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The Impact of Trader Type on the Futures Volatility-Volume Relation

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ABSTRACT

We examine the volatility-volume relation in futures markets using volume data categorized by type of trader. We find that the positive volatility-volume relation is driven by the general public, a group of traders who are distant from the trading floor and therefore without precise information on order flow. Clearing members and floor traders who observe order flow often decrease volatility. Our findings are consistent with Shalen's (1993) hypothesis that uninformed traders who cannot differentiate liquidity demand from fundamental value change increase volatility.

IN THEIR 1993 STUDY, Bessembinder and Seguin suggest that the volatility-volume relation in financial markets may depend on the type of trader. We investigate whether specific types of futures market traders, which we distinguish by the information they possess, actually have different effects on the positive volatility-volume relation.

We use the Liquidity Data Bank (LDB) to test this information effect. The LDB is a database that separates futures volume by four types of traders: market makers, clearing members (such as financial institutions) trading for their own accounts, floor traders trading for other exchange members, and the general public (individual speculators, managed funds, and small hedgers). In addition to allowing us to test the Bessembinder and Seguin (1993) suggestion, the LDB also provides an indirect test of Shalen's (1993) model, which postulates that abnormal volume and price volatility, either above or below equilibrium values, depend on the dispersion of traders' expectations.

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Our analysis follows models that associate price with private information, differentiating traders by either the quality of information they hold or the dispersion of expectations they form based on that information. For futures markets, different types of traders vary in their proximity to the trading floor and the amount of information they receive. Specifically, clearing members can directly observe the source of trades, the short-term direction of prices, and order imbalances in the futures market. They also have private information on the cash market. Thus, clearing members have a wealth of information that is not available to the general public who do not have access to the trading floor. We conclude that clearing members have a more precise interpretation of information signals associated with a change in volume, and that this information enables them to reduce the price volatility of their own trades. Off-the-floor traders (the general public) cannot adequately distinguish the volume associated with liquidity demand from the volume due to a change in fundamental value. This results in an imprecise information signal and a greater dispersion of expectations, thereby increasing price volatility.

Our empirical results show that the general public drives the positive volatility-volume relation found in previous studies. Conversely, trades by clearing members and floor traders often exhibit an inverse relation between volatility and volume. Thus, we find that using trader categories is a better way to describe the link between volatility and volume than is total volume. Our results also indicate that large changes in volume, both positive and negative, are more important in explaining volatility than are average volume levels.

Section I of this paper examines the volatility-volume relation and models of trader behavior. Section II summarizes the data and estimation procedures. Section III provides the results, and Section IV presents the conclusions of the paper.

I. Trader Information, Beliefs, and the Volatility-Volume Relation

Two related types of theories explain the volatility-volume relation. Information theories, such as the mixture of distributions model, use information as the driving force that determines both volatility and volume. Dispersion of beliefs theories associate unusual volume and extremes of volatility to differences in trader beliefs. Dispersion models suggest that the volatility-volume relation depends on who is generating volume and why they are trading. Empirical studies of the volatility-volume relation for various financial instruments show that a significant positive relation exists between volatility and volume, with volatility usually measured as the absolute price change or the squared price change. R^2 values from regressions of volatility on volume typically range from 10 to 35 percent.

A. The Mixture of Distributions Model

In the classic mixture of distributions model, described by Clark (1973), Epps and Epps (1976), Harris (1986), and Tauchen and Pitts (1983), the authors assume that the price variance per transaction is monotonically related to the volume of that transaction. A mixing variable, typically the number of information arrivals (and implicitly their importance), causes the joint volatility-volume relation. Harris (1987) and Jones, Kaul, and Lipson (1994b) also designate the more specific volume per transaction and the number of transactions variables as mixing variables. We include the number of transactions in our model since Clark, Harris (1987), and Tauchen and Pitts relate the number of trades to the number of information events and to unobserved realizations of the stochastic variance.[1]

B. Dispersion of Beliefs and Information Models

Models of heterogeneous trader behavior assess the availability of different types of information or the existence of differing beliefs concerning the importance of information. Models by Harris and Raviv (1993) and Shalen (1993) show that a greater dispersion of beliefs creates excess price variability and excess volume, compared to the equilibrium value. A greater dispersion of beliefs is a lack of consensus about the true price that should result from revealed information. In particular, Shalen's model associates volatility with uninformed traders' dispersion of beliefs, incorrectly formed in response to the noisy liquidity demand of hedgers. This dispersion of beliefs model is relevant for comparing how informed and uninformed traders react to information.[2]

Informed traders have relatively homogeneous beliefs, which they base on their knowledge of the market and the fundamental characteristics of the asset. Therefore, informed traders buy and sell within a relatively small range of prices around the fair value of the asset.

Uninformed (or less-informed) traders cannot observe the transactions of other traders to help them interpret the noisy signals from volume and price changes, resulting in a wider dispersion of beliefs. Therefore, uninformed traders are likely to react to all changes in volume and price as if these changes reflect information, despite their difficulty in differentiating short-term liquidity (hedging) demand from changes in overall fundamental sup-

[1] Previous studies often cite a mixture of distributions as the cause of autoregressive conditional heteroskedasticity (ARCH) effects in financial time series. Diebold (1986), Gallant, Hsieh, and Tauchen (1991), and Lamoureux and Lastrapes (1990) suggest that ARCH effects might capture the entire time series properties of the information mixing variable—for example, the serial correlation of the number of price changes (number of trades). However, Lamoureux and Lastrapes (1990) and Gannon (1994) show that ARCH effects completely disappear when volume is employed as a proxy for information. Conversely, Bessembinder and Seguin (1992, 1993), Foster (1995), and Lamoureux and Lastrapes (1994) show that volume is not sufficient to remove the lagged volatility effects in current variance. Consequently, whether volume adequately explains the variability of volatility or whether lagged volatility is also needed is not completely settled. Further, the role of the number of trades in this relationship has not been empirically examined for futures markets. Other interesting recent studies on the mixture of distributions model include Hiemstra and Jones (1994) and Richardson and Smith (1994).

[2] Admati and Pfleiderer (1988) and Kyle (1985) present other key theoretical information models that include different types of traders with varying amounts of information. These models postulate the behavior of volume and volatility arising from their assumptions.

ply and demand. Uninformed traders' frequent revision of their beliefs can also cause the price fluctuations resulting from their trading to disappear more slowly than those of informed investors after new "information" is revealed.[3] This process of trading is consistent with French and Roll (1986), who state that traders overreact to one another's trades. Therefore, less-informed traders tend to exaggerate price movements, which results in a greater price variability.

C. Informed Futures Traders: Private Information from the Futures Pit and Cash Market

The dispersion of information/beliefs models incorporates the roles of informed trading, liquidity demand, and uninformed trading into the volatility-volume relation. In our study, the larger financial institutions ("clearing members") represent the informed traders. Clearing members of the exchange enjoy the substantial savings in trading costs available to exchange members. By comparison, we define the nonclearing "general public" as uninformed in this study.

In addition to lower trading costs, clearing members have two other advantages compared to the general public. First, they have direct access to the futures pits. This provides them with short-term information about pit dynamics, such as trading activity at specific prices and price trends. Second, they have specific information on their own customers' supply and demand in the cash and futures markets, and more information on the cash markets in general via trading screens and in-house knowledge of the activity in these markets. This private information allows clearing members to better distinguish liquidity demand from fundamental information and to estimate current value more precisely, which translates into a smaller dispersion of beliefs and less price volatility.

The general public, since it is denied access to the trading floor and to cash market information, receives information about trading activity on a delayed or second-hand basis, if it receives such information at all. Consequently, the general public has difficulty in distinguishing liquidity demand from fundamental information. Since the general public possesses less information, we expect them to have a greater dispersion of beliefs and to trade over a wider range of prices around the fair value of the futures contract. The behavior attributed to the general public is consistent with the noise literature; for example, see Black (1986) and DeLong, Shleifer, Summers, and Waldmann (1990a, 1991). DeLong et al. (1990a) examine how the unpredictability of noise traders' beliefs creates excess risk, causing prices to

[3] Ederington and Lee (1993, 1995) show that changes in the price level after publicly announced macroeconomic information are completed within 40 to 50 seconds, while volatility takes 30 minutes to dissipate. However, they do not determine who causes either the price level change or the volatility relating to these announcements. There is no evidence that prior knowledge of public macroeconomic announcements is known or fully anticipated by futures markets participants (see Daigler (1997)).

diverge significantly from fundamental values. DeLong et al. (1991) conclude that noise traders can dominate the market and that noise trades are associated with excess volatility in the markets. DeLong et al. (1990b) show how the positive feedback strategy of uninformed traders is directly associated with trend following and higher volatility.

Empirically examining the volumes of these clearly different groups allows us to determine the role of private information and the dispersion of beliefs in the volatility-volume relation. Empirical studies of the value of similar types of information include Ito, Lyons, and Melvin (1998) for foreign exchange traders and Phillips and Weiner (1994) for Japanese oil dealers. They find that traders who possess (temporary) private information on traders' risk aversion, trading constraints, and the supply and distribution of the underlying asset affect the price and volatility in these markets. Ito, Lyons, and Melvin refer to this information as "semifundamental information."

II. Data and Estimation Procedures

A. The Data

Our study uses the Chicago Board of Trade's Liquidity Data Bank to examine the Customer Trade Indicator (CTI) data that separates total futures volume into four types of traders:

1. CTI1: volume for the local floor trader's own account or for an account that he or she controls. Most local floor traders are market makers ("scalpers").
2. CTI2: volume for the clearing member's house account. Clearing members trade to benefit from mispricing of the futures contracts ("value traders"), as well as for long-term hedging and arbitrage purposes. According to Kodres and Pritsker (1997), the largest percentages of open interest are held by broker-dealers, pension funds, and hedge funds.
3. CTI3: volume for one member executing trades for another member, or an account controlled by other such members (i.e., "other floor traders"). Examples of CTI3 trades include a member filling orders either for a broker ("overflow trading"), or for a fellow member not currently on the floor, or for a trader from the options on futures pit who wants to trade the futures in order to hedge options contracts.
4. CTI4: volume for any other type of off-the-floor customer, including individual traders and managed futures funds. This is the group we refer to as the general public. This category is usually dominated by retail speculative traders, although it also includes some institutions that hedge and speculate. For example, Kodres and Pritsker (1997) show that many smaller insurance companies and pension funds fall into this group because their trading activity is insufficient to justify the cost of a seat.

These CTI categories are used industry wide. Trades are assigned to groups based on the strict definitions identified above; self-designation of trades is not permitted. Wiley and Daigler (1998) examine the characteristics and relations among these four categories of traders.

CTI1 traders are most often liquidity providers who trade in response to the demand of others and profit from the spread. CTI1 traders match the transactions of the other three groups and therefore do not exhibit unique trading characteristics.[4] CTI2s and CTI3s also trade on the floor and thus have up-to-the-minute information about the supply and demand dynamics of the futures and/or cash markets, but they trade for speculative or hedging purposes. CTI4 traders (the general public) are those least likely to have the semifundamental information gained from pit access. Based on these differences in information, we expect CTI4s to have a different volatility-volume relation than CTI2s or CTI3s.

We examine volume data by using daily data spanning two years (June 1986 through June 1988) for five financial futures contracts at the Chicago Board of Trade. The contracts are silver, the Major Market stock index (MMI), municipal bonds (munis), Treasury notes (T-note), and Treasury bonds (T-bond) futures contracts.

In our analysis we use the futures expiration month with the highest open interest so that we can concentrate on the most active contract month. The interest rate contracts are rolled over near the first of the expiration month. The MMI contract is rolled over at its expiration. The largest open interest for silver does not follow a nearby pattern, since the December contract often had the largest open interest from summer until the end of November. Both volume and open interest values used in this analysis are for the contract being analyzed, not for the entire range of futures expiration months.[5]

B. Examining the Conditional Mean and Conditional Variance

We use the same procedure as Bessembinder and Seguin (1992, 1993) and Schwert (1990) and as outlined by Davidian and Carroll (1987). This procedure enables us to compute unbiased estimates of the conditional daily return volatility while simultaneously including the effects of the day of the

[4] Kuserk and Locke (1993) claim and Manaster and Mann (1996) show that floor traders, even market makers, take intraday or overnight positions to speculate, as well as providing short-term liquidity to longer-term traders. However, the primary activity of almost all floor traders is market making—even when they have to take a short-term position.

[5] Using the futures expiration with the largest volume as the selection criteria would create the unwanted feature of skipping back and forth from one expiration month to another for the less liquid futures contracts. Moreover, by using the largest open interest expiration, we avoid using a contract during its expiration period. Alternatively, if we were to lump all expirations together, we would have difficulty accurately measuring a combined price change or volatility, possibly obscuring the true relationship. In any case, the expiration with the largest open interest usually dominates trading volume. On the days when a rollover to the next expiration month occurs, we use the close-to-close return for the new nearby contract to avoid the distortion created by calculating returns across two different contracts.

week, the persistence of volatility, and lagged returns. In this model, equation (1) estimates the conditional return based on lagged returns, the day of the week, and lagged volatility. Equation (2) estimates conditional volatility using transformations of past volatility, day of the week, and trade activity variables. Equation (3) transforms the lagged volatility. The equations are:

$$R_t = \alpha + \sum_{j=1}^{n} \gamma_j R_{t-j} + \sum_{i=1}^{4} \rho_i d_i + \sum_{j=1}^{n} \pi_j \hat{\sigma}_{t-j} + U_t, \tag{1}$$

$$\hat{\sigma}_t = \delta + \sum_{j=1}^{n} \omega_j \hat{U}_{t-j} + \sum_{i=1}^{4} \eta_i d_i + \sum_{k=1}^{m} \mu_j A_k + \sum_{j=1}^{n} \beta_j \hat{\sigma}_{t-j} + e_t, \tag{2}$$

$$\hat{\sigma}_t = |\hat{U}_t|\sqrt{\pi/2}, \tag{3}$$

where R_t is the percent change in the futures price on day t; d_i represents the four dummy variables for the days of the week; $\hat{\sigma}_t$ is the volatility on day t; and A_k are the activity variables of volume, change in open interest, and the number of trades. The residual U_t represents unexpected returns and $\pi = 3.14159$.

We initially use the series of close-to-close returns on each futures contract to estimate equation (1) without lagged volatility estimates. We then apply the volatility transformation defined in equation (3) to the residuals of equation (1). We use these transformed values to estimate equation (2). The fitted volatility values that result from equation (2) are used to reestimate equation (1), and we then reestimate equation (2) with the residuals from the consistent estimation obtained from the second pass of equation (1).

We include the lagged volatility variables to account for the effect of persistence in volatility over time. We use the Schwarz (1978) criterion to set the lag limits to 10 to incorporate the range of significant lags identified for each variable.

The trading activity variables A_k in equation (2) are the expected and unexpected values of both the category volumes and the change in the contract's open interest, plus the number of trades for the day. We partition the volume trading activity variables into expected and unexpected components with an ARIMA (0,1,10) procedure.[6] The ARIMA (0,1,10) calculates the expected (predicted) value using the previous day's volume and the 10-day moving average of the change in volume. The unexpected (residual) value is total volume minus expected volume. Since the levels of open interest for all five futures cat-

[6] Ten lags allows direct comparison with the Bessembinder and Seguin (1993) results. Using the Schwarz (1978) criterion, the optimal number of lags for each return and volume variable is less than, or equal to, 10 in every case. When we refit the ARIMA models by using the optimal number of lags for each futures return and volume variables, only two additional coefficients (out of 180) are significant and there are few changes in significance among the coefficients or categories. Moreover, only four of the 15 optimal lag-length equations have a larger R^2 value than the lag 10 results, but more of these models produce nonnormal errors.

egories are nonstationary in levels, as indicated by augmented Dickey–Fuller tests, we use the first difference of open interest and fit an ARIMA (0,0,10) to determine the expected open interest. We also examine an ARIMA (10,1,0) model, which shows equivalent results to those presented here.

Separating category volumes into expected and unexpected components allows us to examine the extent to which surprises versus trend activity variables affect the volatility-volume relation. Since volume and volatility are simultaneously determined, this partitioning does not imply causality. Further, partitioning open interest gives us a measure of the importance of the change in long-term positions. We concentrate on the expected and unexpected components of the clearing members (CTI2), other floor traders (CTI3), and general public (CTI4). Thus, we are able to associate these categories of volume to Shalen's (1993) conclusion (in her Proposition 2) that volume and price volatility are related to the dispersion of expectations across traders. In particular, Shalen's model has uninformed traders reacting inappropriately to volume caused by liquidity traders, treating it as if it were information. This creates excess variability due to the dispersion of expectations of these traders. This less-informed trading is the behavior we associate with CTI4 traders.

C. Alternative Measures of Volatility for the Conditional Variance

The close-to-close return residuals provide an incomplete measure of the true intraday range of price volatility; therefore we reexamine the volatility-volume relation by individually substituting the Garman and Klass (1980) and high-low range measures of volatility for $\hat{\sigma}_t$ in equations (1), (2), and (3). Since these measures calculate volatility independent of the return equation, we generate a one-pass estimation of equations (1) and (2) to fit the volatility-volume relation using these intraday descriptions of volatility.

Garman and Klass (1980) show the relative efficiency of various measures of volatility; their equation (19) provides the highest efficiency. However, they suggest using the reduced-form estimator employed in our study. The difference between the two, other than very small differences in the coefficients, is that the open/high/low/close cross-terms are eliminated in our equation (4). The correlation between these two volatility measures is greater than 0.95. The results in the regressions are identical for both measures and therefore we drop the cross terms.

The Garman and Klass measure of volatility is almost eight times more efficient than using the close-to-close price to obtain a measure of volatility. This measure is

$$\begin{aligned}\hat{\sigma}_t = \mathrm{Var(GK)} = \tfrac{1}{2}[\mathrm{LN(High)} - \mathrm{LN(Low)}]^2 \\ - [2\mathrm{LN}(2) - 1][\mathrm{LN(Open)} - \mathrm{LN(Close)}]^2,\end{aligned} \tag{4}$$

where Var(GK) is the variance using the Garman–Klass (1980) method, LN denotes the natural logarithm, and High, Low, Open, Close are the high, low, open, and closing prices in the interval being used to determine the volatility.

Table I

Descriptive Statistics

This table presents daily volume descriptive statistics for five futures contracts for four categories of traders. The categories are: floor trader/market maker (CTI1), clearing member (CTI2), other floor trader (CTI3), and the general public (CTI4). Panel A shows the breakdown (in percent) of volume by category and the total daily volume. Since each trade is recorded as both a buy and a sell, the percentages are divided by two in order to sum to 100 percent. Panel B provides the cross-correlations between each pair of volume variables, with CTI1-2 being the correlation between the CTI1 and CTI2 categories. An ARIMA (0,1,10) model calculates the expected (predicted) value using the previous day's volume and the 10-day moving average of the change in volume. The unexpected volume is total volume minus expected volume. MMI is the Major Market Index futures.

Panel A: Average Trader Category Volume as a Percentage of Total Volume

Series	CTI1	CTI2	CTI3	CTI4	Total Daily Avg. Volume
Silver	45.92%	6.59%	10.80%	36.68%	1,901
MMI	50.45%	19.55%	7.17%	22.83%	13,739
Munis	50.49%	18.60%	1.39%	29.54%	9,531
T-notes	45.98%	20.32%	6.95%	26.74%	32,075
T-bonds	55.57%	13.34%	7.08%	24.02%	462,456

Panel B: Cross-Correlations between Trader Categories

Series	CTI1-2	CTI1-3	CTI1-4	CTI2-3	CTI2-4	CTI3-4
Silver						
Expected	0.348	0.583	0.785	0.303	0.183	0.425
Unexpected	0.460	0.525	0.774	0.306	0.350	0.421
Total	0.462	0.601	0.838	0.322	0.350	0.506
MMI						
Expected	0.861	0.857	0.905	0.812	0.763	0.777
Unexpected	0.750	0.769	0.753	0.638	0.622	0.658
Total	0.845	0.844	0.883	0.780	0.734	0.756
Munis						
Expected	0.803	0.723	0.896	0.622	0.896	0.716
Unexpected	0.740	0.389	0.806	0.352	0.751	0.387
Total	0.838	0.599	0.899	0.555	0.861	0.594
T-Notes						
Expected	0.873	0.649	0.860	0.507	0.811	0.470
Unexpected	0.807	0.585	0.833	0.535	0.662	0.473
Total	0.857	0.683	0.862	0.589	0.751	0.538
T-Bonds						
Expected	0.960	0.821	0.950	0.821	0.916	0.839
Unexpected	0.924	0.830	0.933	0.799	0.899	0.819
Total	0.948	0.827	0.947	0.820	0.914	0.839

III. Empirical Results for the Volatility-Volume Relation

A. Volume by Category

Table I provides descriptive statistics concerning the percentage breakdown of total volume into the four CTI categories for each of the five futures contracts and the cross-correlations among trader categories. Categories CTI1 (floor traders) and CTI4 (general public) trade the most contracts for each of the futures, and category CTI3 (orders for other floor traders) shows the smallest levels of trading volume. The large (55.57 percent) value for T-bond floor traders shows that in this pit there is a greater degree of trading among the scalpers, who appear likely to readjust inventory after large block trades enter the pit. Clearing members (CTI2) generate a smaller percentage of the volume for T-bonds than for the MMI, muni, and T-note contracts. Also, the silver futures contract has fewer CTI2 trades than CTI3 trades, the reverse of the more liquid contracts, and silver has proportionally more CTI3 and CTI4 activity than all other futures. After the CTI1 market makers, the general public generates more trades than any other group. The differing proportions across pits are consistent with the findings of other researchers.[7] Table I also shows that cross-correlations between trader category volume pairs vary by contract and tend to increase as the liquidity of the futures increases.

B. Conditional Mean and Conditional Variance Effects

We separate volume and open interest into expected and unexpected components. To identify more precisely the factors affecting volatility, we include other activity variables previously hypothesized by others. These are lagged returns, lagged volatility, days of the week, the change in open interest, and the number of trades.

Table II shows the results of regressing different measures of return volatility on the volume for clearing members, other floor traders, and the general public, along with the activity variables.[8] We omit floor traders (scalpers) from the Table II results because, as Table I shows, they tend to react to new trades rather than create them, and because of their high collinearity with the other variables. Regressions that include the CTI1 traders are summarized in Section III.C.

Panel A of Table II shows the results of the volatility-volume regressions using the daily return standard deviation (close-to-close) formulation. The general public category is more important than clearing members or other floor traders in explaining the close-to-close return volatility, except for the case of muni bond futures, as evidenced by more significant coefficients and/or higher t-values. In fact, the unexpected CTI4 volume is positive and significant for all but muni bonds, and the expected CTI4 volume is positive and significant for all but munis and T-notes. Moreover, although the coefficients on the general public's volume are significant and positive for seven

[7] Kuserk and Locke (1993) report the following volume breakdowns by CTI groups (their Table II) for 12 futures contracts: CTI1, 39.4 percent; CTI2, 16.1 percent; CTI3, 5.6 percent; CTI4, 38.7 percent. Fishman and Longstaff (1992) find that scalpers account for 60 percent of the trades in the soybean pit. Each trade in the LDB is recorded on the database both as a buy and a sell by the appropriate groups. Consequently, total volume in the database is twice the actual volume of contracts. We adjust the percentages to add to 100 percent instead of 200 percent.

[8] We also use the daily dummy variables in the regressions but do not show them here. For 12 of the 15 regressions at least one daily dummy variable is significant, with the T-bond results each having two or three significant dummies. The Wednesday dummy is most often significant, recording 10 of the 22 significant dummies.

of the 10 cases, the volume generated by clearing members and other floor traders is significant for only seven of 20 cases, four of which are negative. The negative coefficients indicate a volatility-reducing relation, which is consistent with these traders being more strongly associated with private information and less likely to trade on noise. Because the type of trading done by the clearing members and other floor traders is not primarily associated with liquidity trading, this negative relation cannot be attributed solely to these groups providing increased liquidity.

Overall, these results strongly support the conclusion that the activity of the less-informed general public is directly and strongly associated with higher volatility, but the volume of clearing members and other floor traders is not. Moreover, unexpected levels of volume, both higher and lower than normal, are more important in explaining volatility than are the expected levels. The other variables, although significant in some cases, do not materially affect the volatility-volume relation. The level of open interest is significant in three of the cases, but the lagged unexpected returns help explain volatility only for the MMI contract. The lagged volatilities and the number of trades are significant for only two of the five futures contracts. The analysis also shows that T-bonds have the largest number of significant coefficients over all trader categories. This indicates the importance of different types of traders in determining volatility for this highly liquid contract.

C. Intraday Volatility-Volume Relation

The volatility-volume relation for close-to-close returns discussed in the previous section does not include the volatility effects occurring within the day, and hence is not the best measure of daily volatility in relation to daily volume. Panels B and C of Table II use the Garman–Klass (1980) and high-low measures of (intraday) volatility to examine this aspect of the volatility-volume relation.

For the high-low model, the general public's volume is always more important than either the clearing member volume or the other-floor-trader volume variables, except for T-notes. For this model 16 of the 20 coefficients are significant and positive for the general public. Clearing members have seven significant coefficients and other floor traders have eight, and the signs are almost equally distributed between positive and negative. Most of the signs for the CTI3 variable (other floor traders) are negative. As with the close-to-close volatility, the unexpected variables are clearly the most important, with the general public's unexpected volume exhibiting the most significant coefficients and overall the largest t-values.[9] The relative impor-

[9] When we use total volume (expected and unexpected) rather than the category volume series, then the unexpected total volumes are significant for all 15 regressions for all volatility measures. The expected total volumes are significant for only three regressions. Hence, using total partitioned volume also shows the relative importance of the unexpected volume variable, but the use of total unpartitioned (no expected and unexpected) volume would "confound the information available," as originally suggested by Shalen (1993). The open interest variables are significant in only three cases. The number of trades are significant for all but the MMI regressions.

Table II

Regressions of Volatility on Expected and Unexpected Category Volume

This table compares volume and volatility for five futures contracts for two years of daily observations. Results are for regressions of volatility on clearing member (CTI2), other floor trader (CTI3), and general public (CTI4) expected and unexpected volume and change in open interest categories, number of trades, lagged volatilities, lagged returns, and daily dummies (not reported). An ARIMA (0,1,10) model calculates the expected volume values using the previous day's volume and the 10-day moving average of the change in volume. The unexpected volume is total volume minus expected volume. The open interest expected value is calculated from an ARIMA (0,0,10) model. The dependent volatility variable is based on the daily standard deviation, Garman–Klass (1980), and high-low measures of volatility. Volumes are in units of 1,000 contracts. Values below the regression coefficients are t-statistics. Test statistics for lagged coefficients are F-statistics for the hypothesis that the sum of the 10 coefficients is zero. For each series there are 528 observations. When missing observations are removed and observations are lost for the calculation of lagged variables, each series has at least 400 degrees of freedom. MMI is the Major Market Index.

Futures Market:	Silver	MMI	Munis	T-Notes	T-Bonds
Panel A: Return Standard Deviation					
Intercept	0.6267	0.9669	0.3128	0.2515	0.2798
	2.37*	3.34**	3.01**	2.71**	1.57
CTI2: Clearing member: Expected	−0.4330	−0.2313	0.1449	0.0019	−0.0213
	−0.74	−2.02*	1.91*	0.11	−3.88**
CTI2: Unexpected	−0.7378	0.0045	0.1622	−0.0019	−0.0106
	−1.62	0.05	2.82**	−0.18	−2.77**
CTI3: Other floor traders: Expected	−0.7564	−0.2577	−0.3974	−0.0341	0.0128
	−1.41	−0.97	−0.72	−0.97	1.62
CTI3: Unexpected	−0.6767	0.0231	0.2285	−0.0243	0.0159
	−2.55*	0.09	0.88	−1.45	2.87**
CTI4: General public: Expected	0.9893	0.2680	−0.0419	−0.0035	0.0110
	2.68**	3.39**	−0.67	−0.25	3.63**
CTI4: Unexpected	1.6685	0.3049	0.0387	0.0258	0.0085
	9.53**	3.78**	0.99	3.56**	3.53**
Expected open interest	−3.2381	−0.4463	−0.1996	−0.0174	0.0166
	−2.41*	−1.38	−1.24	−0.79	1.54
Unexpected open interest	0.2098	−0.2483	−0.0919	0.0058	0.0011
	0.94	−2.88**	2.10*	0.93	0.44
Number of trades	0.0002	−0.0002	0.0013	0.0016	0.0001
	1.25	−1.11	3.65**	6.00**	0.78
Sum of 10 lagged volatilities	0.4168	0.5527	0.0513	0.0175	0.1493
	4.23**	5.91**	0.38	0.15	0.96
Sum of 10 lagged unexpected	0.1902	−0.3461	−0.1468	0.0240	−0.2205
returns	1.52	−2.71**	−1.17	0.21	−1.84
Adjusted R^2	0.321	0.221	0.297	0.324	0.257
Panel B: Garman–Klass Volatility Measure					
Intercept	0.2348	−1.3645	−0.2763	−0.4485	−0.9465
	0.60	−0.29	−4.33**	−6.24**	−6.18**
CTI2: Clearing member: Expected	−0.9875	2.2504	0.0448	0.0243	−0.0145
	−1.08	1.05	0.99	2.14*	−4.21**
CTI2: Unexpected	−1.0576	−0.3618	−0.0222	0.0137	−0.0028
	−1.60	−0.23	−0.62	2.01*	−1.16
CTI3: Other floor traders: Expected	−0.7893	−7.9787	−0.1046	−0.0438	0.0126
	−0.97	−1.52	−0.31	−1.99	2.45*

Table II—*Continued*

Futures Market:	Silver	MMI	Munis	T-Notes	T-Bonds
Panel B (*Continued*): Garman–Klass Volatility Measure					
CTI3: Unexpected	−0.7296	−12.5765	0.0752	−0.0223	0.0110
	−1.79	−2.69**	0.48	−2.08*	3.16**
CTI4: General public: Expected	1.4098	4.6525	0.0075	0.0235	0.0089
	2.47*	3.34**	0.20	2.51*	4.42**
CTI4: Unexpected	2.8184	5.2600	0.0803	0.0108	0.0050
	10.36**	3.36**	3.40**	2.32*	3.25**
Expected open interest	−2.3517	−10.2354	−0.0744	−0.0324	−0.0084
	−1.16	−1.59	−0.77	−2.28*	−1.23
Unexpected open interest	0.2458	−1.5516	0.0361	−0.0043	0.0012
	0.72	−0.91	1.36	−1.14	0.71
Number of trades	0.0010	−0.0102	0.0019	0.0018	0.0006
	4.08**	−2.41*	8.14**	10.94**	5.80**
Sum of 10 lagged volatilities	0.5741	0.3752	0.1046	−0.0509	0.1747
	7.55**	4.10**	1.29	−0.65	1.80
Sum of 10 lagged unexpected returns	0.3124	−13.4226	−0.0355	0.0789	−0.0117
	1.63	−4.56**	−0.47	1.11	−0.16
Adjusted R^2	0.448	0.297	0.628	0.676	0.629
Panel C: High-Low Volatility Measure					
Intercept	0.5624	0.3802	0.1822	−0.0324	−0.2315
	2.70**	0.86	3.25**	−0.53	−2.19*
CTI2: Clearing member: Expected	−0.1364	0.0588	0.0699	0.0509	−0.0130
	−0.33	0.32	1.70	4.31**	−4.36**
CTI2: Unexpected	−0.2366	−0.0148	0.0725	0.0127	−0.0037
	−0.78	−0.11	2.23*	1.93*	−1.78
CTI3: Other floor traders: Expected	−0.4136	−0.4832	−0.3419	−0.0693	0.0083
	−1.10	−1.09	−1.11	−3.12**	1.92
CTI3: Unexpected	−0.3425	−0.8478	−0.0141	−0.0227	0.0078
	−1.80*	−2.14*	−0.10	−2.15*	2.61**
CTI4: General public: Expected	0.4899	0.2910	−0.0239	0.0072	0.0081
	1.85	2.41*	−0.70	0.79	4.56**
CTI4: Unexpected	1.2257	0.8095	0.0543	0.0130	0.0081
	9.74**	6.12**	2.49*	2.83**	6.14**
Expected open interest	−0.7397	−0.8844	−0.0816	−0.0109	0.0008
	−0.79	−1.61	−0.93	−0.77	0.13
Unexpected open interest	0.1051	−0.0828	0.0159	0.0070	0.0023
	0.66	−0.57	0.67	1.90	1.59
Number of trades	0.0005	−0.0004	0.0023	0.0021	0.0004
	4.18**	−1.16	9.79**	12.50**	4.30**
Sum of 10 lagged volatilities	0.6261	0.7123	0.1070	0.0425	0.3802
	8.40**	11.61**	1.30	0.59	4.07**
Sum of 10 lagged unexpected returns	0.1814	−1.0979	−0.0802	0.0063	−0.0508
	2.01*	−4.25**	−1.16	0.09	−0.81
Adjusted R^2	0.452	0.529	0.684	0.720	0.676

*, ** Significant at the 5 percent level and at the 1 percent level or greater, respectively.

tance of the unexpected volume variables over expected volume for all sets of results supports the hypothesis that traders who lack information about order flow and pit dynamics are unable to distinguish the liquidity demand of large hedgers from the volume associated with changes in fundamental value.

The open interest variables are significant in only one of 20 cases, and the lagged returns are only significant for the MMI contract and the silver high-low formulation (three of 20 cases).[10] The lagged volatilities are significant in five of the 10 cases, but the number of trades is significant in nine of the 10 cases. Our findings support Harris's (1987) suggestion that the number of trades represents an important variable in the volatility-volume relation.

Interestingly, refitting the model without the number of trades causes the lagged volatilities to be significant in all 10 cases, suggesting that these variables may be imperfect proxies for one another. Moreover, the t-values for the lagged volatilities are always smaller when we include the number of trades. This illustrates the importance of the number of trades in the model and implies that lagged volatility may be less important than past studies suggest. We note that six of the seven cases in which lagged volatility is significant (for all three formulations) are for silver and the MMI contract, the least liquid of the contracts.[11] Also, the correlation between volume and the number of trades for stocks given in Jones, Kaul, and Lipson (1994b) ranges from 0.613 to 0.643 across capitalization groups. Our corresponding correlations are 0.336 (silver), 0.848 (MMI), 0.793 (munis), 0.797 (T-notes), and 0.702 (T-bonds).

Our results differ from the stock market tests of Jones et al. (1994b), who show that the volatility-volume relation is actually a volatility-number of trades relation and that volume has no explanatory power. The volume-number of trades relation in our results show a high correlation (0.70 to 0.85 for the more liquid contracts) between these variables.

When we include CTI1 in the analysis then (across all three volatility measures) 17 of the 30 CTI1 coefficients are significant, and 11 of these are negative. Hence, pure floor traders (scalpers) tend to reduce volatility, since they take the opposite position of other traders—that is, CTI1 traders pro-

[10] Eliminating the crash effect for the MMI contract (from October 15 to October 28) reduces the R^2 values, especially for the Garman–Klass (1980) formulation; moreover, the lagged returns remain significant. Separating the MMI contract into pre-crash and post-crash series decreases the R^2 values for each of the three measures of volatility, often substantially, but it does remove the lagged returns as a significant variable. Limit days for T-bonds/T-notes due to the stock market crash were removed from the database for the days when volume was adversely affected.

[11] The effects of the bid-ask spread and lack of liquidity are examined by calculating Roll's (1984) bid-ask estimator for the silver contract using all transactions prices for selected days. The average estimated bid-ask spread is 0.74 cents with a (daily) standard deviation of 0.19 (all spread estimates are positive). The average transaction price change is 0.46 cents, with 61 percent of the price changes being 0.50 cents, and fewer than five percent of the changes are greater than 0.50 cents. The noise created by the bid-ask spread would have the greatest effect on the high and low prices. Applying the above numbers to the high-low measure for silver reduces this range by 8.2 percent and creates a variability of 4.1 percent for the range. However, because the volatility-volume results for silver are consistent with those of the liquid contracts, any effect of the bid-ask spread seems to be negligible. The bid-ask spread would have a much smaller effect on more liquid contracts. Measures of volatility using the open and/or close prices would be affected even less by the spread, since daily open and close prices use the median price of the first/last minute of trading (a committee sets the closing price when there is insufficient liquidity). These daily closing prices are the data used by other researchers.

vide short-term liquidity. When we use four (three) CTI variables, the number of significant coefficients are 8 (12), 13 (10), and 22 (23) for CTI2, CTI3, and CTI4, respectively. The general public remains as the most important variable, with all 22 of its significant coefficients being positive. The coefficients for the other variables remain mixed in sign. There are two additional positive, significant coefficients for CTI3 and one less for CTI2 for the four variable results compared to the results presented here.

D. The Model Fit and Directional Volatility Results

We examine the explanatory power of several volatility-volume models in Table III. The adjusted R^2 values for the standard deviation approach using the complete model (all activity variables) in Panel A are similar to the values reported by Bessembinder and Seguin (1993), although they are higher here for T-bonds using category volumes. The adjusted R^2 values for the intraday volatility measures with the CTI categories in Panels B and C, ranging from 30 percent for the MMI (Garman–Klass (1980)) to 72 percent for T-notes, are substantially higher than both the values for the close-to-close volatility model and the values reported by other researchers for intraday measures of the volatility-volume relation. Our adjusted R^2 results using three CTI categories are significantly higher than the majority of contracts—including silver—studied by Cornell (1981), who uses a five-day averaging window of volume in the regression equation. Our results also demonstrate a stronger explanatory relation than those of Chang and Schachter (1997) and Grammatikos and Saunders (1986), who use high-low and Garman–Klass variance estimators, respectively. When we use all four category variables, then the adjusted R^2 results are only zero to two percent higher than when we use only the CTI2, CTI3, and CTI4 variables for all volatility formulations, with one case having an improvement of four percent.

Table III also provides a comparison of the explanatory power for our category volume model to simpler models. We label the category volume model as the "complete model with CTI categories" in the middle set of columns of Table III. The "complete model with total volume" omits the breakdown into CTI volumes, and the simple models use only total or category volume as independent variables, without any additional variables.

The CTI complete model shows an increase in R^2 of up to seven percent over the total volume complete model, although in most cases the improvement is five percent or less. The similarity in R^2 values between total volume and CTI volume complete models is due to the correlation of 0.94 between CTI4 (the general public), the group that dominates the positive volatility-volume relation, and total volume. However, comparing the complete model to the simple model shows a dramatic improvement of 15 to 48 percent (with an average of 27 percent) for total volume and 9 to 45 percent (and an average of 23 percent) for CTI volume for the intraday volatility measures. The typical improvement for the standard deviation formulation is a more modest 5 to 10 percent (17 percent for the MMI contract). Thus, the inclusion of

Table III

R^2 Values for Regressions of Volatility on Volume for Different Models and Measures of Volatility

This table shows volume on volatility regressions for five futures contracts for two years of daily observations. This table presents a comparison of adjusted R^2 values for simple and complete models of volatility on volume. The simple model uses only volume (without partitioning into expected and unexpected categories). The complete model includes expected and unexpected volumes, changes in open interest categories, number of trades, lagged volatilities, lagged returns, and daily dummies. The "total volume" column employs only expected and unexpected total volumes, with the "CTI categories" model using expected and unexpected volumes for clearing members, other floor traders, and general public traders. The complete model as shown is first estimated without a direction dummy variable and then is reestimated with a dummy variable (direction dummy model). The dummy indicates increasing or decreasing volatility. An ARIMA (0,1,10) model calculates the expected volume values using the previous day's volume and the 10-day moving average of the change in volume. The unexpected volume is total volume minus expected volume. The dependent volatility variable is based on the daily standard deviation, Garman–Klass (1980), and high-low measures of volatility. MMI is the Major Market Index.

	Simple Model		Complete Model		Direction Dummy Model	
	Total Volume	CTI Categories	Total Volume	CTI Categories	Total Volume	CTI Categories
Panel A: Standard Deviation						
Silver	0.200	0.301	0.251	0.321	0.567	0.538
MMI	0.019	0.048	0.192	0.221	0.575	0.477
Munis	0.195	0.222	0.288	0.297	0.536	0.523
T-notes	0.214	0.211	0.318	0.324	0.517	0.552
T-bonds	0.095	0.185	0.196	0.257	0.538	0.480
Panel B: Garman–Klass						
Silver	0.242	0.352	0.399	0.448	0.505	0.547
MMI	0.003	0.049	0.273	0.297	0.296	0.314
Munis	0.374	0.412	0.621	0.628	0.648	0.654
T-notes	0.413	0.422	0.662	0.676	0.672	0.685
T-bonds	0.289	0.431	0.590	0.629	0.620	0.652
Panel C: High-Low						
Silver	0.237	0.315	0.419	0.452	0.665	0.680
MMI	0.017	0.080	0.503	0.529	0.591	0.607
Munis	0.435	0.464	0.679	0.684	0.747	0.748
T-notes	0.463	0.474	0.705	0.720	0.760	0.777
T-bonds	0.337	0.477	0.635	0.676	0.763	0.787

factors such as lagged volatilities and the number of trades (and, for the MMI contract, the lagged returns) has a pronounced effect on the proportion of the variability of volatility that can be explained by our models.

The last two columns in Table III show the results after adding a dummy variable that is set to one when volatility increases from the previous day and zero otherwise. This variable allows for a nonlinear change in the dispersion of beliefs when markets are "noisy"—that is, the volatility-volume relation appears to strengthen when volatility increases. When the dummy variable is added to the standard deviation formulation, R^2 values typically increase by 20 percent or more. Using the high-low measure of volatility, the increase in R^2 is 6 to 23 percent for CTI category volume and 6 to 24 percent for total volume. The increase for the Garman–Klass (1980) measure is only 1 to 3 percent (except for silver), suggesting that the direction measure adds little to explain the fit of the Garman–Klass results. Coefficients on this variable are positive and highly significant in every regression. Moreover, the importance of the activity variables is similar to that found in the Table II results. In particular, the general public and the unexpected components of the volume variables remain the most important factors affecting volatility.[12]

The methodology for this model assumes that the errors are normal. Misspecification errors may occur if normality does not hold. However, only a few equations have nonnormal errors. We test all models reported here and find that the errors are significantly nonnormal in only nine of 90 regressions. Only three of the nonnormal equations use the CTI category volumes emphasized in this paper. The other six occur when we use only total volume. Five of the nonnormalities are for T-notes and muni bonds and three are for T-bonds. Six of the nine use the high-low formulation (including all three of the nonnormal CTI equations), two use Garman–Klass, and one uses the standard deviation formulation. Fifteen of the equations that use the Schwartz-criterion-determined optimal lag results (not shown here), rather than the inclusive value of 10 discussed here, exhibit nonnormal errors.

IV. Conclusions

An important new finding that emerges from our study is that the positive volatility-volume relation is determined by the general public. We associate the influence of the general public on volatility to their distance from the futures trading pit. Their distance creates a lack of private, semifundamental information, which in turn creates a greater dispersion of beliefs. This finding is consistent with the Harris and Raviv (1993) and Shalen (1993) models, in which groups with more disagreement cause a stronger volatility-volume relation.

Moreover, the relation between clearing members and other floor traders with volatility is often negative. This suggests that information about futures pit trading and order flow from trading activities may actually help reduce risk and therefore enhance the value of holding a seat.

[12] In fact, when we add the direction dummies, the unexpected variables are significant for 25 of 45 CTI coefficients, but the expected variables are significant for only 16 of the 45 coefficients. Both the number of significant CTI coefficients and the proportion of positive and negative significant coefficients remain almost identical to the nondirectional results. Only four of 90 coefficients change sign, and none of these are significant. All of the directional dummy coefficients are highly significant and an additional seven lagged volatility coefficients are significant, as compared to the nondirectional results.

We show that when the high-low intraday volatility measure is used, models that incorporate trader type, number of trades, and lagged volatility can explain as much as 72 percent of the variability in volatility. Further, adding a dummy variable to identify increasing or decreasing volatility improves the explanatory power of the model.

We also find that the unexpected volume series (changes in volume) for the general public is consistently more important than the expected volume series (normal level of volume) in explaining volatility. This supports the hypothesis that traders who lack information about order flow and pit dynamics are unable to distinguish liquidity demand from fundamental value change.

In associating the general public with increases in volatility, our results are consistent with those of Jones, Kaul, and Lipson (1994a), who find that public, rather than private, information is the major source of short-term volatility. They also support the hypothesis in the noise literature (see DeLong, Shleifer, Summers, and Waldmann (1990a, 1991)) that noise traders are associated with excess volatility and that they can dominate a market. Data sets, such as the Liquidity Data Bank, that make available trading volume by type of trader, can help researchers investigate these types of issues, and may provide answers for questions such as which type of trader is more consistently profitable in the futures markets.

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