# VOLATILITY AND LIQUIDITY IN FUTURES MARKETS

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## ABSTRACT

We study the provision of liquidity in futures markets as price volatility changes. For both active and inactive contracts, customer trading costs do not increase with volatility. However, for three of the four contracts studied, the nature of liquidity supply changes with volatility. Specifically, for relatively inactive contracts, customers as a group trade more with each other (and less with market makers) on higher volatility days. By contrast, for the most active contract, trading between customers and market makers increases with volatility.

We also find that market makers' income per contract decreases with volatility for one of the least active contracts in our sample, but is not significantly affected by volatility for the other contracts. These results are consistent with the idea that, for inactive contracts (where the cost of market making is relatively high), market makers are hurt by volatility, and customers step forward to provide liquidity through standing limit orders.

# Volatility and Liquidity in Futures Markets

The U.S. futures markets use a centralized "open-outcry" system designed to facilitate trading between customers (end-users) and floor traders. Customer order flows are directed to floor brokers who offer them openly on the futures pit. Another set of orders come directly from locals (floor traders trading exclusively for their own accounts). Evidence indicates that, when executing personal trades, locals act "as if" they are market makers, absorbing customer order imbalances (Silber, 1984; Smidt, 1985; Kuserk and Locke, 1993). An important function of market makers is to provide immediacy (i.e., immediate liquidity) for customers. The price of providing immediacy is measured by the difference between the prices at which customers buy and sell orders. An active futures market, with many locals competing for a large number of trades, is particularly suited to meet the high demand for immediacy by futures customers (Grossman and Miller, 1988).

In this paper, we investigate how the cost of immediacy changes as volatility increases in futures markets. The change in the cost of immediacy depends, in turn, on how the demand for and supply of immediacy changes as volatility increases. Grossman and Miller (1988) argue that customers' demand for immediacy increases with volatility since it becomes more risky for them to wait to adjust their positions, given the higher probability of a large adverse price change. We first document this increased demand for immediacy; then, we study whether market makers or outside customers satisfy the additional immediacy, and at what cost. Since futures floor traders have no affirmative obligation to provide liquidity, the issue is of interest to policy makers and futures exchanges. More generally, our analysis shows how the microstructure of securities markets affects the provision of liquidity.

Whether it is profitable for market makers to provide additional liquidity when volatility increases depends on the marginal cost[2] of market making in the contract. If the marginal cost of market making is initially low (as with active contracts), this additional immediacy is likely to be supplied by market makers, and at low cost to customers. For relatively inactive contracts, at least two different scenarios are possible. One, when volatility increases, futures floor traders may continue to supply immediacy to customers, but at higher cost. If the cost is too high, customers may be discouraged from trading and this would delay price adjustment to a shock. Volatility would tend to persist.[3]

An alternative scenario for inactive contracts is that, on higher volatility days, customers themselves provide immediacy to other customers through standing limit orders, and this leads to lower trading costs for customers. Limit orders are held in "decks" by floor traders, and kept out of view from rival traders. When volatility increases, limit orders are more likely to be activated.[4] Liquidity supply through the use of limit orders may lower trading costs because trades between customers involve a transfer but no

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[2]The marginal cost of market making is related to the additional price risk incurred by market makers on higher volatility days. For active contracts, the number of market makers is high, and the additional price risk is more easily diversifiable through inter-dealer trading. By contrast, the fixed cost of market making is related to the cost of maintaining a market presence. Grossman and Miller (1988) discuss the determinants of market making costs.

[3]An example of such an occurrence is provided in "***Futures***" magazine, April 1996. Political uncertainty in Italy during February, 1996 resulted in a widening of bid-ask spreads in the Italian bond futures markets. Customers withdrew from the market and locals lost money.

[4] Handa and Schwartz (1995) conclude that limit-order traders are compensated for providing liquidity by the relative volatility of transactions prices in the short run. Kumar and Seppi (1994) model the strategic use of limit versus market orders.

aggregate transactions costs.[5]

We study four futures contracts using a detailed transactions data base. The data allows us to distinguish between trades for futures customers and floor traders' personal trading.[6] Table 1, which ranks the four contracts according to their activity levels[7], summarizes our results. For all four contracts, there is increased demand for liquidity (higher customer trading volume) as volatility increases. Excepting for the T-bond futures, there is either an increase in trading between customers as volatility increases (hogs and soybean oil futures), or no change (T-bill futures). Most important, although these three contracts are far less active than the T-bond futures, customers' trading costs (realized bid-ask spreads) do not increase with volatility.

The results support our hypothesis that customers may be able to keep trading costs down by acting as their own liquidity providers. Also, for live hogs (one of the least active contracts), market maker revenues per contract decline with volatility. This suggests that the cost of market making is relatively high for inactive contracts, so that market makers do not find it profitable to supply additional liquidity when volatility increases.

Results for the T-bond futures are in sharp contrast to the other three contracts.

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[5]Suppose customer A's market order to buy a futures contract is executed against customer B's limit order to sell a futures contract at 104 and 13/32. If the true value of the futures contract is 104 and 12/32, then customer A is paying customer B 1/32 in liquidity costs--but this is a transfer between customers, and no market maker is profiting from this transaction.

[6]Futures floor traders generally act as market makers when they execute trades for their personal account. See, for example, Silber (1984) and Kuserk and Locke (1993).

[7]Values for these variables are taken from table 3 and 4. Assume market making costs are inversely related to the average daily trading volume and the number of market makers. Then we can view the contracts as being ranked in ascending order by the cost of market making.

Customers in this contract trade more with market makers on higher volatility days. Even though customers are not paying higher realized bid-ask spreads, market makers still find it profitable to provide additional liquidity when volatility is higher. The reason may be that competition between market makers is far more intense in the T-bond futures than other contracts. The large number of market makers in this contract may allow an individual market maker to diversify away the increased price risk taken on when trading with customers.

The remainder of the paper is organized as follows. Section I describes our samples and provides measures of trading activity for the four futures contracts. Section II estimates the correlation between customer trading volume and volatility, and analyzes whether floor traders or customers supply the additional demand for liquidity. Section III estimates how customers' trading costs and floor traders' revenues are related to volatility. Section IV concludes.

## I. Sample Description and Measures of Trading Activity

### *A. Sample Description*

The sample period covers 30 randomly selected trading days for the 6 month time period starting August 1, 1990 for the following futures contracts: T-bond futures and soybean oil futures trading on the Chicago Board of Trade (CBOT); the 91 day T-bill futures and the live hog futures trading on the Chicago Mercantile Exchange (CME). The data, known as the Computerized Trade Reconstruction (CRT) data, is from the Commodity Futures Trading Commission (CFTC) and includes the following variables, dated by a 15 minute time bracket: trade price and quantity (number of contracts), a

Customer Type Indicator (CTI) code indicating whether the trade was made for an outside customer (CTI 4) or a floor trader's personal account (CTI 1)[8], whether the transaction was a buy or a sell, and a code for the floor trader executing the trade. In addition, settlement prices are used to measure the daily price change and mark daily positions to market.

As a measure of volatility, we use the volume-weighted average of the absolute change in all contract prices for a particular commodity.[9] To illustrate, suppose three different T-Bill futures contracts trade on day t, each corresponding to a different contract expiration month. Volatility for day t is calculated as follows. First, for each contract, we find the difference in settlement prices between day t and the previous <u>trading</u> day. Next, we calculate a weighted average of the absolute value of the price change for each contract, using each contract's relative trading volume on day t as the weight.

The average daily volatility is computed for the whole 30 day sample period, and, separately, for the three 10 day periods when volatility was highest (high sample), lowest (low sample) and in-between (medium sample). These sub-samples were created as follows. We rank the days in sample into three sub-samples according to the value of the absolute price change variable. We refer to the 10 days with the lowest absolute price changes as the

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[8]The other indicators are CTI 2 (trades executed for a clearing member's house account) and CTI 3 (trades for another member present on the exchange floor).

[9]We have repeated some of our tests using the following alternative volatility measures. One, the high-low price difference for the day (difference between the maximum and minimum price for a day). Two, the average difference between the first trade prices of successive brackets for each day (except for the last bracket of the day, for which we take the difference between the first and last trade prices). For these tests, the qualitative results do not change.

low sample. The 10 highest price change days form the high sample. The remaining 10 days constitute the medium sample.

While the 30 days were selected at random, we wished to establish that the sample was representative. Table 2 compares the average daily price volatility in our random sample with the average volatility for every trading day during 1990 and 1991. Average volatility for our random sample was similar to the average volatility during the period July, 1990 through December, 1990.[10] For example, volatility for hogs futures during our 30 day sample period was 0.61 cents per pound. This number compares favorably with the volatility of 0.52 cents per pound for the period of July, 1990 to December, 1990. Within our sample, however, there were substantial variations in daily volatility. For example, mean volatility for hogs is almost 8 times greater in the high volatility sample relative to the low volatility sample.

*B. Trading Activity in Four Futures Markets*

In this section, we present some sample statistics describing trading activity in the selected futures pits. Daily means of numbers of floor traders, trades and trading volume for live hogs futures and 91 day T-bill futures, both trading on the CME, are shown in table 3. The number of traders each day combines traders executing personal trades as well as traders executing customer trades. For live hogs, a total of 70 floor traders trade on an average day, 54 of whom trade for their own accounts and 37 trade for customers (clearly, some traders do both). Volume for customers and floor traders' personal trading are almost

[10]While the volatility of the agricultural commodities is bounded above by the daily price limit, we had no occurrence of this in our 30 day sample.

identical. For T-bill futures, only 44 floor traders trade on an average day, of whom 31 trade for their own accounts. Customer trading volume is higher than personal trading volume; and the average trade size is three times that for live hogs futures.

Similar statistics for the T-bond and soybean oil futures, both trading on the CBOT, are shown in table 4. The T-bond futures pit is far more active than the other three futures contracts. Compared to live hogs futures, for example, there are 9 times as many trades and 32 times more volume on an average day. Also, volume for floor traders trading for their own accounts is almost two-and-a-half times the customer trading volume. This indicates that most trades occur between floor traders. The soybean oil futures is also a fairly active contract, although it is dwarfed by the activity in the T-bond futures pit. However, similar to T-bond futures, personal trading represents a high proportion of total trading activity.

Summarizing, the T-bond futures is considerably more active than the other three contracts. Also, trading volume in the T-bond futures is dominated by floor traders' personal trading. The other three contracts are quite similar in their activity levels, although soybean oil futures has somewhat higher average daily trading volume and a higher proportion of personal account trading relative to the remaining two contracts.

### *C. Sample Averages for Trading Imbalances, Customer Trading Costs and Market Maker Revenues*

Our analysis concerns the relationship between trading costs and volatility, and whether this relationship depends on the trading pattern of customers and maker makers. To obtain a preliminary picture of trading patterns and trading costs, we offer, in this section, a description of trading imbalances (the difference between purchases and sales for customer trades), customer trading costs and market makers' revenues, both for the full sample and the sub-samples. Trading imbalances are calculated for each 15 minute trading bracket, and then averaged over the number of brackets in a day to obtain the daily imbalance.

Statistics for net as well as relative trading imbalance (defined, for each day, as the net imbalance divided by the total trading volume) are presented in table 5. We focus on the relative imbalances, since that is the variable we will use in our tests.[11] For the T-bond futures, the relative imbalance increases monotonically with volatility for customers--indicating decreased trading by customers with each other when volatility increases. For hogs and soybean oil futures, customer imbalances decrease with volatility--although, for soybean oil futures, the relationship is not monotonic. This indicates that, for hogs and soybean oil futures, customer trades are crossing against limit orders more frequently on high volatility days. For T-bill futures, relative imbalances do not change much with volatility.

Statistics for mean and median values of customer trading costs and market maker revenues are presented in table 6. For T-bond futures, mean and median customer trading costs decrease monotonically with volatility. For hogs, too, median customer costs tend to be lower with volatility, while for the remaining two contracts, median costs tend to be higher with volatility. Ex-post, costs for customers are revenues for market makers. We expect, therefore, to see floor traders' revenues per contract to decrease with volatility for

[11]We justify our use of this variable in footnote 13.

T-bond and hogs futures, and increase with volatility for the remaining two contracts. Table 6 confirms that the expected pattern does indeed hold for these contracts.

## II. The Supply of Liquidity As Volatility Changes

### *A. The Relationship Between Customer Trading Volume and Volatility*

In this section, we examine the relation between volume and volatility. Some of our results depend on the assumption that the volatility measure is exogenous of volume. This would be the case if, for example, an exogenous change in liquidity-motivated trading is associated with higher price volatility. Here, volume and volatility are contemporaneously correlated. Alternatively, volume and volatility could be causally linked. For example, an informational event may increase the heterogeneity of informed traders' expectations of future cash flows and cause an increase in trading volume. Higher volatility could also increase uncertainty for uninformed traders, increasing their required risk premium for holding a futures contract.

To establish the nature of the relationship between customer trading volume and volatility, we run the following regression:

$$CV_t = a_0 + a_1 V_t + e_t \tag{1}$$

where, for day t, $CV_t$ is the (unsigned) customer trading volume and $V_t$ is a measure of volatility. The regression is run twice. In the first case, $V_t$ is the absolute change in the end-of-day settlement prices between day t and day t-1. In this case, the coefficient $a_1$ estimates the contemporaneous correlation between customer trading volume and volatility. In the second case, $V_t$ is the absolute change between the price of the first trade of day t and the trade price 15 minutes after the first trade[12]. Here, $a_1$ estimates whether volatility at the beginning of the trading day predicts customer trading volume during the entire day.

Table 7 reports the results. From panel A, customer trading volume and volatility are contemporaneously correlated in all four contracts, since $\hat{a}_1$ (the estimated value of $a_1$) is positive and significant for all four contracts. For example, customer trading volume in live hogs futures increases by about 2 contracts for every 1 cent increase in price volatility. However, the panel B results show that opening volatility does not predict customer trading volume for that day. For example, when the beginning-of-day volatility is used as a right-hand-side variable, $\hat{a}_1$ is no longer significant for the live hogs futures. These results offer little support for a causal link from volatility to volume.

*B. The Supply of Liquidity as Volatility Changes*

Liquidity for customer orders may be supplied directly by floor traders or indirectly by other customers through the placement of limit orders held by floor traders. In other words, when a market order enters the pit, the broker charged with executing the order will seek to fill the order at the best price quoted from all other traders and brokers in the pit. Brokers holding executable limit orders may bid or offer such orders, seeking to attract customer market orders or locals. The likelihood that a market order will be executed against a standing limit order will depend on market conditions, such as price volatility.

[12]Sometimes there is no trade exactly 15 minutes following the first trade. This is a problem for distant expirations in particular. For this reason, we use the trade price closest to the 15 minute mark. We also use the expiration which has the highest customer trading volume for that day.

Our data set allows us to infer the proportion of liquidity supplied by market makers ex-post by calculating customers' transactions imbalance. The net transactions imbalance for customers is the number of contracts absorbed (temporarily) by other traders, especially locals, in each bracket. If market makers step back from the market as volatility increases, then customer imbalances will decrease with volatility. For our tests, we focus on a related variable: the relative customer trading imbalance, $RC_{it}$, for each trading bracket i of day t. For day t, $RC_{it}$ is calculated as a ratio of the net customer transactions imbalance (the signed customer volume) over total customer trading volume in bracket i[13].

Table 8 presents the median of abs($RC_{it}$), the absolute value of $RC_{it}$, over the three sub-samples high, medium, and low. We test for the stability of customer imbalance across levels of volatility by performing pair-wise comparisons on our three samples (i.e., whether the distribution of customer imbalance is the same for each pair of samples). We use the Kruskal-Wallis non-parametric test for these comparisons. The comparisons show that, except for T-bills futures, trading patterns change with volatility in all contracts. Customer imbalances decrease with volatility for hogs (between the low and high volatility samples) and soybean oil futures (between the medium and high volatility samples). These results indicate that, for live hogs and soybean oil futures, customers trade more with each other

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[13]The reason we divide the net trading volume by the total trading volume is as follows. Suppose that net volume is +10 contracts in two separate brackets, but the total customer volume is 20 contracts in bracket one and 100 contracts in bracket two. If we used net volume as a proxy for net liquidity demand by customers, we would say that the net liquidity demand is the same during both brackets. In the second bracket, however, 90 percent of customer trading volume is with other customers. In this sense, the supply of liquidity is greater by customers in the second bracket and the net liquidity demand is lower.

when volatility increases. T-bond futures go against this pattern, with imbalance levels increasing between the low and high volatility samples. This indicates that customers are trading more with market makers as volatility increases.

To summarize, except for T-bond futures, customer imbalances decrease or (in the case of T-bill futures) stay the same as volatility increases. These results are consistent with our notion that, an increase in volatility may trigger standing limit orders, increasing inter-customer trades at the expense of customer-market maker trades. We conjecture that the result for T-bond futures may be explained by the high degree of competition between market makers in this contract. There are ten times as many market makers in the T-bond futures pit, compared to soybean oil and live hogs futures.

## III. The Price of Liquidity as Volatility Changes

### *A. The Relationship Between Customer Trading Costs and Volatility*

When customers supply more liquidity on higher volatility days, the net demand for liquidity by customers is lower on these days. As a result, customers' trading costs per contract may decrease with volatility for those futures contracts where trading between customers increase with volatility. On the other hand, when market makers are the marginal liquidity suppliers on higher volatility days, they may charge customers a higher bid-ask spread to compensate for the extra price risk.

We estimate the relationship between customer trading costs and volatility as follows. Customer trading costs are calculated each day for each trader for all customer trades executed by that trader. Customer costs per contract are computed as the volume-weighted average buy price minus the volume-weighted average sale price (i.e., it is the opposite of customer profits). $CS_t$ denotes customers' trading costs per contract for day t. To determine the relationship between trading costs and volatility, we run the following regression:

$$CS_t = a_0 + a_1D_{1t} + a_2D_{2t} + a_3N_t + a_4C_t + e_t \tag{4}$$

In the regression, $D_{1t}$ and $D_{2t}$ are dummy variables. For day t, $D_{1t}=1$ if day t is in the high sample and 0 otherwise, and $D_{2t}=1$ if day t is in the medium sample and 0 otherwise. If customers' trading costs increase when average daily volatility increases from its level in the low sample to its level in the high sample, $\hat{a}_1$ will be positive. If customers' costs also increase when average daily volatility increases from its level in the low sample to its level in the medium sample, $\hat{a}_2$ will also be positive. $N_t$ is the total number of floor traders executing personal trades on day t. It is a proxy for market maker competition, and so we expect $\hat{a}_3$ to be negative. $C_t$ is customers' net trading volume on day t. $\hat{a}_4$ is expected to be positive, because higher net volume may: one, indicate an increase in adverse selection costs for market makers; and two, constitute an increase in liquidity demand.

The results are reported in table 9. $\hat{a}_1$ and $\hat{a}_2$ are not significantly different from zero for any contract at the 5% or 10% level of significance. For all four futures contracts, customer trading costs do not change with volatility. This is true both for an increase in average daily volatility from low to medium levels as well as an increase from low to high levels. $\hat{a}_3$, the coefficient of the floor trader variable, has the right sign for two of the four contracts. However, whether positive or negative, $\hat{a}_3$ is very close to zero in all cases. $\hat{a}_4$, the coefficient of the net volume variable, has the right sign for all but soybean oil futures. It, too, is not significant for any contract.

*B. The Relationship Between Floor Trader Revenues and Volatility*

The predicted relation between floor trader revenues and volatility depends upon whether the former are successful in anticipating high volatility days; and whether marginal costs of market making are high or low. If market makers correctly anticipate volatility, then they may increase the spread charged on customers' trades[14] and earn higher revenues per contract when volatility increases. If marginal costs of market making are high, then market makers have an incentive to charge higher spreads and maintain profits.

We calculate revenues across all floor traders trading for their own account each day. Any open positions are marked to market using settlement prices. For each day, we sum all market makers' trading revenues to get $REV_t$, the aggregate trading revenues of all market makers for day t. $REV_t$ is regressed on the two volatility dummies (defined in section IIIA), $N_t$, the number of floor traders and $C_t$, customers' net trading volume on day t as follows:

$$REV_t = a_0 + a_1 D_{1t} + a_2 D_{2t} + a_3 C_t + a_4 N_t + e_t \tag{5}$$

Market makers' aggregate revenues may increase with volatility because of the positive correlation between customer volume and volatility. So, we also calculate $MS_t$,

[14]This is not inconsistent with customers as a group paying lower spreads on high volatility days. The spread on intra-customer trades is zero, and, if there are more of these trades, the average spread could fall or remain constant.

market makers' revenues per contract, similar to the way we calculate $CS_t$, customers' trading costs per contract. We repeat regression 5 with $MS_t$ as the left-hand-side variable.

Tables 10 lists the results for floor traders' aggregate revenues. For live hogs, $\hat{a}_1$ is negative and significant at the 5% level, indicating that floor traders' aggregate revenues decrease when volatility increases from low to high levels. For T-bonds, too, $\hat{a}_1$ is negative, but significant at the 13% level. For T-bills, $\hat{a}_2$ is negative, indicating that revenues decrease when volatility increases from low to medium levels. However, it is only significant at the 13% level. These results, showing a negative relation between aggregate revenues and volatility are, perhaps, surprising considering the positive correlation between volume and volatility established earlier. The only other variable of significance is $\hat{a}_3$ for soybean oil, indicating a positive relationship between customers' net trading volume and market makers' aggregate revenues. The signs on the floor trader variable are all of the right sign, although none are significant.

Table 11 shows the results for floor traders' revenues per contract. The results are similar to those for floor traders' aggregate revenues. For live hogs, revenues per contract decrease with volatility. $\hat{a}_1$ is negative for live hogs and significant at the 5% level. For T-bonds and T-bills, too, there is weak evidence that floor traders' revenues per contract decrease with volatility. For T-bonds, $\hat{a}_1$ is negative, but significant only at the 13% level. For T-bills, $\hat{a}_2$ is negative and significant at the 12% level. For soybean oil, there is no relation between volatility and per contract revenues. For all contracts, the coefficients on the customer trading volume and the number of market makers variables have the right signs, but are not significant.

Taken together, the evidence presented in tables 10 and 11 suggest that market markers' aggregate and per contract revenues tend to decrease with volatility, although the decrease is statistically significant for live hogs only. The results indicate that market makers may have been surprised by volatility.

## IV. Conclusion

We study how the provision of market liquidity changes when price volatility changes. Our findings support the notion that, for relatively inactive contracts, as volatility increases, there is an increased propensity for customers to trade against standing limit orders. Liquidity provision becomes more profitable (because of increased volatility) for price-sensitive customers. However, our results also indicate that liquidity provision becomes less profitable for market makers (at least in one of the less active contracts), since they suffer a loss in income on higher volatility days. Customer trading costs (for both market orders and standing limit orders) do not increase with volatility, indicating that the net supply of liquidity on higher volatility days does not decrease.

For the most active contract in our sample, also, costs do not increase with volatility for customers. However, they trade more with market makers when volatility increases. Apparently, the provision of liquidity remains profitable for market makers in relatively active contracts even on higher volatility days, perhaps due to the low cost of market making in these contracts.

**Table 1**
**Summary of Results**

Contracts are ranked by average daily volume and the number of floor traders trading for their own accounts (1=highest value; 4=lowest value). Values were obtained from tables 3 and 4. The sample period is 30 randomly selected trading days between August 1, 1990 and January 31, 1991 for four contracts: hogs, T-bills, T-bonds and soybean oil.

| | Ranking by (1=highest 4=lowest) | | As volatility increases | | | |
|---|---|---|---|---|---|---|
| Futures contract | Average daily trading volume | Number of market makers | Demand for liquidity | Trading between customers | Customer trading costs | Market maker revenues per contract |
| T-bond | 1 | 1 | Increases | Decreases | No change | No change |
| Soybean oil | 2 | 2 | Increases | Increases | No change | No change |
| T-bills | 3 | 4 | Increases | No change | No change | No change |
| Live hogs | 4 | 2 | Increases | Increases | No change | Decreases |

**Table 2**
**Price Volatility for Selected Futures Contracts, 1990-91**

Price volatility is measured by the mean absolute value of the change in settlement prices between consecutive trading days. An observation for day t is the settlement price for the contract with the highest trading volume on day t. The sample period is 30 randomly selected trading days between August 1, 1990 and January 31, 1991 for four contracts: hogs, T-bills, T-bonds and soybean oil. The high, medium and low samples consist of the 10 highest, medium and lowest daily price volatility days, respectively.

| | Hogs | T-Bonds | T-bills | Soybean Oil |
|---|---|---|---|---|
| Price quotation | Cents per pound | Points and Multiples of 1/32 of a point | IMM 3 month T-bill index | Cents per pound |
| Maximum daily fluctuation | 1.5 cents ($600 per contract) | 3 points ($3000 per contract) | None | 1 cent ($600 per contract) |
| Time Period | Mean absolute price change | Mean absolute price change | Mean absolute price change | Mean absolute price change |
| Whole sample | 0.61 | 0.55 | 0.039 | 0.16 |
| High sample | 1.07 | 1.11 | 0.077 | 0.31 |
| Medium sample | 0.62 | 0.39 | 0.03 | 0.12 |
| Low sample | 0.14 | 0.13 | 0.01 | 0.05 |
| 1/1/90-6/30/90 | 0.44 | 0.43 | 0.048 | 0.22 |
| 7/1/90-12/31/90 | 0.52 | 0.45 | 0.046 | 0.18 |
| 1/1/91-6/30/91 | 0.42 | 0.40 | 0.044 | 0.21 |
| 7/1//91-12/31/91 | 0.37 | 0.37 | 0.033 | 0.24 |

**Table 3**
**Trading Activity in Selected Futures Pits at the Chicago Mercantile Exchange**

Trading for own account (customers) refers to days on which a floor trader traded for its own (customers') account(s). The table shows the mean numbers of traders, trades and trading volume per day. The sample period is 30 randomly selected trading days between August 1, 1990 and January 31, 1991 for four contracts: hogs, T-bills, T-bonds and soybean oil.

| | Trading for Own Account | Trading for Customers | Total |
|---|---|---|---|
| | Hogs Futures | | |
| Number of traders per day | 54 | 37 | 70 |
| Number of trades per day | 1,752.43 | 2,261 | 4,013.43 |
| To buy | 883.77 | 1,119.5 | 2,003.27 |
| To sell | 868.66 | 1,141.50 | 2,010.16 |
| Trading volume per day | 6,433.2 | 6,431.9 | 12,865.10 |
| Purchase volume | 3,206.27 | 3,226.27 | 6,432.54 |
| Sale volume | 3,226.93 | 3,205.63 | 6,432.56 |
| Average trade size | 3.67 | 2.84 | 3.21 |
| Average buy size | 3.63 | 2.88 | 3.21 |
| Average sell size | 3.71 | 2.81 | 3.20 |
| | 91 Day Treasury Bill Futures | | |
| Number of traders per day | 31 | 24 | 44 |
| Number of trades per day | 754.53 | 811.77 | 1,566.30 |
| To buy | 382.53 | 386.44 | 768.97 |
| To sell | 372 | 425.33 | 797.33 |
| Trading volume per day | 6761.97 | 7722.23 | 14,484.20 |
| Purchase volume | 3398.6 | 3683.9 | 7,082.50 |
| Sale volume | 3363.37 | 4038.33 | 7,401.70 |
| Average trade size | 8.96 | 9.51 | 9.25 |
| Average buy size | 8.88 | 9.53 | 9.21 |
| Average sell size | 9.04 | 9.49 | 9.28 |

**Table 4**
**Trading Activity in Selected Futures Pits at the Chicago Board of Trade**

Trading for own account (customers) refers to days on which a floor trader traded for its own (customers') account(s). The table shows the mean numbers of traders, trades and trading volume per day. The sample period is 30 randomly selected trading days between August 1, 1990 and January 31, 1991 for four contracts: hogs, T-bills, T-bonds and soybean oil.

| | Trading for Own Account | Trading for Customers | Total |
|---|---|---|---|
| | Treasury Bond Futures | | |
| Number of traders per day | 515 | 233 | 562.00 |
| Number of trades per day | 29,441 | 7,818 | 37,259.00 |
| To buy | 14,756.37 | 3,853.27 | 18,609.64 |
| To sell | 14,684.63 | 3,964.73 | 18,649.36 |
| Trading volume per day | 288,670.4 | 119,598.3 | 408,268.70 |
| Purchase volume | 144,143.3 | 59,888.43 | 204,031.73 |
| Sale volume | 144,527.10 | 59,709.87 | 204,236.97 |
| Average trade size | 9.81 | 15.30 | 10.96 |
| Average buy size | 9.77 | 15.54 | 10.96 |
| Average sell size | 9.84 | 15.06 | 10.95 |
| | Soybean Oil Futures | | |
| Number of traders per day | 52 | 42 | 70 |
| Number of trades per day | 1570.23 | 1165.13 | 2,735.36 |
| To buy | 757.03 | 595.7 | 1,352.73 |
| To sell | 813.2 | 569.43 | 1,382.63 |
| Trading volume per day | 10,318.77 | 7504.43 | 17,823.20 |
| Purchase volume | 5018.84 | 3817.36 | 8,836.20 |
| Sale volume | 5299.93 | 3687.07 | 8,987.00 |
| Average trade size | 6.57 | 6.44 | 6.52 |
| Average buy size | 6.63 | 6.41 | 6.53 |
| Average sell size | 6.52 | 6.48 | 6.50 |

**Table 5**
**Sample Means of Relative Trading Imbalances and Net Trading Volume for Customers and Floor Traders**

Relative trading imbalances for customers and floor traders are measured by dividing the net trading imbalance by that group's trading volume each day. The sample period is 30 randomly selected trading days between August 1, 1990 and January 31, 1991 for four contracts: hogs, T-bills, T-bonds and soybean oil. The high, medium and low samples consist of the 10 highest, medium and lowest daily price volatility days, respectively.

| Variable | Hogs | T-Bonds | T-Bills | Soybean Oil |
|---|---|---|---|---|
| Relative customer trade imbalance | 0.193 | 0.157 | 0.383 | 0.234 |
| High sample | 0.180 | 0.163 | 0.385 | 0.214 |
| Medium sample | 0.184 | 0.162 | 0.385 | 0.262 |
| Low sample | 0.214 | 0.147 | 0.378 | 0.237 |
| Net customer trading volume | 374.43 | 4336.33 | 693.77 | 491.37 |
| High sample | 312 | 7386.7 | 1076.4 | 761.1 |
| Medium sample | 460 | 2883.4 | 593.6 | 310.7 |
| Low sample | 351.3 | 2738.9 | 411.3 | 402.3 |
| Relative floor traders' trade imbalance | 0.167 | 0.059 | 0.323 | 0.166 |
| High sample | 0.179 | 0.051 | 0.292 | 0.149 |
| Medium sample | 0.156 | 0.065 | 0.338 | 0.181 |
| Low sample | 0.165 | 0.061 | 0.339 | 0.167 |
| Floor traders' net trading volume | 258.4 | 1398.07 | 178.97 | 334.7 |
| High sample | 286 | 910.10 | 181.8 | 359.7 |
| Medium sample | 313.5 | 1321.2 | 205.9 | 366.9 |
| Low sample | 175.7 | 1962.9 | 149.2 | 277.5 |

## Table 6
## Sample Means and Medians of Customer Trading Costs and Floor Trader Revenues

The top number in each cell is the sample mean; the number below is the median. Customer trading costs are measured on a per contract basis. Floor trader revenues are measured both on an aggregate and on a per contract basis. The sample period is 30 randomly selected trading days between August 1, 1990 and January 31, 1991 for four contracts: hogs, T-bills, T-bonds and soybean oil. The high, medium and low samples consist of the 10 highest, medium and lowest daily price volatility days, respectively.

| Variable | Live hog | T-Bond | T-bill | Soybean oil |
|---|---|---|---|---|
| Minimum price change per contract | $10 | $31.25 | $25 | $6 |
| Customer trading costs | $8.00<br>$20.41 | $11<br>$13 | $58.50<br>$45.00 | $26.40<br>$20.40 |
| High sample | -$1.40<br>$13.20 | $7<br>$13 | $107.50<br>$60 | $37.20<br>$31.20 |
| Medium sample | $32.80<br>$2.80 | $10<br>$10 | $37.50<br>$19.00 | $19.20<br>$9.60 |
| Low sample | -$7.60<br>$38 | $17<br>$19 | $30.00<br>$47.50 | $22.20<br>$23.40 |
| Floor traders' total revenue | $10,256<br>$3,810 | $322,579.40<br>$217,100.40 | $10,632.5<br>$11,287.5 | $24,336<br>$18,003 |
| High sample | -$14,704<br>-$29,660 | -$103,625<br>$188,550.90 | $36,635<br>$41,125 | $42,000<br>$44,268 |
| Medium sample | $17,856<br>-$16,150 | $256,432.40<br>$169,074.90 | -$19,620<br>$3,950 | $21,616.20<br>$15,693 |
| Low sample | $27,612<br>$15,270 | $814,540.70<br>$575,863 | $14,882.5<br>$13,000 | $9,396<br>$6,684 |
| Floor traders' revenue per contract | $3.40<br>$1.88 | $2.40<br>$1.30 | $4<br>$4.75 | $4.02<br>$3.84 |
| High sample | -$3.40<br>-$6.80 | -$0.07<br>$0.88 | $8.25<br>$8.75 | $6.00<br>$6.30 |
| Medium sample | $5.20<br>$0.80 | $0.085<br>$1.30 | -$1.95<br>$2.00 | $4.20<br>$4.26 |
| Low sample | $8.40<br>$8.00 | $6.40<br>$4.60 | $5.43<br>$5.50 | $1.74<br>$1.44 |

## Table 7
## Price Volatility and Liquidity Demand by Customers

The regression model is:

$$CV_t = a_0 + a_1 V_t + e_t$$

where, for day t, $CV_t$ is the absolute value of customer trading volume, and $V_t$ is the price volatility. In panel A, $V_t$ is the absolute value of the change in settlement prices between consecutive trading days. In panel B, $V_t$ is the absolute price change between the first trade of the day and the trade 15 minutes after. The sample period is 30 randomly selected trading days between August 1, 1990 and January 31, 1991 for four contracts: hogs, T-bills, T-bonds and soybean oil. T-statistics are in parentheses. Significant values are starred. N is the number of observations, and F is the value of the F-statistic.

| Parameter | Hogs | T-bonds | T-bills | Soybean Oil |
|---|---|---|---|---|
| Panel A: Contemporaneous Correlation Between Volume and Volatility | | | | |
| $a_0$ | 298.58* (5.379) | 3815.06* (9.465) | 232.15* (6.183) | 404.29* (7.686) |
| $a_1$ | 1.844* (2.286) | 1167.70* (2.343) | 14.86* (2.04) | 606.78* (2.406) |
| N | 29 | 29 | 29 | 29 |
| R-square | 0.158 | 0.16 | 0.13 | 0.17 |
| F | 5.226 | 5.488 | 4.157 | 5.789 |
| Panel B: Causal Relation Between Volume and Volatility | | | | |
| $a_0$ | 208.97* (6.776) | 4241.35* (12.202) | 189.58* (7.537) | 283.97* (5.781) |
| $a_1$ | 0.6 (0.468) | 665.18 (0.5) | 14.39 (1.499) | 340.07 (0.629) |
| N | 29 | 29 | 29 | 29 |
| R-square | 0.008 | 0.009 | 0.07 | 0.01 |
| F | 0.219 | 0.25 | 2.246 | 0.396 |

**Table 8**
**Price Volatility and Liquidity Supply by Customers**

abs($RC_{i,t}$), the absolute value of the relative customer imbalance, is calculated as the net customer volume over total customer volume during bracket i of day t. The chi-square statistic tests whether the median values of abs($RC_{it}$) are equal between each pair of our three samples (high, medium, low). p values are in parenthesis. Significant values are starred. The high, medium and low samples consist of the 10 highest, medium and lowest daily price volatility days, respectively, where daily price volatility is the absolute value of the change in settlement prices from the previous trading day. The sample period is 30 randomly selected trading days between August 1, 1990 and January 31, 1991 for four contracts: hogs, T-bills, T-bonds and soybean oil.

| Sample and Tests | Hogs | T-bonds | T-bills | Soybean oil |
|---|---|---|---|---|
| All | 0.154 | 0.13 | 0.306 | 0.196 |
| High (H) | 0.136 | 0.149 | 0.311 | 0.189 |
| Medium (M) | 0.156 | 0.129 | 0.305 | 0.196 |
| Low (L) | 0.174 | 0.116 | 0.305 | 0.199 |
| $\chi^2$ $H_0$: H=M | 1.7 (0.19) | 1.42 (0.23) | 0.04 (0.84) | 2.744* (0.098) |
| $\chi^2$ $H_0$: M=L | 1.77 (0.18) | 0.24 (0.62) | 0.4 (0.53) | 0.53 (0.47) |
| $\chi^2$ $H_0$: H=L | 6.88* (0.009) | 3.56* (0.06) | 0.15 (0.7) | 0.8 (0.38)) |

## Table 9
## Price Volatility and Customer Trading Costs

The regression model is:

$$CS_t = a_0 + a_1 D_{1t} + a_2 D_{2t} + a_3 N_t + a_4 C_t + e_t$$

where, for day t, $CS_t$ is the realized bid-ask spread paid by customers on their trades, $N_t$ is the number of market makers, and $C_t$ is customers' net trading volume. $D_{1t}$ = 1 for high price volatility days and 0 otherwise. $D_{2t}$ = 1 for medium volatility days and 0 otherwise. The high, medium and low samples consist of the 10 highest, medium and lowest daily price volatility days, respectively, where daily price volatility is the absolute value of the change in settlement prices from the previous trading day. The sample period is 30 randomly selected trading days between August 1, 1990 and January 31, 1991 for four contracts: hogs, T-bills, T-bonds and soybean oil. T-statistics are in parentheses. Significant values are starred. N is the number of observations, and F is the value of the F-statistic.

| Parameter | Hogs | T-bonds | T-bills | Soybean oil |
|---|---|---|---|---|
| $a_0$ | -0.72★ | 0.01 | 0.05 | 0.14 |
| | (-2.208) | (0.204) | (0.755) | (1.533) |
| $a_1$ | -0.09 | -0.003 | 0.03 | 0.04 |
| | (-0.839) | (-0.248) | (1.455) | (1.598) |
| $a_2$ | 0.03 | -0.007 | 0.002 | -0.004 |
| | (0.312) | (-0.567) | (0.132) | (-0.137) |
| $a_3$ | 0.009 | 0.00005 | -0.002 | -0.001 |
| | (1.246) | (0.211) | (-0.614) | (-0.764) |
| $a_4$ | 0.005 | -0.00004 | 0.0002 | -0.0003 |
| | (1.540) | (-1.408) | (0.481) | (-1.255) |
| N | 29 | 29 | 29 | 29 |
| R-square | 0.28 | 0.10 | 0.13 | 0.18 |
| F | 2.4 | 0.702 | 0.910 | 1.350 |

**Table 10**
**Price Volatility and Market Makers' Total Revenues**

The regression model is:

$$\mathbf{REV_t = a_0 + a_1D_{1t} + a_2D_{2t} + a_3C_t + a_4N_t + e_t}$$

where, for day t, $REV_t$ is aggregate market maker revenues for day t, $C_t$ is customers' net trading volume and $N_t$ is the number of market makers. $D_{1t}$ = 1 for high price volatility days and 0 otherwise. $D_{2t}$ = 1 for medium volatility days and 0 otherwise. The high, medium and low samples consist of the 10 highest, medium and lowest daily price volatility days, respectively, where daily price volatility is the absolute value of the change in settlement prices from the previous trading day. The sample period is 30 randomly selected trading days between August 1, 1990 and January 31, 1991 for four contracts: hogs, T-bills, T-bonds and soybean oil. T-statistics are in parentheses. Significant values are starred. N is the number of observations, and F is the value of the F-statistic.

| Parameter | Hogs | T-bonds | T-bills | Soybean oil |
|---|---|---|---|---|
| $a_0$ | 96.09<br>(0.507) | 722.03<br>(0.268) | 38.19<br>(1.216) | 3.94<br>(0.047) |
| $a_1$ | -113.72*<br>(-1.754) | -1011.7<br>(-1.539) | 57.03<br>(0.566) | 32.83<br>(1.235) |
| $a_2$ | -33.12<br>(-0.531) | -561.68<br>(-0.913) | -14.74<br>(-1.538) | 11.04<br>(0.434) |
| $a_3$ | 1.84<br>(1.086) | 0.56<br>(0.376) | 0.20<br>(0.219) | 0.55*<br>(2.101) |
| $a_4$ | -2.39<br>(-0.564) | -0.39<br>(-0.068) | -1.52<br>(-1.224) | -0.55<br>(-0.323) |
| N | 29 | 29 | 29 | 29 |
| R-square | 0.15 | 0.09 | 0.23 | 0.28 |
| F | 1.123 | 0.617 | 1.860 | 2.470 |

## Table 11
## Price Volatility and Market Makers' Per Contract Revenues

The regression model is:

$$MS_t = a_0 + a_1 D_{1t} + a_2 D_{2t} + a_3 C_t + a_4 N_t + e_t$$

where, for day t, $MS_t$ is market maker revenues per contract for day t, $C_t$ is customers' net trading volume and $N_t$ is the number of market makers. $D_{1t}$ = 1 for high price volatility days and 0 otherwise. $D_{2t}$ = 1 for medium volatility days and 0 otherwise. The high, medium and low samples consist of the 10 highest, medium and lowest daily price volatility days, respectively, where daily price volatility is the absolute value of the change in settlement prices from the previous trading day. The sample period is 30 randomly selected trading days between August 1, 1990 and January 31, 1991 for four contracts: hogs, T-bills, T-bonds and soybean oil. T-statistics are in parentheses. Significant values are starred. N is the number of observations, and F is the value of the F-statistic.

| Parameter | Hogs | T-bonds | T-bills | Soybean oil |
|---|---|---|---|---|
| $a_0$ | 0.032 | 0.0187 | 0.01* | 0.012 |
| | (0.653) | (0.985) | (1.668) | (0.766) |
| $a_1$ | -0.031* | -0.007 | 0.001 | 0.006 |
| | (-1.804) | (-1.546) | (0.447) | (1.084) |
| $a_2$ | -0.01 | -0.006 | -0.003 | 0.003 |
| | (-0.566) | (-1.378) | (-1.625) | (0.524) |
| $a_3$ | 0.0004 | $4.24(10)^{-6}$ | $3(10)^{-5}$ | $6.26(10)^{-5}$ |
| | (0.957) | (0.407) | (0.811) | (1.257) |
| $a_4$ | -0.001 | $-2.79(10)^{-5}$ | $-3.2(10)^{-4}$ | $-2.66(10)^{-4}$ |
| | (-0.591) | (-0.701) | (-1.346) | (-0.82) |
| N | 29 | 29 | 29 | 29 |
| R-square | 0.16 | 0.11 | 0.22 | 0.14. |
| F | 1.149 | 0.786 | 1.734 | 1.008 |

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