to use liquidity-demanding orders. Therefore, the aggregate effective spread is positive on average, although it becomes negative in intervals in which executions of customer limit orders dominate.

The effective spread estimates reported in Table V suggest that the choice of order type has a large effect on customer execution costs. Essentially, by submitting limit orders off-exchange traders are able to reduce their execution costs by competing with locals for market orders. These spread estimates also imply that looking at the effective spreads for different order types can usefully complement an analysis of the effective spread for all customer orders in evaluation of market rule changes.

The category of liquidity-demanding orders includes several types of orders that may face different execution costs. Therefore, the effective spreads for three common types of liquidity-demanding orders including market, discretionary, and marketable limit orders are examined separately. The results are presented in Table VI. Interestingly, the effective spreads appear to be lowest for discretionary orders, even though these orders tend to be relatively large. The additional time spent by brokers to execute discretionary orders appears to translate into lower execution costs. In the index futures markets, marketable limit orders have the highest effective spreads: 3.7 basis points in the S&P 500 futures and

**TABLE VI**

Effective Spreads for Liquidity-Demanding Customer Orders, in Hundredths of a Percent

| | *Market orders* | | *Discretionary orders* | | *Marketable limit orders* | |
|---|---|---|---|---|---|---|
| | *Mean* | *Number of spreads* | *Mean* | *Number of spreads* | *Mean* | *Number of spreads* |
| Index | | | | | | |
| S&P 500 | 2.94 | 20,099 | 1.53 | 11,426 | 3.66 | 17,848 |
| Nasdaq-100 | 7.00 | 18,134 | 4.16 | 3,380 | 10.32 | 11,418 |
| Currency | | | | | | |
| Euro | 1.75 | 12,888 | * | * | 1.70 | 3,550 |
| Yen | 1.93 | 9,259 | * | * | 1.54 | 2,444 |
| Agriculturals | | | | | | |
| Lean hogs | 6.31 | 7,415 | 1.09 | 1,028 | 4.17 | 1,456 |
| Live cattle | 3.39 | 8,767 | 0.21 | 2,552 | 1.92 | 2,838 |

*Note.* Effective spread is calculated as the mean customer buy price minus the mean customer sell price, with prices weighted by trade size, over a 5-min interval. Orders are classified as marketable limit orders by using estimated bid and ask prices at the time of order submission. Limit orders submitted before the market opening, as well as orders with missing submission time, are classified by using estimated bid and ask prices at the time of execution. Trades for which the order arrival time exceeds the reported execution time are removed.

*Indicates insufficient data for calculation of effective spreads.

10.3 basis points in the Nasdaq-100 futures. This finding is consistent with Peterson and Sirri (2002) and Werner (2003), who examine marketable limit orders in equity markets. However, in the currency and agricultural pits the effective spreads of marketable limit orders are below those of market orders.

It is also noteworthy that the effective spreads for limit orders tend to be greater in absolute value than the spreads for market orders. This finding is likely to be explained by the difference between customer limit orders and locals' quotes. Exchange locals compete for market orders through an open-outcry auction and the trade goes to the local who bids or offers the best price. As a result, a market order is often executed at a better price than the best bid or offer that existed before the order was announced. In contrast, when brokers bid or offer customer limit orders, they may not be able to quote aggressively (i.e., the brokers cannot bid a price higher or offer a price lower than the limit price). Therefore, conditional on execution, limit-order traders tend to earn higher spreads than the spreads paid by market order traders.

## Trading Revenues for Different Types of Customer Orders

A complementary approach to the analysis of effective spreads for different types of customer orders is to examine customer trading revenues. Trading revenues for customer orders are calculated as follows: $\text{Revenue}_t = D_t(SP_t - P_t)/P_t$, where $SP_t$ is the contract settlement price for the day, $P_t$ is the trade price, and $D_t$ is an indicator variable equal to 1 for customer buys and $-1$ for customer sells.[14] The trading revenues include both the execution costs and the profits or losses derived from trade timing. Therefore, looking at trading revenues (in addition to the analysis of customer execution costs) allows possible adverse selection costs incurred by off-floor customers to be examined.

The trading revenues for different types of customer orders are shown in Table VII. Revenues for customer orders tend to be negative. This finding is consistent with Chang and Locke (1996), who looked at all customer orders. Absolute values of trading revenues for market orders are equal to about half-spread in the index futures markets, but they are less than half-spread in the other contracts. In some of the contract

[14]A similar measure was originally proposed by Beebower and Priest (1980) to estimate trading costs for stocks. Fishman and Longstaff (1992), Chang and Locke (1996), and Chakravarty and Li (2003), among others, use a similar approach to calculate trading profits in futures markets.

**TABLE VII**

Trading Revenues Based on Settlement Prices, in Hundredths of a Percent

| | Liquidity-demanding orders | | | | | | |
|---|---|---|---|---|---|---|---|
| | *Market* | *Discretionary* | *Stop* | *Market on close* | *Marketable limit* | *Limit* | *Other* |
| S&P 500 | | | | | | | |
| Mean | −1.32 | −2.90 | −0.19 | −0.41 | −0.97 | 1.40 | −0.42 |
| Median | −1.33 | −1.47 | 0 | 0 | 0 | 0 | 0 |
| *N* | 904,943 | 179,843 | 165,456 | 23,576 | 274,296 | 663,184 | 146,841 |
| Nasdaq-100 | | | | | | | |
| Mean | −3.99 | 0.76 | 0.15 | −3.33 | −5.25 | −1.59 | 0.62 |
| Median | −2.52 | 0 | 5.19 | −2.01 | −1.85 | −2.65 | 0 |
| *N* | 322,618 | 70,585 | 44,294 | 5,092 | 123,270 | 263,954 | 215,197 |
| Euro | | | | | | | |
| Mean | −0.20 | 2.74 | −0.44 | −0.33 | −0.61 | −0.80 | −0.21 |
| Median | −1.06 | −1.06 | −1.09 | 0 | −1.07 | 0 | −1.06 |
| *N* | 142,866 | 2,399 | 28,528 | 6,181 | 38,561 | 106,540 | 19,845 |
| Yen | | | | | | | |
| Mean | −0.63 | 4.68 | −0.22 | −0.97 | −0.64 | −0.27 | 0.35 |
| Median | −1.07 | 2.14 | −2.15 | −1.06 | −1.07 | 0 | −1.06 |
| *N* | 88,238 | 2,031 | 25,436 | 5,869 | 28,675 | 59,423 | 14,405 |
| Lean hogs | | | | | | | |
| Mean | −1.95 | 5.29 | 1.13 | −1.66 | −1.84 | −2.98 | −3.39 |
| Median | −0.81 | 2.87 | 0 | 0 | 0 | 0 | −2.86 |
| *N* | 105,192 | 22,632 | 27,313 | 5,929 | 22,367 | 65,230 | 10,157 |
| Live cattle | | | | | | | |
| Mean | −1.07 | 2.49 | 1.34 | −0.48 | −0.24 | −3.23 | −4.44 |
| Median | 0 | 0 | 0 | 0 | 0 | 0 | −3.31 |
| *N* | 141,212 | 41,597 | 32,286 | 6,889 | 37,696 | 101,358 | 15,650 |

*Note.* Trading revenues for customer orders are calculated as follows: $\text{Revenue}_t = D_t(SP_t - P_t)/P_t$, where $SP_t$ is the contract settlement price for the day, $P_t$ is the trade price, and $D_t$ is an indicator variable equal to 1 for customer buys and −1 for customer sells. Trading revenues are weighted by transaction size in calculation of means and medians. Orders are classified as marketable limit orders using estimated bid and ask prices at the time of order submission. Limit orders submitted before the market opening, as well as orders with missing submission time, are classified by using estimated bid and ask prices at the time of execution. Trades for which the order arrival time exceeds the reported execution time are removed.

markets, mean revenues of limit-order traders are below those of customers using market orders. This finding suggests that customers using limit orders incur adverse selection costs. The size of the trading losses incurred by limit-order traders tends to be small, however. Median revenues are often 0, especially for limit orders. Interestingly, mean revenues for discretionary orders are positive in currencies and agricultural futures, suggesting that traders using discretionary orders in these markets may have superior information. At the same time, the mean revenue for discretionary orders in the S&P 500 futures market is negative.

## Are Customer Limit Orders Systematically Picked Off by Market Makers?

An issue related to customer trading costs is whether customer limit orders are systematically picked off by market makers. It may take significant time for an off-exchange customer to cancel a limit order. Because of their direct access to the trading pit, exchange locals are able to react to changing market conditions much faster than off-exchange customers. Manaster and Mann (1999) argue that exclusive access to customer order flow may also allow locals to time their trades better than off-floor traders. Consequently, limit orders submitted by off-exchange traders are likely to face increased risk of adverse selection.[15]

Manaster and Mann (1999) and Ferguson and Mann (2001) suggest that when locals want to take a position to profit from an anticipated price movement they sometimes allow off-exchange customers to buy low and sell high. Under this scenario, one would expect to see a systematic price movement away from executed customer limit orders. This hypothesis is tested by looking at returns surrounding customer limit-order trades with market makers. Average tick-by-tick returns for 10 ticks before and 30 ticks after customer limit-order trades with exchange locals are examined.[16]

Figure 1 plots the cumulative average returns (CARs) surrounding customer limit-order trades with locals. The figure shows positive return drifts before limit-order sells and negative return drifts before limit-order buys. These price changes are likely to cause the exposure and subsequent execution of the limit orders by making the limit price the best quote. In all markets after the trade there appears to be a small price movement against the executed limit order.

A summary of CARs reported in Table VIII shows that most of the posttrade CARs do not exceed one basis point, although they tend to be statistically significant. These posttrade returns lend some evidence to the hypothesis proposed by Manaster and Mann (1999) and Ferguson and Mann (2001) that locals allow off-floor customers to buy low and sell high so that the locals can take positions ahead of anticipated price

[15]Handa and Schwartz (1996) and Harris and Hasbrouck (1996), among others, discuss the adverse selection problem faced by limit-order traders. In an empirical study of NYSE stocks, Werner (2003) shows that limit orders tend to get picked off.

[16]Given that Manaster and Mann (1996) show that locals tend to reduce inventory by half in the next trade, a 30-tick posttrade interval is likely to be sufficient. This interval ranges from about 3.9 minutes in the S&P 500 futures to about 20.8 minutes in the lean hog futures. If locals trade primarily based on order flow information, they are unlikely to predict price changes over longer horizons. Furthermore, the time intervals that examined exceed the median holding time of profitable trades documented by Locke and Mann (2005).

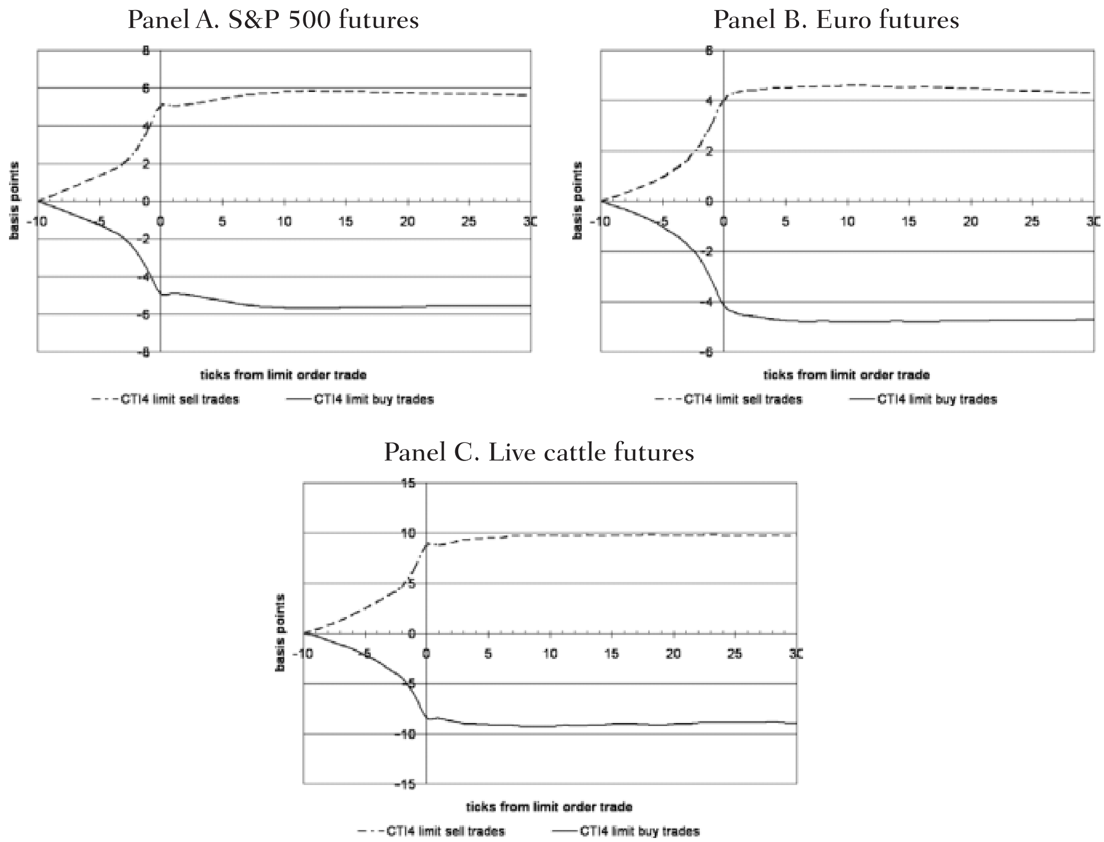


**FIGURE 1**
Cumulative average returns around limit-order trades of off-exchange customers with exchange locals.

First ten and last 30 ticks of each trading day are removed from the analysis. Orders classified as marketable limit orders are excluded from the analysis. The figures for Nasdaq-100, Japanese Yen, and lean hog futures are not reported for brevity but available upon request.

movements. Given that the posttrade returns are small, however, it could not be determined whether customer limit orders are systematically picked off by exchange locals.

An alternative way to examine whether exchange locals are able to pick off customer limit orders is to compare trading revenues for customer market and limit orders in trades with locals. If the adverse selection costs faced by customer limit orders are significant, customers can be expected to lose more on average when they use limit orders. The results presented in Table IX seem to be consistent with this expectation, although in the S&P 500 market the average trading revenues for customer market orders are below those for customer limit orders. Given that customer limit orders have negative effective spreads, the finding that customer revenues in limit-order trades with market makers are lower than the respective revenues for market-order trades suggests that the customer limit orders are often picked off.

**TABLE VIII**
Estimated Cumulative Average Returns Surrounding Limit Order Trades of Off-Exchange Customers with Exchange Locals, in Hundredths of a Percent

| *Event interval, ticks* | *Limit buy trades* | *Limit sell trades* | *Limit buy trades* | *Limit sell trades* |
|---|---|---|---|---|
| | *Panel A. Index futures* | | | |
| | *S&P 500* | | *Nasdaq-100* | |
| (−10; 30) | −5.56 (0.049) | 5.62 (0.059) | −16.15 (0.197) | 15.57 (0.242) |
| (−10; −1) | −3.78 (0.022) | 3.85 (0.024) | −10.34 (0.095) | 10.34 (0.111) |
| (−1; 30) | −1.78 (0.042) | 1.77 (0.051) | −5.82 (0.171) | 5.23 (0.207) |
| (0; 30) | −0.66 (0.041) | 0.57 (0.050) | −2.46 (0.168) | 1.84 (0.203) |
| Number of trades | 243,823 | 247,217 | 82,666 | 81,184 |
| | *Panel B. Currency futures* | | | |
| | *Euro* | | *Yen* | |
| (−10; 30) | −4.73 (0.091) | 4.31 (0.090) | −3.84 (0.093) | 3.60 (0.106) |
| (−10; −1) | −3.18 (0.042) | 3.09 (0.052) | −2.59 (0.049) | 2.65 (0.053) |
| (−1; 30) | −1.55 (0.079) | 1.23 (0.079) | −1.25 (0.080) | 0.96 (0.091) |
| (0; 30) | −0.57 (0.077) | 0.28 (0.079) | −0.36 (0.078) | 0.02 (0.089) |
| Number of trades | 37,957 | 33,731 | 20,094 | 18,963 |
| | *Panel C. Agricultural futures* | | | |
| | *Lean Hogs* | | *Live Cattle* | |
| (−10; 30) | −15.58 (0.510) | 15.34 (0.425) | −8.93 (0.265) | 9.79 (0.263) |
| (−10; −1) | −11.39 (0.232) | 10.67 (0.199) | −6.13 (0.136) | 6.47 (0.119) |
| (−1; 30) | 4.19 (0.462) | 4.67 (0.380) | −2.80 (0.232) | 3.32 (0.233) |
| (0; 30) | −0.67 (0.450) | 1.00 (0.372) | −0.52 (0.229) | 1.00 (0.230) |
| Number of trades | 12,430 | 17,162 | 16,339 | 20,191 |

*Note.* The table reports average tick-by-tick returns around customer limit-order trades with exchange locals. Standard errors are given in parentheses. The first 10 and last 30 ticks of each trading day are removed from the analysis. Orders classified as marketable limit orders are excluded from the analysis.

Overall, the evidence from the analysis of trading revenues and returns around customer limit-order trades with market makers suggests that the adverse selection costs faced by customer limit orders are small on average. The gains to locals in trades with customers using limit orders may also appear small because they are estimated by averaging across trades done by locals for different reasons. For example, some trades may be initiated by locals in expectation of timing profits, and others may be done to close a profitable position established earlier or for inventory-control purposes (for example, a "scratch trade" by a scalper).

**TABLE IX**
Trading Revenues Based on Settlement Prices of Customer Trades with Market Makers, in Hundredths of a Percent

| | *Mean* | *SEM* | *Median* | *N* | *Mean* | *SEM* | *Median* | *N* |
|---|---|---|---|---|---|---|---|---|
| | | | | *Index futures* | | | | |
| | *S&P 500* | | | | *Nasdaq-100* | | | |
| Market orders | −1.40 | 0.193 | −1.47 | 719,855 | −3.37 | 0.988 | −2.65 | 196,837 |
| Limit orders | 0.65 | 0.267 | 0 | 500,692 | −3.65 | 1.124 | −4.52 | 167,687 |
| | | | | *Currency futures* | | | | |
| | *Euro* | | | | *Yen* | | | |
| Market orders | −0.10 | 0.179 | 0 | 116,707 | −0.29 | 0.162 | 0 | 75,479 |
| Limit orders | −1.19 | 0.219 | 0 | 74,149 | −0.53 | 0.226 | 0 | 41,738 |
| | | | | *Agricultural futures* | | | | |
| | *Lean hogs* | | | | *Live cattle* | | | |
| Market orders | −2.31 | 0.469 | −2.88 | 68,450 | −1.43 | 0.335 | −3.14 | 73,206 |
| Limit orders | −3.51 | 0.688 | −3.01 | 34,158 | −4.17 | 0.443 | −3.15 | 42,959 |

*Note.* Trading revenues for customer orders are calculated as follows: $\text{Revenue}_t = D_t(SP_t - P_t)/P_t$, where $SP_t$ is the contract settlement price for the day, $P_t$ is the trade price, and $D_t$ is an indicator variable equal to 1 for customer buys and −1 for customer sells. Trading revenues are weighted by transaction size in calculation of means and medians. Orders classified as marketable limit orders and orders for which the order arrival time exceeds the reported execution time are removed.

This issue can be examined further by analyzing individual trader positions, which is left for future study.

## SUMMARY AND CONCLUSION

Locke and Venkatesh (1997) and Ferguson and Mann (2001) argue that the appropriate measure of execution costs in futures markets can be obtained by aggregating across all customer trades. Surprisingly, Ferguson and Mann (2001) show that in many intraday intervals this measure is negative. Estimating the aggregate customer execution costs is useful in policy analysis, but different traders have different needs, which are best served by different types of orders. The choice of the order type is an important determinant of execution costs. Therefore, in addition to the analysis of the aggregate customer execution costs, it is important to examine execution costs separately for liquidity-demanding and limit orders.

It is shown that limit orders account for a significant proportion of the customer order flow in open-outcry futures markets. Limit-order traders supply liquidity to other customers, in effect competing with market makers. Furthermore, the limit-order traders frequently provide liquidity to market makers. It is also found that off-floor customers frequently submit marketable limit orders rather than market orders, presumably to control the execution price uncertainty. The author knows of no other study that directly examines composition of the customer order flow in open-outcry futures markets. The determinants of customer choice of order type are examined, and it is shown that higher bid–ask spreads increase probability of limit-order submissions. Increased price volatility appears to reduce limit-order submission frequency, consistent with adverse selection costs being an important consideration for off-floor customers.

This study is also the first to examine execution costs, execution speed, and trading revenues for different types of customer orders in futures markets. The results show that, although the effective spreads for liquidity-demanding orders are almost always positive, limit-order traders tend to earn the liquidity premium by buying low and selling high. Therefore, the finding of Ferguson and Mann (2001) that customer effective spreads are often negative is likely to be explained by frequent trades of market makers against customer limit orders. It is also shown that customer limit orders incur adverse selection costs, although such costs appear to be small. The execution quality statistics documented in this study will be useful to futures traders and policy makers.

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