Liquidity Supply and Volatility: Futures Market Evidence*

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ABSTRACT

We study the provision of liquidity in futures markets as price volatility changes. We find that 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 high-cost, inactive contracts, market makers are react to temporary increases in volatility by raising their bid-ask spreads significantly, and customers provide increased liquidity through standing limit orders. An implication of our results is that electronic systems, where market maker participation is not required, are able to supply adequate liquidity during volatile periods.

Liquidity Supply in Volatile Periods: Evidence From Open Outcry Futures Markets

Futures markets have traditionally used a centralized "open-outcry" system designed to facilitate trading between customers and floor traders. Electronic trading systems clearly will replace the floor, sooner rather than later (Sarkar and Tozzi 1998). Central to the transition from futures pit to electronic trading systems is the concept of liquidity. A critical factor in liquidity provision is the fixed cost, the opportunity cost to liquidity suppliers of being available for business (Grossman and Miller 1988). Fixed costs might be higher for open outcry markets since the dealer must be present on the floor even when the market is currently inactive, whereas screen trading makes more efficient use of time. For example, one trader can trade multiple contracts on a screen system. High volume contracts may be better traded on specialized dealer markets such as the futures trading pits whereas it may be efficient to trade a relatively inactive contract through electronic media.

A related aspect of the choice between open outcry and electronic trading is the source of liquidity supply. Domowitz (1993) distinguishes between “insider liquidity”, or liquidity provided by dealers or market makers, and “outsider liquidity”, or liquidity provided by other speculative trading. Insider liquidity is prominent on open outcry markets, through local’s trading. With their proprietary trading, locals act "as if" they are market makers, absorbing customer order imbalances and providing immediacy for customers (Silber, 1984; Smidt, 1985; Kuserk and Locke, 1993).[1] “Outsider liquidity” may be provided by customers with their limit orders, or arms length speculative trading. In electronic systems, liquidity is supplied by the “outsider, ” large institutional traders, broker/dealers, or others willing to post quotes.

In this paper, we focus on changes in the provision of liquidity across volatility levels. In particular, we ask whether open outcry markets provide relatively more “inside” or “outside” liquidity during volatile periods. We also study whether the nature of liquidity supply depends on the general activity level of the contract. Our evidence shows that customers supply a larger share of liquidity for relatively inactive contracts when volatility increases. The implication is that electronic trading systems, with exclusive outside liquidity, need not suffer liquidity outages during volatile periods. Since futures floor traders have no affirmative obligation to bid, offer, or even remain in the futures pit, our results are also of interest to futures regulators concerned with market volatility and illiquidity.

For our measure of liquidity, we calculate the cost of immediacy implied by floor trader transactions, as described in Locke and Venkatesh (1996). 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 hedging customers' demand for immediacy increases with volatility since it becomes more risky for them to wait. We first document this increased demand for immediacy; and then examine the provision of the additional immediacy and its cost.

The propensity for market makers to provide 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, 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. First, when volatility increases, locals may continue to supply immediacy to customers at an increased cost. Volatility would tend to persist as trading is inhibited by the increased bid-ask spread. In a second scenario, as volatility increases, existing limit orders are more likely to be activated.[3] Increased trading against limit orders lowers aggregate customer trading costs because such trades involve a transfer between customers.[4] Obviously, due to increased volatility, these transfers are likely to be higher, but nonetheless they remain transfers. In some sense, our tests are an indirect investigation into the relative prevalence of limit orders in the markets that we study.

We study four futures contracts using detailed transactions data. These data allow us to distinguish between trades for futures customers and floor traders' personal trading. Our results support the hypothesis that during increased volatility periods, customer trading lowers aggregate customer trading costs through outside liquidity provision in less active markets. This suggests that the marginal cost of market making is relatively high for inactive contracts, so that market makers apparently price themselves out of the market when volatility increases. Results for the high-volume T-bond futures are in sharp contrast to the other three contracts we study. Customers in this contract trade more with market makers on higher volatility days. Further, customer costs do not rise with volatility. One interpretation of this finding is that market makers are more competitive in the T-bond futures, due to large numbers.

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 describes the empirical link between customer trading volume and volatility, and analyzes the extent to which floor traders or customers accommodate the increased liquidity demand. Section III estimates how customers' trading costs and floor traders' revenues are related to volatility. Section IV concludes.

I. Sample Description and Measures of Volatility and Trading Activity

A. Sample Description

Our sample is thirty days randomly selected from the 6-month time period starting August 1, 1990, for the following futures contracts: T-bond and soybean oil futures from the Chicago Board of Trade (CBOT), and T-bill and live hog futures from the Chicago Mercantile Exchange (CME). The transactions data is known as the trade register data, and was generously supplied by the Commodity Futures Trading Commission (CFTC). The trade register includes the following variables, dated by a 15-minute time bracket: price; quantity; a Customer Type Indicator (CTI) of whether the trade was for an outside customer (CTI 4) or a floor trader's personal account (CTI 1)[5]; buy versus sell; and, a code for the floor trader executing the trade. In addition, settlement prices from the CFTC's permanent records data base were obtained to measure the daily price change and mark daily positions to market.

B. Volatility Measure

As our measure of volatility for sample classification, we use the volume-weighted average of the absolute change in the daily closing or settlement prices for all expirations of a particular contract.[6] 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 trading 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. Our random 30-day sample is divided into three 10-day sub-samples based on the day's volatility rank, the 10 highest (High sample), lowest (Low sample), and in-between (Medium sample).

C. Are the Volatility Measures Representative?

While the 30 days were selected at random, we wished to establish that the sample was representative. Table 1 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 sample was similar to the average volatility during the period July 1990 through December 1990.[7] For example, volatility for hogs 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.

D. 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 hogs 91-day T-bill futures, both trading on the CME, are shown in the upper half of table 2. The "number of traders" each day combines traders executing personal trades as well as traders executing customer trades. For 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 (with some obvious overlap). Volume for customers and floor traders' personal trading are almost identical. For T-bills, 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 hog futures.

Similar statistics for the T-bond and soybean oil futures, both trading on the CBOT, are shown in the lower half of table 2. As is well known, T-bond futures are far more active than the other three futures contracts. Compared to hogs, 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 involve the proprietary account of a floor trader. Soybean oil is also a fairly active contract, although it is dwarfed by the activity in the T-bond futures pit. However, similar to T-bonds, personal trading represents a high proportion of total trading activity.

Summarizing, T-bonds are considerably more active than the other three futures contracts. Also, trading in the T-bonds involves substantially more personal trading by floor traders. The other three contracts are quite similar in their activity levels, although soybean oil has somewhat higher volume and a higher proportion of personal account trading relative to the remaining two futures.

E. Trading Imbalance, Customer Trading Costs and Market Maker Revenues

Our analysis concerns the relationship between trading costs and volatility, and the extent to which 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 customer trade imbalances, 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 are presented in table 5. We focus on the relative imbalances, since that is the variable we will use in our tests. The relative imbalance is the ratio of customer trade imbalance to customer volume during a bracket. For T-bonds, 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, customer imbalances decrease with volatility--although, for soybean oil, the relationship is not monotonic. Overall, these findings are consistent with customer trades crossing with limit orders more frequently on high volatility days for soybean oil and hogs. For T-bills, relative imbalances do not change much across volatility levels.

Statistics for mean and median values of customer trading costs and market maker revenues are presented in table 4. Recall that our measure of customer costs is a direct calculation of revenue flows from customers to market makers. On a per-contract basis, costs may be lowered by customer trades crossing, which involve no flow of revenue to market makers. For T-bonds, 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. We expect, to see floor traders' revenues per contract to decrease with volatility for T-bond and hogs futures, and increase with volatility for the remaining two contracts. Again, if there is significant inter-market maker trading, this will reduce market makers per contract revenues. The results presented in table 4 confirms that the expected pattern, the inverse of customer costs, does indeed hold for these contracts.

II. The Supply of Liquidity While 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. The likelihood that a market order will be executed against a limit order will depend on market conditions, such as price volatility.[8]

Our data allow us to infer the proportion of liquidity supplied by market makers ex-post by calculating customers' transactions imbalance. Customer’s net trading is the number of contracts temporarily absorbed by other traders, especially locals, in each bracket. As volatility increases, if market makers react by raising liquidity premia, then customer imbalances may actually decrease. To normalize, we calculate the relative customer imbalance, for each trading bracket. For day t, this measure, labeled RC_{it}, is calculated as a ratio of net customer trade imbalance to total customer trading volume in bracket i[9].

Table 5 presents the median of abs(RC_{it}), or the absolute value of RC_{it}, over the three sub-samples high, medium, and low. We test for the equality of customer imbalance across levels of volatility by performing pair-wise comparisons on our three samples. The comparisons show that, except for T-bills, trading patterns change significantly 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 hogs and soybean oil, customers trade more with each other when volatility increases. This pattern is reversed for T-bonds, with imbalances increasing between the low and high volatility samples. This indicates that customers are trading more with market makers as volatility increases in the bond pit.

To summarize, customer imbalances decrease or stay the same as volatility increases, except in the high-volume T-bonds. 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 market maker trades. The contrary result for T-bonds 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 pit, compared to soybean oil and hogs.

III. The Price of Liquidity as Volatility Changes

A. The Relationship Between Customer Trading Costs and Volatility

When customers trade with each other more on high volatility days, the net demand for liquidity is lower. As a result, customers' trading costs per contract will 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 premium to compensate for increased 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. 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 using OLS:

$$CS = a_0 + a_h D_{ht} + a_m D_{mt} + a_3 N_t + a_4 C_t + e_t$$

In the regression, D_{ht} and D_{mt} are dummy variables. For day t, D_{ht}=1 if day t is in the high sample and 0 otherwise, and D_{mt}=1 if day t is in the medium sample and zero 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, a_h 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, a_m will also be positive. N_t is the total number of floor traders executing personal trades on day t. The number of floor traders present has been applied as a proxy for the relative degree of competition, and so we expect a_3 to be non-positive. C_t is customers' net trading volume on day t. 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 6. The estimates of a_h and a_m 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. The estimate of a_3, the coefficient of the floor trader variable, has the expected sign for two of the four contracts. However, whether positive or negative, a_3 is very close to zero in all cases. The estimates of a_4, the coefficient of the net volume variable, have the expected sign for all but soybean oil futures. This variable, however, 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 their bid ask spreads and earn higher revenues per contract when volatility increases. This will be especially true if the marginal cost of market making is relatively high.

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 and obtain REV_t, the aggregate trading revenues of all market makers for day t. This measure is regressed using OLS, on the two volatility dummies defined above, N_t, the number of floor traders, and C_t, customers' net trading volume on day t as follows:

$$REV_t = a_0 + a_h D_{ht} + a_m D_{mt} + a_3 C_t + a_4 N_t + e_t \qquad (5)$$

Tables 7 lists the results for floor traders' aggregate revenues. For live hogs, 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, a_h is negative, but not significant at the 10% level. For T-bills, a_m is negative, indicating that revenues decrease when volatility increases from low to medium levels, but it is not significant at the 10% 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 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 expected, although none are significant.

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

Table 8 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. a_h 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, a_h is negative, but not significant at the 10% level. For T-bills, a_m is negative and not significant at the 10% 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 7 and 8 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. Some liquidity provision appears increasingly attractive for hedgers as volatility increases. At the same time these results indicate that liquidity provision becomes less attractive for some market makers. Aggregate customer trading costs, when customers can submit limit and market 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.

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Notes

[1] Manaster and Mann (1996) infer other speculative behavior on the part of locals in addition to direct liquidity provision.

[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] 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.

[4] 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.

[5] 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).

[6] 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.

[7] 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.

[8] The analysis in this section depends on the assumption that the volatility measure is exogenous of volume. We expect volume and volatility to be correlated, as overwhelming prior research indicates, but any causal link is problematic for our purposes. We find through a variety of tests that customer trading volume and volatility are contemporaneously correlated in all four contracts, as expected. However, we are unable to find that preceding volatility, under a variety of measures and tests, has a causal relationship with customer volume.

[9] 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.

Table 5
Price Volatility and Liquidity Supply by Customers

The absolute value of the relative customer imbalance is calculated as net customer trading as a ratio of customer volume during bracket i of day t. The chi-square statistic tests whether the median value of this imbalance is equal across each pair of our three sub-samples. Associated p values are given below the chi-square statistic. Significant values are starred. The high, medium and low samples consist of the 10 highest, medium and lowest daily price volatility days. The sample 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.

Median absolute customer imbalance	Hogs	T-bonds	T-bills	Soybean oil
Full sample	0.154	0.130	0.306	0.196
High sample	0.136	0.149	0.311	0.189
Medium sample	0.156	0.129	0.305	0.196
Low sample	0.174	0.116	0.305	0.199
Chi-square statistics				
High versus medium	1.7	1.4	0.0	2.7*
p-value	*-0.19*	*-0.23*	*-0.84*	*-0.10*
Medium versus low	1.8	0.2	0.4	0.5
p-value	*-0.18*	*-0.62*	*-0.53*	*-0.47*
High versus low	6.9*	3.6*	0.2	0.8
p-value	*-0.01*	*-0.06*	*-0.70*	*0.38*