Slippage and the Choice of Market or Limit Orders in Futures Trading

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Abstract

Retail futures traders face uncertainty regarding the actual price they will obtain when they enter or exit a futures position. Not infrequently, the actual price differs from the expected price. This price ‘surprise,’ known as slippage, may be substantial and varies with factors reflecting market conditions, floor broker motivations, and the type of order placed. Using unique data from an introducing brokerage for CBOT futures contracts on wheat, corn, and soybeans, we first quantify the time-to-clear and magnitude of slippage that results from clearing time delays. We then identify factors that affect both time-to-clear and slippage on market orders, finding that both increase with order size and decrease with market depth. Slippage is also increasing in price volatility. Finally, we analyze individual trader choice between market and limit orders and find that the likelihood of placing limit orders (where regulations require floor brokers to compensate retail traders for the cost of adverse fills), is increasing in price volatility and order size but decreasing in market depth.

“sometimes the slippage on an execution is so large that you wonder whether your pit broker was asleep when the stop order was activated. A series of “bad fills” can induce paranoia in the most rational of minds.”

W. Gallacher, *Winner Take All – A Brutally Honest and Irreverent Look at the Motivations and Methods of Top Traders*, 1994, p.

I. Introduction

Retail futures traders bear the risk that the price they actually receive will differ from their expected price at initiation of a trade. Such a price ‘surprise,’ which can be substantial, is known as slippage. One view is that slippage systematically occurs to the detriment of the party placing the trade and results from floor brokers taking advantage of uninformed traders. Given the information asymmetry that exists between retail traders who possess stale and incomplete information regarding market conditions and floor brokers who observe real-time trading activity as well as the composition of their order book, systematically unfavorable slippage is quite plausible.[2] An alternative view is that slippage is benign and largely a by-product of actively-traded markets where floor brokers are sometimes incapable of immediately filling incoming orders due to heavy trading volume and rapidly fluctuating prices.

Regardless of its source, slippage represents a potentially significant cost to traders. To assess the frequency and magnitude of slippage, we use a unique sample of over 7,000 Chicago Board of Trade (CBOT) wheat, corn, and soybean futures order tickets for 70 retail traders – the data was gathered from an anonymous introducing brokerage and covers a three year time span.[3] Among other things, the order tickets report the exact time at which the order was placed with the introducing brokerage, size of the order, underlying commodity, and price at which the order was subsequently executed. Using CBOT time and sales transactional data, we can accurately estimate the time at which the order actually cleared.[4] Thus we can estimate the elapsed time for each executed trade.

Since we know the price at which the order cleared, calculating estimated slippage is straightforward once the trader's expected price at the time the order is placed is identified. If futures market prices satisfy weak-form efficiency and do not contain predictable trends, the most recent prior transaction price will be a reasonable proxy for a retail trader's expected price

[2] A retail trader is an individual who trades for his or her own account or for a firm, but who is not a member of an exchange. They are not directly involved in the open outcry auction in the pits and thus rely on secondary information. Daigler and Wiley (1999) show that volume generated by off-floor traders contributes to higher return volatility while volume generated by local traders (scalpers) and clearing firms trading on their own account does not. Their interpretation is that off-floor traders are relatively uninformed.

[3] These traders also account for approximately 16,000 orders for options. The options data, however, is not utilized in this analysis.

[4] As we note in the data section, orders are stamped with both a submission time and an execution time. Introducing Brokerages, however, often stockpile completed orders and stamp them with an execution time all at once during lulls in trading. Thus, the stamped execution time is of little value.

on a market order.[5,6] For limit orders, expected price is less subjective and should be equal to the limit price recorded on the actual order. The difference between execution price and expected price then provides our measure of slippage.[7]

Our evidence indicates that on average, after taking account of bid-ask bounce, slippage on market orders is not significantly different from zero. For limit orders, execution should only occur when the market price penetrates the limit price. While floor brokers can certainly err in executing limit orders, market regulations require the floor broker to cover the cost of adverse fills. Thus, limit order slippage is bounded from below at zero. While there are a limited number of limit orders that show positive slippage, the vast majority clear at the limit price and hence have zero slippage. Thus, the lament of retail traders that "the system" is biased against them is clearly not supported by the data, either for market orders or for limit orders. However, for market orders, there is significant cross sectional variation in slippage. For example, slippage on wheat contract market orders ranges from -2.25¢ to 1.75¢ per bushel. These values equate to a $112.50 loss to a $87.50 gain per contract relative to the trader's expected price at the time the order was placed. In comparison, the one-way commission paid by our retail traders is $14. Thus, the cost of slippage on market orders is potentially economically important to retail traders.

We next analyze the cross-sectional determinants of market order time-to-clear and find that it is increasing in order size and decreasing in market depth. Clearly time-to-clear and slippage

[5] Prior research such as Gray (1979) suggests that predictable trends are not present in futures prices, at least not over the short term (see also Black; 1986, Kuserk and Locke; 1993, Liu, Thompson, and Newbold; 1992, Martell and Trevino; 1990, and Working; 1954, 1967).

[6] Reported transactions prices will bounce between the bid and ask price. On average, reported transactions prices will be at the midpoint. Thus, for a buy order that is expected to clear at the ask price, expected price should actually be equal to the most recent transaction price plus ½ of the bid-ask spread. Similarly, for a sell order, expected price should actually be equal to the most recent transaction price minus ½ of the bid-ask spread.

[7] For a buy order, we calculate slippage as expected price minus actual price. For a sell order, the relationship is reversed and slippage is calculated as actual price minus expected price. For each calculation, a positive value is slippage in the retail trader's favor.

are closely related – delays in execution go hand-in-hand with slippage. Our analysis of the absolute value of market order slippage shows that it too is increasing in order size and decreasing in market depth. In addition, the absolute value of slippage is increasing in market volatility.

Traders are certainly not defenseless when conditions indicate that slippage on market orders is likely. One way for retail traders to control adverse slippage is to simply submit limit orders rather than market orders.[8] When we analyze individual trader choice between market and limit orders, we find that traders are more likely to submit limit orders for larger orders, when market volatility is high, and when market depth is low. This provides convincing evidence suggesting that individual traders are sensitive to the possibility of adverse slippage.

The rest of our paper proceeds as follows. Section II describes the order flow process and briefly describes existing literature on slippage. Hypotheses regarding factors that should affect the magnitude of time-to-clear and slippage are developed in Section III. In section IV we describe the data and report univariate statistics on time-to-clear and slippage. Cross-sectional analysis of factors affecting both quantities is reported in section V. Section V also includes a probit analysis of when retail traders are more likely to submit market as opposed to limit orders. Finally, a conclusion is provided in Section VI.

II. The Order Process and Prior Research.

A. The Order Process

[8] The benefit of a limit order is that it is protected from negative slippage. The cost, however, is that the market price might not penetrate the limit price and the order might expire unfilled. In addition, limit orders may incur an adverse selection cost if they are systematically "picked off" by informed traders establishing positions ahead of price movements (Ferguson and Mann; 2001, Manaster and Mann; 1999).

To understand why slippage can occur, one simply has to look at the order process displayed in Figure 1. A retail order starts with a Retail Trader contacting the Associated Person at the Introducing Brokerage where he or she maintains an account. This generates a paper ticket with a time stamp and the details of the order. The ticket is then passed to the Introducing Brokerage's Order Desk. Here, similar orders may be consolidated before the information is electronically transmitted to the Clearing Firm that represents the Introducing Brokerage on the floor of the exchange. The Clearing Firm's Trading Booth clerk rewrites the order data, producing a paper floor ticket. This ticket is either hand-carried by the Runner to the Floor Broker Clerk or the information is "arbed" directly to the Floor Broker in the pit via hand signals. The Floor Broker Clerk assists the actual Floor Broker by organizing the deck of orders. Finally, the Floor Broker clears the order via open outcry against orders held by other Floor Brokers or against proprietary trades by Floor Traders.[9]

There are a total of seven agents involved in the execution of a commodity futures order. The speed at which each agent processes an order ultimately affects the likelihood and magnitude of slippage on that order. With the exception of the Floor Broker, all of the agents involved in the order process are paid flat salaries.[10] Thus, while they are expected to offer fast and efficient service, their incentives for doing so are muted. The Floor Broker, however, earns a commission for each executed contract. In addition, he bears the risk of loss on limit orders if they are cleared at an adverse price. Thus the Floor Broker's incentives are much stronger than the other six participants in the order process.

[9] A floor trader owns a seat on the exchange and operates as a clearing member. They are scalpers, day traders, position traders and arbitragers who trade for their own accounts. Floor traders may affect slippage by bidding or offering at prices within the bid-ask spread.

[10] If a retail trader loses more than the amount held as margin with the Introducing Brokerage and the Clearing Firm cannot collect the debt, the Introducing Brokerage must pay the Clearing Firm and may force the Associated Person to repay the brokerage. As such, the Associated Person bears the risk Retail Trader insolvency.

This multi-stage order clearing process can affect slippage due to potential time delays between when an order is placed and when it is subsequently filled. One can easily imagine periods when the various agents are not at the top of their respective games (particularly on mornings after televised playoff games for Chicago sports team), resulting in order delays. The greater is the time delay, the greater is the range of prices at which an order might be cleared.

B. Prior Research

Academic research on trading rules routinely incorporate some estimate of trading costs (see e.g. Knez and Ready; 1996, Lukac and Brorsen; 1990, or Ready; 2002). Practitioners in the futures markets also emphasize the importance of incorporating trading costs – particularly slippage – when evaluating trading strategies (see e.g. Calhoun; 1989, Crabel; 1990, Radnoty; 1991, Tharp; 1993, Gallacher; 1994, Kaufman; 1995, Covington Bryce; 1996, and Myers; 1998.) To date, however, little research exists regarding the frequency and magnitude of slippage across various markets. Greer, et al (1992) examine slippage for a small sample of stop orders placed by a small commodity futures fund in 11 different commodity, currency, and financial contracts. On average, slippage is negative in each commodity, averaging approximately .14% of contract value. This equates to a $38.16 cost to the commodity fund in addition to traditional transactions costs such as commission.[11]

Frino and Oetomo (2005) evaluate slippage on four major financial futures traded on the Sydney Futures Exchange. They consider only orders that were large enough to require a split fill. The price at which the first leg of the fill occurred becomes their base price and slippage on subsequent legs is calculated relative to the base price. The primary finding of Frino and Oetomo

[11] Greer, et al. analyze stop orders exclusively since stop orders, by definition, provide the retail trader's expected transaction price. In addition, unlike with limit orders, floor traders do not need to compensate retail traders when slippage costs are incurred.

is that the magnitude of their measure of slippage increases with order size. While there are many similarities between their research and ours, there are important differences. First, the Sydney Futures Exchange is strictly an automated electronic trading system (since 1999) whereas the Chicago Board of Trade is not. Second, we measure slippage relative to the price prevailing in the market immediately prior to the trade being place, not relative to the fill price of the first leg of a split-filled order. Because of this, we are able to include all trades, not just larger traders.

Kurov (2005) analyzes trading on the Chicago Mercantile Exchange (CME) which has similar trading architecture to the CBOE. He analyzes 13 months of computerized trade reconstruction (CTR) data from the Commodities Futures Trading Commission for CME futures contracts on the S&P 500, NASDAQ 100, Euro, Yen, live cattle, and lean hogs.[12] The CTR data effectively recreates all trading floor activity. While Kurov (2005) does not actually calculate slippage, he is able to summarize characteristics of all retail trader orders and reports the estimated time from trading floor time stamp to execution. In addition, Kurov (2005) analyzes order strategy for retail traders and finds that market volatility and bid-ask spread impact retail trader choice between market and limit orders. While our dataset is much smaller than Kurov's, our work is distinctive in that we are able to track orders from the introducing brokerage through the time of execution. This provides a more accurate measure of execution time, and also enables us to get a relatively precise estimate of slippage. In addition, since we have data on all limit orders submitted by our traders rather than the subset that is actually executed, we are able to provide a distinctive analysis of retail trader choice between various types of orders.

[12] Our data spans 5/24/1999 to 3/26/2002 while Kurov (2005)'s data spans 6/1/2000 to 6/30/2001. During these time periods, the CBOT and the CME were separate and competing exchanges. In October 2006, however the CBOT and CMT merged, with floor trading to be consolidated at the CBOT location.

III. Bias in Slippage and Factors Expected to Affect both Time-to-Clear and Slippage

A. The Disadvantaged Position of Retail Traders.

Floor traders are privy to a wealth of information including the history of transaction prices and order size, source of those trades, current depth represented by outstanding limit and stop orders, movements in the cash market, and esoteric items like the noise level in the pit (Coval and Shumway; 2001). Retail traders, however, are limited to a small subset of this information. At best, retail traders may have access to real-time tick data.[13] If floor brokers and floor traders take advantage of private information and collude, then market order slippage should be systematically biased against the retail trader.[14] If, as clearing agents contend, the order process is impartial because collusion is not only illegal, but actively monitored and enforced, then slippage should be unbiased.

Hypothesis 1: On average, slippage on market orders will be negative.

B. Motivation of the Floor Broker

Floor broker compensation comes in the form of commissions – the more trades that they clear, the wealthier they become. Thus, floor brokers have ample incentive to provide quick and accurate trade execution. In addition, floor brokers face the possibility of fines and potential

[13] Real-time tick data is available to retail trader, but it is costly at approximately $500 per month. Even real-time tick delayed is delayed by at least 15 seconds due to human entry and satellite data transmission lag. Alternatively, a retail trader can query the associated person at their introducing brokerage just prior to placing a trade. Retail traders using the internet obtain free 10-minute delayed prices.

[14] Disciplinary action against floor traders is one indication of a tilted playing field. Sarkar and Wu (2000) also provide some evidence, showing that prior to the implementation of a "top-step" rule in the CME S&P 500 futures pit, dual traders provided inferior execution of customer trades relative to personal trades. A "top-step" rule prohibits dual traders from making personal trades if they previously made a trade from the top-step of the pit that day.

sanction (not to mention loss of future order flow) if they are negligent in performing their duties.

Given floor brokers' strong incentives, some orders are likely to receive higher precedence. First, larger orders generate larger commissions. In addition, larger orders are typically submitted by retail traders with deeper pockets who are likely to account for significant future order flow. These large order retail traders are also likely to be more sophisticated than the average retail trader and may be more likely to challenge adverse order fills via the arbitration process.[15] For these reasons, we expect floor brokers to pay greater attention to larger orders. Larger orders, however, should also be more difficult to fill. As noted by Frino, Oetomo, and Wearing (2004), larger orders may generate a temporary order imbalance, resulting in longer time-to-clear and incurring a liquidity cost. Larger orders may also require split fills. In addition, larger orders may be perceived to be from more informed traders. Hence, in addition to incurring a liquidity cost, larger orders may cause a permanent revision in market price.

Because of these countervailing factors, it is not entirely clear what will be the impact of order size on time-to-clear and slippage. Our expectation in both instances, however, is that there will be a positive relationship.

Hypothesis 2a: Market order time-to-clear will be positively related to order size.

Hypothesis 2b: Market order slippage will be positively related to order size.

C. Price Volatility and Market Depth

[15] A former compliance officer for a large introducing brokerage who was formerly a floor trader and then a floor broker stated that "small traders simply don't know their rights and, with the small trades they place, the amount they have to gain is far less than the cost of the hassle of taking the trade to arbitration…large traders on the other hand 'wield a big stick' and will take a case to arbitration just to make the floor broker miserable."

High price volatility will clearly affect the magnitude of slippage. Indeed, Greer, et al. (1992) shows that extreme intraday price movements generate large values of slippage on stop orders. Price volatility, however, may not have an impact on time-to-clear.

Market depth is likely to have an impact on both time-to-clear and slippage. High market depth implies that many participants stand willing to be counterparties to incoming orders.[16] Depth can be provided by open positions that are looking to close out, the limit order books of floor brokers, and floor traders looking to trade for their own account. Our expectation is that high market depth, measured as both trading volume and open interest, will lead to shorter time-to-clear and less slippage. Conversely, floor brokers will have to work harder to clear orders when market depth is low and time-to-clear and slippage should increase according.[17]

Prior research has suggested that open interest is a proxy for hedging (uninformed) demand since speculators (informed) typically don't carry positions overnight (Bessembinder and Seguin; 1993.) Thus, periods of low open interest and low liquidity may also be periods of high asymmetric information. If the system does contain any bias against retail traders, these may also be periods where floor brokers are more likely to collude with other floor traders, leading to longer clearing times and greater slippage.[18]

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[16] Kyle (1983) defines market depth as the order flow required to move the futures price one percent. Bessembinder and Seguin (1993) also include open interest as a measure of market depth. While intraday measures of volume are best, most studies use cumulative values at the end of each day.

[17] Market depth and price volatility are correlated (Bessembinder and Seguin; 1993) so these statements implicitly assume volatility is being held constant.

[18] Futures floor traders often have direct relationships with specific floor brokers. Thus, while the floor trader is not directly aware of the composition of a floor broker's deck, the floor broker may signal that he is clearing a large limit order and expects to be clearing a large offsetting order shortly thereafter. The floor broker will then clear the large limit order by trading with the floor trader at different clearing prices with some favorable and some unfavorable for the floor trader given the prevailing bid-ask spread. The floor broker then clears the offsetting limit order in the deck with the same floor trader at a net profit to the floor trader. This gives the floor trader a profit and increases the likelihood that the floor broker receives full commissions by clearing trades at or better than the limit price. This phenomenon is called 'dressing up the local' and gives a floor broker greater assurance of not incurring a loss on a large limit order and being held to the limit. It also generates 'split fills' on large limit orders where different parts of the same order are cleared at different prices.

Hypothesis 3a: Market order time-to-clear should increase with price volatility.

Hypothesis 3b: Market order slippage should increase with price volatility.

Hypothesis 3c: Market order time-to-clear should decrease with market depth.

Hypothesis 3d: Market order slippage should decrease with market depth.

Similar hypotheses could be stated for limit orders. A fair comparison of time-to-clear between market orders and limit orders, though, is difficult. This is because our clock on market orders starts when the order is placed with the introducing brokerage. For limit orders, however, our clock generally starts when the order is already in the floor brokers' deck and the market price penetrates the limit price. As will be seen later, most slippage values for limit orders are zero – the limit orders are executed at exactly the limit price. This is at least partly due to the manner in which we calculate time-to-clear and slippage for limit orders. It also reflects the fact that floor brokers are "held to the limit" and must compensate retail traders for fills that occur at worse than the limit price.[19] Thus, we certainly expect time-to-clear and slippage on limit orders to be less than the corresponding values for market orders. This outcome, however, is virtually certain and does not warrant separate hypotheses.

IV. Data and Univariate Analysis of Time-to-Clear and Slippage.

A. Data

[19] While negative slippage is possible for a limit order, we never observe it since the actual order ticket will always record a clearing price that is equal to or better than the limit price.

Our data is drawn from a sample of 16,019 separate orders placed by 69 retail traders between May 1999 and March 2002 at a particular introducing brokerage.[20] The orders consist of individual paper tickets (painstakingly entered into an electronic database) that record an identifying number, customer number, order quantity, type of order (market, limit, stop, etc.), date and time that the order was received by the brokerage, fill price, and the time stamp indicating when the order was recorded filled by the brokerage. In addition, information on the ticket indicates the commodity, delivery month and, in the case of options, the strike price, whether the order was for futures contracts or options, whether it was to sell or buy, the limit price, and whether the party placing the order granted the floor broker "discretion".[21]

The orders span a wide variety of underlying commodities including Wheat, Corn, Soybeans, Cocoa, Pork Bellies, Live Cattle, Lean Hogs, Swiss Francs, S&P 500 Minis, etc. Approximately one-third of the orders are for futures contracts while two-thirds are for options. To keep our analysis tractable, we exclude options and focus solely on market and limit orders for futures contracts.[22] We also restrict our analysis to orders for CBOT Wheat, Corn and Soybeans. These are the three most heavily traded CBOT contracts for our traders and account for about 45 percent of our futures contract orders. While the analysis could be extended to the other commodities, this would require obtaining additional time and sales transaction data from

[20] The average trader had 7 years of trading experience, almost $700,000 in reported net worth, opened a margin account with $13,250, and paid $28 in round-turn commissions for each futures position.

[21] Discretion enables a floor broker to execute a limit order at a potentially worse price than the limit price specified on the order. When discretion is offered, the number of points the floor broker is authorized to deviate from the limit price is specified. While fills may occur at worse than the original limit price, the added flexibility also enables a floor trader to wait and see whether a fill can be made at better than the limit price, resulting in price improvement. In most instances, discretion will be added to a limit order some time after it was originally submitted, i.e. when the retail trader is worried that the order will not fill. Thus, discretion is used to increases the likelihood that a limit order will be filled.

[22] There are a variety of more esoteric order types such as stop orders, fill-or-kill orders, market-on-open orders, and one-cancels-the-other orders. Since these represent a small fraction of the data relative to market and limit orders, they are excluded from our analysis. Orders that were cancelled, voided, or incomplete (missing key data) are also excluded.

the various exchanges on which these commodities trade. Monetary constraints prevent us from doing so.

CBOT floor trading occurs Monday through Friday from 9:30 am until 1:30 pm. A much less active electronic trading session occurs from 6:30 pm to 6:00 am. For each contract, the underlying asset is 5,000 bushels of the applicable commodity. Expiration months are March, May, July, September, and December for Corn and Wheat, January, March, May, July, August, September, and November for Soybeans. For each contract the minimum price tick is ¼ cent which equates to $12.50 per contract. Margin requirements for hedgers are $750 for Soybean, $850 for Corn, and $1,250 for Wheat. Margin requirement are approximately $400 greater for traders who are categorized as speculators.

Table 1 provides a summary of our market and limit orders for CBOT wheat, corn and soybean contracts. We have a total of 748 market orders and 1,734 limit orders for which we have adequate data. Orders for wheat account for 69 percent of market orders and 73 percent of limit orders. Corn is the next most actively traded contract, accounting for 22 percent of market orders and 19 percent of limit orders. Soybeans account for the remainder of both order types.

Both market and limit orders are equally divided between buy and sell orders. In addition, mean (median) order sizes for both market and limit orders are the same at 8.2 (5) contracts. Larger orders are less likely to be filled all at once. Approximately 6 percent of our market orders are split fills while less than 1 percent of the limit orders are split fills (details are not presented in Table 1.) For the split fill market orders, the average order size is 37 contracts. The majority of orders are in the nearby contract, i.e. the one that is next to expire. Finally, approximately 30 percent of our orders occur before or during the first ten minutes of trading.

Limit orders that are placed away from the current market price often will not execute. For our sample of limit orders, 78 percent are eventually executed while 22 percent are not. We calculate moneyness as the difference between the initial limit price and the market price for the most recent tick prior to the order being placed. For buy orders, moneyness is calculated as limit price minus market price, while for sell orders, it is calculated as market price minus limit price. Thus, in either case, positive moneyness value indicates an order that should be immediately executable while a limit order with negative moneyness will be held in the floor brokers deck of orders until the market attains the limit price or the order is cancelled. For all submitted limit orders, mean (median) moneyness values are -0.48¢ (-0.50¢). Thus most limit orders are placed at slightly worse than the current market price. For the subset of cleared limit orders, mean (median) values of moneyness are -0.32¢ (-0.25¢). One reason why there is so little difference in initial moneyness values for executed and non-executed limit orders is that limit orders are often updated. Thus, if the market moves away from the limit price, the retail trader may contact the introducing brokerage and alter the limit price – updating occurs for approximately 20 percent of our limit orders.

B. Univariate Statistics on Time-to-Clear and Slippage.

Table 2 reports summary statistics on time-to-clear and slippage for our orders. Since we require an estimate of market price just prior to the order being placed in order to calculate slippage for market order, we exclude orders that were placed outside the regular trading period from 9:30 am to 1:30 pm. For consistency, this exclusion also applies to limit orders. We also exclude observations where the reported clearing price was outside the high-low price range for the day.

Remember from the introduction that we have a precise record of when an order is placed, but an imprecise record of when an order actually clears. To estimate time-to-clear for market orders, therefore, we search the CBOT time and sales transactional data for the first occurrence of the recorded clearing price subsequent to the time when the order was placed. The ensuing time lag is our minimum estimate of time-to-clear. We also calculate a maximum estimate of time-to-clear which is equal to the minimum estimate plus the additional time lag until the next reported CBOT transaction that generates a price change.[23] As long as the order cleared in the first window of opportunity, the actual time-to-clear should lie somewhere in between the minimum and maximum estimate. Unfortunately, the CBOT time and sales data can be subjected to price gapping when the market is highly volatile. Thus, the data may indicate a price jump from 250¢ per bushel to 251¢ while in reality price transitioned from 250¢ to 250.50¢ to 251¢. While this will not significantly affect our slippage calculations, it introduces error into our time-to-clear estimates.[24]

For limit orders, time-to-clear is slightly more complicated. First, we limit ourselves to limit orders that actually cleared. We start the clock when the CBOT time and sales transaction data first reports a price that is equal to the final limit price specified in the order. For minimum time-to-clear, the clock stops at the first occurrence of a price equal to the price at which the order clears. In most instances, the order clears at the limit price so the minimum clearing time is zero. Just as with a market order, the maximum time-to-clear is calculated as minimum time-to-clear plus the time lag until the next CBOT reported price change.

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[23] To economize on data entry effort and storage space, the CBOT time and sales data reports price and time only when a new futures price occurs on the floor. For example, assume that a new wheat price of $3.00 per bushel was obtained at the 10:00 am and that five subsequent trades also occurred at $3.00 per bushel at one minute increments, followed by a trade at $3.01 at 10:06. The CBOT tape will only show the 10:00 trade at $3.00 and the 10:06 trade at $3.01. If our data has a trade placed at 9:59 and cleared at $3.00, we will calculate a minimum time-to-clear of one minute and a maximum time-to-clear of seven minutes.

[24] *DO WE HAVE ANYTHING THAT BACKS UP THE ASSERTION THAT THE CBOT TAPE HAS GAPS?*

For market orders as a whole, the average value of minimum time-to-clear is 198 seconds with a median of 28 seconds. For maximum time-to-clear, the average is 240 seconds and the median is 76 seconds. For limit orders, the average minimum time-to-clear is 117 seconds while the median is zero seconds. The median of zero seconds is not surprising given that our clock starts when the market hits the limit price and most limit orders are subsequently executed at the limit price. Mean (median) maximum time-to-clear for limit orders is 152 (18) seconds.

As a time-to-clear benchmark, Kurov (2005) documents mean (median) time-to-clear for market order in lean hog and live cattle pits of 98.3 (38) seconds and 113.1 (41) seconds respectively. His time clock begins when the order is receipt stamped on the trading floor, not at the introducing brokerage. Thus, if similar floor-based delays occur in the corn, soybean, and wheat pits, this suggests that our median order takes a maximum of approximately 40 seconds to make it from the associated person taking the order at the introducing brokerage to the trading floor.

With delays in clearing comes the possibility of slippage. Calculating slippage is straightforward. For market orders, we identify the closest previous transaction reported in the CBOT time and sales transaction data for that commodity. For market buy orders, we then subtract the clearing price from this pre-submission price. For market sell orders, we subtract the pre-submission price from the clearing price.[25] Across market orders for all three contracts, slippage averages only -.109 cents or slightly less than -1/8¢ per contract (to the trader's detriment). This is approximately half of the minimum price movement in these contracts. Indeed, a t-test for whether observed slippage is significantly different from -1/8¢ has a p-value of 0.402.

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[25] A retail trader's access to information is limited. Thus, his or her expected price might be based on transaction data that predates the pre-submission price that we utilize in our slippage calculation.

While no bid-ask spread is posted, market order slippage of -1/8¢ is likely attributable to buy orders clearing at the asking price and sell orders clearing at the bid price. Since the most recent transaction price utilized in our slippage calculation is equally likely to be at either the bid or ask – on average it is in the middle – slippage of -1/8¢ is exactly what one would expect in an unbiased trading environment. Thus the retail trader's lament that the trading process is biased against them – our hypothesis 1 - appears not to be supported by the data.

While market order slippage on average is not significantly different from what one would expect from bid-ask bounce, there is a reasonable amount of cross-sectional variation. The standard deviation of market order slippage is .486¢ with a minimum value of -3.5 cents and a maximum of 3 cents. Since the underlying for these contracts is 5,000 bushels of either wheat, corn or soybeans, these minimum and maximum values correspond to a loss of $175 and a gain of $150 relative to the trader's expected price. Given that the one-way commission paid by our retail traders is $14, we consider the potential cost of slippage on market orders to be economically meaningful.

For limit orders, median slippage across all three contracts is zero – most are cleared at the limit price. There are no negative values as floor traders are "held to the limit". A limited number of positive values with price improvement, however, generate the positive average limit order slippage value of 0.03¢. Whether price improvement results from deliberate delay by floor traders in a market that is trending in the retail trader's favor or price improvement reflects the censored result of inadvertent floor trader delay/inattention is unclear. While there is some variation in limit order slippage, it is significantly less than that which is observed for market order slippage – the standard deviation of limit order slippage is 0.152¢. One way, therefore, that retail traders can protect themselves from adverse slippage is to submit limit orders rather than market orders. We will explore this in greater detail later in the paper.

C. Regression Analysis of Time-to-Clear and Slippage

To assess whether the factors described in hypotheses 2a through 4d affect cross-sectional variation in time-to-clear and slippage, we rely on multivariate regressions. Unfortunately, time-to-clear is bounded from below at zero and is, therefore, not normally distributed. While slippage is approximately normally distributed, all of our hypotheses concern the magnitude of slippage, not its signed value. Thus, our slippage analysis focuses on the absolute value of slippage. Like time-to-clear, this is bounded from below at zero and is not normally distributed. To account for non-normality, therefore, we rely on Generalized Linear Models (rather than Ordinary Least Squares) with the assumption that error terms follow a gamma distribution. This is a reasonably good approximation given the characteristics of our dependent variables.

In our analysis, we use three related measures as our proxies for market volatility. The first measure is the standard deviation of CBOT reported prices for the ten minutes prior to the placement of the order. The second measure is the range of prices over the same ten minute interval. Our third measure is the number of reported price changes reported during the ten minute window.[26] For market depth, we utilize both total daily trading volume and open interest, both recorded in thousands of contracts. Order size is recorded on the actual order ticket and therefore requires no proxy. We also control for whether the order was placed in the nearby

[26] Kurov (2005) measures market volatility as the standard deviation of the last 15 continuously compounded returns based on estimated ask prices.

contract (i.e. the next to expire contract) and whether the order was placed during the first ten minutes of the trading day when trading activity is typically high.

Summary statistics for these independent variables are reported in the Table 2 for market orders and all executed limit orders. The data reported in Table 2 is for each individual commodity. In our discussion here, we limit ourselves to market orders as a whole and limit orders as a whole. For market orders, mean (median) order size is 7.4 (5) contracts. For limit orders, the mean is slightly lower at 7.0 contracts but the median is the same at 5 contracts.

Of our three measures of price volatility, the number of reported price changes is the easiest to conceptualize.[27] Mean (median) values for price change frequency are 22.1 (17) for market orders and 29.5 (25) for limit orders. Price range and standard deviation of prices show the same pattern of being larger when limit orders are submitted. Mean (median) price range is 1.14 (1) for market orders and 1.34 (1.25) for limit orders. For standard deviation of prices, values are 0.34 (0.29) for market orders and 0.39 (0.33) for limit orders.

While time and sales data for the pre-market period is available in the CBOT data, we exclude it from our calculations. Thus, for the 25 to 30 percent of our orders placed at the opening, there may be only a few minutes worth of prior market data and our calculated price volatility measures may be biased. Trading, however, is typically heavier at the opening. Indeed, the mean and median values for all three measures of price volatility are greatest during the first 10 minutes of trade (results not presented in tables.) Prior research also documents that bid-ask spreads are greatest at the open (Ferguson and Mann; 2001). Since trading at the open is unique,

[27] While price change frequency is a measure of volatility, it also provides a lower bound on the volume of transactions occurring during the interval. For example, assume that five buy orders at the ask price occur in a row followed by one sell order at the bid price. If bid and ask don't change during this trade sequence, the CBOT time and sales transaction data will record only two transactions – the first and last ones that generated the price changes.

in subsequent regression analysis we will always include a dichotomous variable for trades placed during the opening ten minutes of trading.

For daily volume and open interest (our proxies for market depth), our mean (median) values for market orders are 20.3 (17.9) and 87.5 (76.3) thousand contracts respectively. For limit orders mean (median) values are approximately the same - 19.1 (17.4) thousand contracts for daily volume and 85.3 (77.6) thousand contracts for open interest.

GLM regression results where market order time-to-clear is the dependent variable are presented in Table 3. In each specification, dummy variables for corn and wheat are included to control for unobserved differences in each pit's trading environment. We also exclude outlying observations where our minimum estimated clearing time is greater than 10 minutes.

Positive coefficient estimates for order size (significant at the five percent level in specifications 1 and 2 and at the ten percent level in specification 3) demonstrate that time-to-clear increases with order size. A coefficient estimate of 1.64 in specification 1 indicates that a one standard deviation increase in order size from 5 contracts to 15 contracts results in a 16.4 second increase in time-to-clear. Thus, while floor brokers may pay greater attention to larger orders, the difficulty in finding counterparties actually leads to longer clearing times.[28]

In addition to order size affecting time-to-clear, specifications 1-3 also demonstrate that price volatility has an impact. Coefficient estimates for price range, the standard deviation of prices, and price change frequency are all negative with price range and price change frequency being significant at the five percent level. These results, however, are not robust. When either open interest or daily volume is included as an independent variable all of the price volatility

[28] Whether an order is executed via a splitfill does not affect these results. Moreover, coefficient estimates for splitfill (not displayed in tables) are not close to being statistically significant.

measures become statistically insignificant.[29] Estimated coefficients for both open interest and daily volume (specifications 4 and 5) are negative and statistically significant at the one percent level. Results for these two variables are even stronger (results not presented in tables) when none of the price volatility measures are included in the regression.

With increased clearing time it is likely that there will be increased slippage. Regression results for slippage are presented in Table 4. In these regressions, we include the observations with long clearing times that were excluded in our time-to-clear analysis. As with time-to-clear, we find that the absolute value of slippage increases with order size. For each of the first three specifications where market depth variables are not included, each coefficient estimate is significant at the five percent level. The economic magnitude of these estimates, however, is small. The coefficient estimates of approximately 0.003 indicate that a one standard deviation increase in order size from 5 to 15 contracts generates an increase in slippage of only 0.03 cents.

The absolute value of slippage also depends on market conditions. Coefficient estimates demonstrate that slippage increases with all three measures of price volatility. Here our results are quite robust with statistical significance at the five percent level for the range of prices, the standard deviation of prices, and the log of price change frequency.[30] In addition, the absolute value of slippage is negatively related to market depth as proxied by either open interest or log of daily trading volume. Coefficient estimates for these two variables are both significant at the five percent level. The results for price volatility also do not change significantly when either measure of market depth is included.[31]

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[29] Log daily volume is positively correlated with each of the price volatility measures with correlation coefficients ranging between 0.11 and 0.50. Open interest is positively correlate with price change frequency, but effectively uncorrelated with the other two price volatility measures.

[30] Mann and Manaster (1996) document that futures price volatility is positively correlated with bid-ask spread. Hence, part of the relationship between slippage and price volatility is likely attributable to bid-ask bounce.

[31] In their analysis of slippage on stop orders placed by a single commodity trading fund, Greer et al (1992) also found that slippage increased with daily price range and with order size. They found no evidence, however, that

The last item of interest in the slippage regressions is whether the order was placed during the opening ten minutes of trades. This control variable was never significantly different from zero when included in the clearing time regressions. Here, however, order-on-open always has a positive estimated coefficient and is statistically significant at the one percent level

The picture that emerges from our analysis of time-to-clear and the absolute value of slippage seems internally consistent. Hypotheses 2a and 2b stated that both time-to-clear and the absolute value of slippage would increase with order size. Our evidence consistently shows this to be the case as both measures of trade execution quality decline with order size. We also find convincing support for hypotheses 3a-3d regarding the relationship between trade execution quality and market conditions. We find that time-to-clear and the absolute value of slippage increase with our proxies for price volatility and decrease with our proxies for market depth.

D. Choosing Between Market and Limit Orders.

In the introduction we asserted that slippage was a significant concern to retail traders. If so, then one way for retail traders to minimize the adverse effects of slippage is to simply submit limit orders instead of market orders. In particular, a trader could submit a marketable limit order. Indeed, Table 1 documented that slippage on limit orders is minimal relative to slippage on market orders. Our final analysis assesses whether retail traders respond to the possibility of adverse slippage by substituting limit orders for market orders when conditions suggest that slippage is likely. If so, then this will provide empirical evidence to back up our claim that slippage is truly a concern of retail traders.

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slippage and market depth are related. Note that Greer et al (1992) analyze the signed value of slippage, not the absolute value of slippage.

Following Kurov (2005) we estimate Probit model regressions where the dependent variable is coded 1 for market orders and 0 for limit orders – results are presented in Table 5. Our dependent variables are essentially the same as in our previous analysis of time-to-clear and slippage.[32] If the factors that are conducive to long time-to-clear and high slippage affect the choice between market and limit orders then this suggests that retail traders really are concerned about the possibility of adverse slippage.[33]

Previously, we noted that market order slippage increased with order size. Consistent with this being a cause for concern for our traders, we find that coefficient estimates for log order size are negative and statistically significant at the five percent level in all five specifications reported in Table 5. The coefficient estimates of approximately -.08 indicates that the probability of a market order declines by approximately 3 percent when there is a one standard deviation increase in log order size. Similar results have been documented for equity markets. Harris and Hasbrouck (1996) for example report that limit order on SuperDOT are generally larger than market orders.

Consistent with our prior results, we also find that market orders are less likely when market prices are more volatile. This is also consistent with prior research on limit versus market orders in equity markets (see e.g. Bae, Jang, and Park; 2003, Ranaldo; 2004). Kurov (2005), however, finds that limit orders are less likely with high price volatility. Coefficient estimates for each of our three proxies for price volatility are negative and significant at the five percent level or better. Including measures of market depth do not affect any of these results. Moreover, coefficient estimates for open interest and daily trading volume are both positive and significant at the five

[32] For two of our dependent variables, order size and the number of recorded price changes in the prior ten minute interval, we first transform them to their log equivalent. This transformation leads to cleaner results in the non-linear probit regression.
[33] We include an additional dichotomous variable that denotes whether the order in question was part of a spread, e.g. where the retail trader simultaneously placed long and short positions in the same commodity, typically in contracts with different expiration dates.

percent level or better. As with order size, these results suggests that retail traders are concerned about the possibility of adverse slippage.

In our earlier analysis of time-to-clear and slippage, we included order-on-open as a control variable. Despite the fact that slippage is greater during the opening of the trading session, order-on-open is not a significant factor in the choice between market and limit orders (results not presented in tables.) We do however include two additional controls. The first is whether the order is part of a spread – with a spread order the retail trader typically goes long (buys) one contract and short (sells) another. The two legs of the spread might be the same commodity but with different expiration dates or the legs might be in different commodities. We also include whether the order is for the nearby contract. Coefficient estimates for spread are positive and significant at the one percent level in all five specifications while coefficient estimates for nearby are negative and significant at the five percent level or better in each specification.

IV Conclusion

Our paper provides the first direct analysis of slippage. Using a unique data set that documents the trades of 69 retail traders, we track orders from the moment they are submitted to the introducing brokerage until the time that they clear on the CBOT trading floor. In doing so, we make three contributions. First, we demonstrate that the common complaint of retail traders – that "the trading system is systematically biased against them and in favor of professionals on the floor of the exchange" – does not appear to be true. On average, orders execute rapidly. The typical time it takes an order to clear is well under two minutes. In addition, the slippage that results from this time delay is approximately equal to what one would expect from buying at the ask price and selling at the bid price. Thus, participants on the floor of the exchange do not appear to be colluding to the detriment of retail traders.

Our second contribution is to show that while slippage is not a problem on average, there is significant and predictable cross-sectional variation in slippage. Thus, some market conditions are conducive to long time-to-clear and significant slippage. We find that time-to-clear and slippage are greater for larger orders and when market depth is lacking. Similarly, when there is greater price volatility, both time-to-clear and slippage are greater.

Our final contribution is to document that risk-averse traders are sensitive to the possibility of large values of slippage. When conditions suggest that slippage is likely, retail traders are more likely to submit limit orders which, while subject to the possibility that the order does not clear, are significantly less affected by slippage.

Figure 1: Steps in the Order Process.

(1) Order is placed.
(2) The associated person hands the order to the Introducing Brokerage's order desk.
(3) The IB order desk transmits order to the clearing firm's trading booth clerk where the order is rewritten.
(4) The clerk hands the order to the runner.
(5) The runner delivers the order to the floor broker's clerk.
(6) The floor broker's clerk delivers the order to the floor broker.
(7) The floor broker offers the order to the crowd which is accepted by another floor broker or a floor trader as the counterparty.

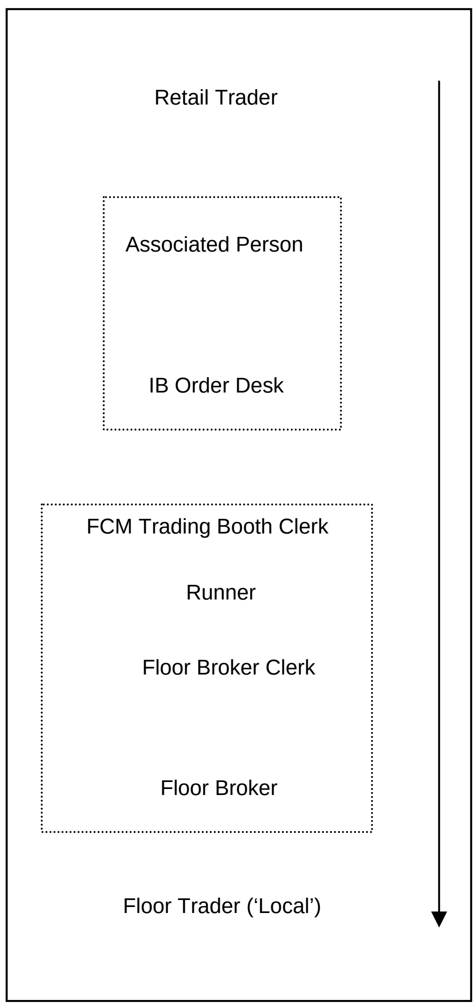

Table 1
Composition of Orders

Number of Orders is the total for that commodity and order-type. *Buy* is the fraction of orders that were to buy as opposed to sell. *Number of Contracts* is the quantity per order. *Nearby* (0,1) indicates that the order was placed in the nearby futures contract. *Order On Open* (0,1) indicates that the order occurred in the first ten minutes of the trading session. For limit orders we distinguish between the number of orders placed and the number that actually cleared. For buy limit orders, *Moneyness* is limit price minus market price just prior to the order being placed. For sell limit order, *Moneyness* is market price just prior to the order being placed minus limit price.

	Wheat	*Corn*	*Soybeans*	*All Commodities*
Market Orders				
Number of Orders	516	164	68	748
Buy	0.47	0.59	0.46	0.50
Number of Contracts	9.0 (5)	6.3 (3)	8.7 (5)	8.2 (5)
Nearby	0.57	0.65	0.70	0.60
Order at Open	0.29	0.24	0.16	0.26
Limit Orders				
Number of Submitted Orders	1,263	321	72	1,734
Buy	0.50	0.48	0.52	0.50
Number of Contracts	7.8 (5)	8.1 (5)	11.3 (5)	8.2 (5)
Nearby	0.73	0.51	0.73	0.69
Order at Open	0.32	0.34	0.26	0.32
Number of Cleared Orders	975	273	107	1,355
Submitted Order Moneyness	-0.30 (-0.50)	-0.64 (-0.25)	-0.91 (-0.875)	-0.48 (-0.50)
Cleared Order Moneyness	-0.35 (-0.25)	-0.20 (0)	-0.40 (-0.25)	-0.32 (-0.25)

Table 2
Time-to-Clear and Slippage

For market orders, *Minimum Time-to-clear* is time of first reported CBOT transaction after the order time where market price equals fill price minus order time. *Maximum Time-to-clear* is *Minimum Time-to-clear* plus the time lag until the next reported CBOT price change. For Limit Orders, *Minimum Time-to-clear* is time of the first reported CBOT transaction after the order time where market price equals fill price minus time of the first reported CBOT transaction after the order time where market price equals limit price. *Maximum Time-to-clear* is *Minimum Time-to-clear* plus the time lag until the next reported CBOT price change. *Slippage* is reported in cents per contract. For buy orders, *Slippage* is calculated as the trader's expected price minus fill price. For sell orders, *Slippage* is calculated as fill price minus the trader's expected price. See the text for details on how expected price is calculated for Market Orders and for Limit Orders. Values reported in each cell are means and (medians). *σ Slippage* is the standard deviation of slippage while *Observations* is the number of observations for which we are able to calculate slippage. In each cell, the upper value is the mean while the lower value (in parentheses) is the median.

	Wheat	***Corn***	***Soybeans***	***All Commodities***
Market Orders				
Minimum Time-to-clear	161.21 (43)	168.86 (11)	535.64 (11)	197.56 (28)
Maximum Time-to-clear	211.36 (84)	196.92 (39)	559.82 (43)	240.19 (76)
Slippage	-0.123 (0)	-0.007 (0)	-0.230 (-0.25)	-0.109 (0)
σ Slippage	0.440	0.471	0.734	0.486
Observations	453	136	63	652
Limit Orders				
Minimum Time-to-clear	131.02 (0)	60.12 (0)	137.50 (0)	116.89 (0)
Maximum Time-to-clear	168.85 (20)	87.51 (18)	169.93 (15)	152.16 (18)
Slippage	0.028 (0)	0.042 (0)	0.023 (0)	0.030 (0)
σ Slippage	0.125	0.203	0.205	0.152
Observations	876	249	98	1,223

Table 3
Price Volatility and Market Depth

For the ten minute window before each order is placed, *Price Change Frequency* is the number of market price changes, *Price Range* is the range of market prices, and *Price σ* is the standard deviation of market prices. *Daily Volume* is the total day's trading volume in thousands of contracts at the CBOT for that particular contract. *Open Interest* is the total number of long positions outstanding in thousands of contracts for that particular contract.

	Market			***Limit***		
	Corn	**Soybean**	**Wheat**	**Corn**	**Soybean**	**Wheat**
Price Change Frequency	26.3 (22)	30.9 (29)	20.0 (16)	26.1 (23)	25.3 (21)	23.9 (21)
Price Range	0.94 (0.75)	1.16 (1.00)	1.18 (1.00)	0.94 (0.75)	1.26 (1.00)	1.42 (1.25)
Price σ	0.27 (0.21)	0.33 (0.29)	0.36 (0.30)	0.28 (0.22)	0.37 (0.35)	0.42 (0.35)
Daily Volume	38.8 (36.7)	23.4 (24.4)	14.4 (13.9)	35.7 (32.3)	21.2 (22.5)	15.2 (14.7)
Open Interest	169.9 (186.7)	60.0 (70.3)	62.4 (68.8)	177.8 (182.2)	62.4 (69.6)	66.0 (72.2)

Table 4
Market Order Time-to-Clear

GLM (gamma distribution) regressions of *Time-to-Clear* for market orders. *Order Size* is the number of contracts ordered. For the ten minute window before each order is placed, *Price Range* is the range of market prices, *Price σ* is the standard deviation of market prices, and *Log Price Change Frequency* is the log of the number of market price changes. *Order On Open* (0,1) indicates that the order occurred in the first ten minutes of the trading session. *Open Interest* is the total number of long positions outstanding in thousands of contracts for that particular contract. *Log Daily Volume* is the log of total day's trading volume in thousands of contracts at the CBOT for that particular contract. *Wheat* and *Corn* (0,1) identify orders placed in the wheat and corn markets. All t-statistics (in parenthesis below coefficients) are calculated using heteroscedasticity consistent errors. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, * respectively.

	1	*2*	*3*	*4*	*5*
Order Size	1.639	1.678	1.447	1.220	1.446
	(1.99)**	(2.04)**	(1.86)*	(1.68)*	(1.74)*
Price Range	-6.175			-4.033	-3.940
	(2.16)**			(1.33)	(1.35)
Price σ		-15.016			
		(1.49)			
Log Price Change Frequency			-11.908		
			(2.32)**		
Open Interest				-0.314	
				(2.76)***	
Log Daily Volume					-15.035
					(2.56)***
Order on Open	-2.558	-4.471	-2.840	-0.177	1.997
	(0.30)	(0.53)	(0.35)	(0.02)	(0.23)
Wheat	17.121	18.413	9.581	16.914	8.430
	(1.44)	(1.54)	(0.73)	(1.49)	(0.73)
Corn	30.452	31.113	29.821	66.829	41.607
	(1.44)	(2.08)**	(2.10)**	(3.60)***	(3.04)***
Constant	47.404	45.016	80.208	67.878	193.387
	(4.31)***	(3.96)***	(3.43)***	(4.78)***	(3.19)***
# of Obs.	639	639	639	639	639
Log Likelihood	-3,338	-3,300	-3,334	-3,319	-3,329

Table 6
Magnitude of Market Order Slippage

GLM (gamma distribution) regressions of *absolute value of slippage* for market orders. *Order Size* is the number of contracts ordered. For the ten minute window before each order is placed, *Price Range* is the range of market prices, *Price σ* is the standard deviation of market prices, and *Log Price Change Frequency* is the log of the number of market price changes. *Open Interest* is the total number of long positions outstanding in thousands of contracts for that particular contract. *Daily Volume* is the total day's trading volume in thousands of contracts at the CBOT for that particular contract. *Order On Open* (0,1) indicates that the order occurred in the first ten minutes of the trading session. *Wheat* and *Corn* (0,1) identify orders placed in the wheat and corn markets. All t-statistics (in parenthesis below coefficients) are calculated using heteroscedasticity consistent errors. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, * respectively.

	1	*2*	*3*	*4*	*5*
Order Size	0.003 (2.08)**	0.003 (1.96)**	0.004 (2.04)**	0.002 (1.39)	0.003 (1.78)*
Price Range	0.096 (4.38)***				
Price σ		0.342 (3.71)***			
Log Price Change Frequency			0.067 (5.05)***	0.096 (3.52)***	0.090 (3.20)***
Open Interest				-0.002 (4.74)***	
Log Daily Volume					-0.047 (2.35)**
Order on Open	0.168 (4.60)***	0.164 (4.57)***	0.213 (4.23)***	0.213 (5.52)***	0.219 (4.80)***
Wheat	-0.186 (1.97)*	-0.186 (1.96)**	-0.162 (1.67)*	-0.137 (1.53)	-0.171 (1.82)*
Corn	-0.186 (1.97)**	-0.189 (1.87)*	-0.217 (2.16)**	0.031 (0.28)	-0.155 (1.55)
Constant	0.355 (3.75)***	0.352 (3.66)***	0.261 (2.58)***	0.281 (2.64)***	0.642 (3.44)***
# of Obs.	659	651	659	659	659
Log Likelihood	78.31	64.98	72.28	86.01	77.36

Table 5
Choosing Between Market and Limit Orders

Probit regressions for whether an order is a market (coded 1) or limit order (coded 0). *Log Order Size* is log of the number of contracts ordered. For the ten minute window before each order is placed, *Price Range* is the range of market prices, *Price σ* is the standard deviation of market prices, and *Log Price Change Frequency* is the log of the number of market price changes. *Open Interest* is the total number of long positions outstanding for that particular contract in thousands of contracts. *Daily Volume* is the total day's trading volume in thousands of contracts at the CBOT for that particular contract. *Spread* (0,1) denotes whether order is a spread. Nearby (0,1) denotes whether the underlying contract is the one closest to expiration. All t-statistics (in parenthesis below coefficients) are calculated using heteroscedasticity consistent errors. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, * respectively.

	1	***2***	***3***	***4***	***5***
Log Order Size	-0.077 (2.14)**	-0.074 (2.93)***	-0.084 (2.31)**	-0.080 (2.19)**	-0.073 (2.02)**
Price Range	-0.094 (2.40)**				
Price σ		-0.326 (2.19)**			
Log Price Change Frequency			-0.111 (3.06)***	-0.134 (3.50)***	-0.178 (4.53)***
Open Interest				0.001 (2.09)**	
Daily Volume					0.010 (4.41)***
Spread	0.539 (6.76)***	0.553 (6.90)***	0.546 (6.85)***	0.539 (6.75)***	0.540 (6.72)***
Nearby	-0.183 (2.91)***	-0.183 (2.93)***	-0.142 (2.15)**	-0.160 (2.42)**	-0.195 (2.92)***
Constant	-0.151 (1.64)	-0.155 (1.62)	0.347 (2.49)**	0.313 (2.22)**	0.348 (2.47)**
# of Obs.	2,089	2,067	2,089	2,089	2,089
Log Likelihood	-1,293	-1,278	-1,293	-1,290	-1,283

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