VOLUME RELATIONSHIPS AMONG TYPES OF TRADERS IN THE FINANCIAL FUTURES MARKETS

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INTRODUCTION AND TOPIC IMPORTANCE

Trading volume reflects the supply and demand for a financial instrument. As such, the recent research into volume as a measure of information liquidity needs, and speculative demand (including noise trading) raises important issues concerning the structure of markets. The associated literature examines potential factors, such as information, that drive the volatility–volume relationship. Moreover, futures markets participants view volume as an important determinant of the strength of a market move, thereby influencing the behavior of prices.

Information has long been recognized as a key element in price formation [to illustrate, see Bookstaber and Pomerantz (1989) and Ross (1989) for information models] for example, French and Roll (1986) link private information to stock market price movements. Volume is the conduit through which information is impounded into price changes. Stra-

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tegic models, such as the one developed by Admati and Pfleiderer (1988), show how traders (liquidity, informed, and uninformed) adjust the timing of their trades to hide informed volume or to minimize their cost. Models such as those developed by Brock and Kleidon (1992) associate the intraday U-shaped pattern of volume, volatility and bid–ask spreads to portfolio rebalancing. Shalen (1993) adds the realistic aspect of the dispersion of beliefs as the major reason for volume and price variability.

The objective of this research is to examine the trading volume of four different *types of traders* over time to compare the roles of different types of market participants and to examine the linkages among these groups. Hence, these results will potentially enhance knowledge of the relationship between volume and information. Using a unique database from the Chicago Board of Trade, this study analyzes the time-series and cross-correlation volume relationships among these four trading groups and examines the differences in their trading behavior. The time-series analysis of volume shows that 2–5 days of historical volume contribute information that helps to explain current volume for each group. Moreover, the findings of earlier researchers and information concerning position turnover are used to impute differing trading actions for each group, supporting the hypothesis that the groups trade because of different types of information or motives.

Analysis of volume by group provides evidence concerning which group trades most frequently in each of five futures contracts, tests the stability of the volume series, and examines the relationships among the volume categories. The results show that

1. After scalpers, the general public trades most frequently.
2. Volume series are nonnormal, but are stationary over the time period in question.
3. Lagged volume tends to provide significant information about current volume for 2–4 days, then decays quickly for most futures contracts.
4. There is a strong coincident correlation between pairs of groups.

The differences in the trading behavior of the four groups are attributed to differences in their beliefs and trading motives. In fact, the data suggest that one group may be leading the other groups, which would support the "sequential arrival of information" hypothesis proposed by Copeland (1976, 1977). Interpreting that hypothesis for futures markets implies that information generates volume and then speculators trade on the resultant price and volume information.

MODELS OF VOLUME AND TRADER BEHAVIOR

Pure and Sequential Information Models

Grossman and Stiglitz (1980) provide a theoretical argument that markets and prices play an important role in conveying information from the informed to the uninformed. Their Conjecture 7 states that markets will be thinner when the percentage of informed individuals is either very low or very high. Their work would suggest a different mix of traders on low-volume contracts than would be observed for high-volume contracts.

Huffman (1992) constructs a model where different types of traders have access to different information sets. He shows that the volume of trade can be highly correlated with the information conveyed in prices. Wang (1994) also develops a model of competitive stock trading with both informed and uninformed traders. He examines the joint behavior of returns and volume to identify the underlying heterogeneity of investors, finding that volume is related to the activity of each trading group in the market at any given time, with the different groups possessing different degrees of information.

The sequential arrival of information model is developed and extended by Copeland (1976, 1977), Jennings and Barry (1983), Jennings, Starks, and Fellingham (1981), and Morse (1980). This model assumes that information is disseminated sequentially from one group to another. This movement of information creates numerous price changes while also creating volume.

Dispersion of Beliefs and Information

Jang and Ro (1989) develop a general equilibrium model that illustrates how volume reacts to information. In particular, they show that the volume reaction to a release of information is an increasing function of the dispersion of belief changes caused by the information. Moreover, Jang and Ro show that price change is *insufficient* to determine the information content of trades; that is, that volume is also needed. Blume, Easley, and O'Hara (1994) also link volume to the dispersion of beliefs, and show that the sequences of volume (and prices) can be informative. They link the quality (precision) of information to volume.

Shalen (1993) and Harris and Raviv (1993) provide detailed dispersion of beliefs models. In particular, Shalen develops a noisy rational expectations model showing that the degree of the dispersion of beliefs is a measure of the additional expected volume associated with noisy information. The model is based on the liquidity trading of hedgers masquerading as informed trading, creating a dispersion of expectations. These expectations are then acted upon by speculators. Thus, speculators confuse the liquidity demand of hedgers with true information and therefore overreact to changes in liquidity demand. Also important in Shalen's model is that the expected volume of trade depends on both the current *and* preceding rounds of belief dispersions. This suggests that volume in uninformed trader categories is likely to increase in response to an increase in liquidity trading, and the relationship should persist over one or more lags.

Overall, trading volume has become an important element in the literature. Therefore, examining the characteristics of volume, especially across types of traders, should provide a better understanding of the possible link to information and liquidity, as well as to the interrelationships among different trading groups.

Trader Categories and Inferences about Trading Motives

Silber (1984) examines the role of scalpers in futures markets. He defines scalpers as a specialized group of floor traders who act as market makers by providing liquidity to the pit. According to Silber's (and the traditional) definition, scalpers trade on liquidity demand rather than on information. The price of liquidity is the spread on limit orders, with the average scalper profit being less than the spread because of break-even trades and losses on holding positions. Silber says that scalpers will hold inventory only as long as is necessary to turn a profit, only briefly deviating from zero inventory positions, whereas speculators hold on to positions until anticipated price moves are realized, generally for much longer time periods. His empirical results confirm this difference in holding periods between scalpers and hedgers or speculators.

Kuserk and Locke (1993) identify scalpers as floor traders who trade for their own accounts, buying at the bid and selling at the ask price. Scalpers also can make income from speculative trades. In fact, the Manaster and Mann (1991) results show that active speculative position taking is undertaken by market makers.

TRADER MOTIVATION AND DATA

Information and Basic Trading Motives

Building on the work of Silber and Kuserk and Locke, as well as the information and dispersion of beliefs models, this study imputes different motives and different types of trading behavior to the trader categories identified by futures exchanges. Further, some trader categories are expected to possess fundamental information about the direction of prices and the demand of other traders, whereas other groups will attempt to discover this information by examining prices and volume; this is labeled *technical* (speculative) trading. This latter group frequently interprets noise as information. Consequently, the models of speculative and fundamental (hedging) behavior (differences of opinion/beliefs), such as those by Harris and Raviv (1993) and Shalen (1993), are appropriate for futures markets.

If temporal relationships among trading volumes of different groups exist, then the sequential arrival of information hypothesis may be correct. An interpretation of this hypothesis for futures markets is that a group with fundamental information (based on analysis and/or market demand information) creates volume for that group, which in turn causes other groups to trade based on the new information apparent in prices and volume. For example, public information via government announcements results in changes in futures positions due to differing beliefs concerning the importance of that information. If such trades create imbalances in relative prices (say between futures and cash instruments, or futures and options on futures), then arbitragers will trade on these imbalances. Technical traders may then trade based purely on the observed volume of the other groups. One representation of the trading response to information, consistent with this hypothesis, is presented in Figure 1. The next subsection examines how volume data by type of trader are used to provide insights into these relationships.

Data

This study separates total futures volume into four types of traders.

CTI1: volume for the floor traders's own account or an account which (s)he controls, that is, locals.

CTI2: volume for the clearing member's house account, that is, commercial clearing members.

CTI3: volume for floor traders executing trades for other floor traders or an account controlled by other such traders. Includes arbitrage and spread trading between futures and options on futures contracts.

CTI4: members filling orders for the public.

These groups should show different patterns of volume because of their differing trading motives. The next subsection examines the key components of these motives.

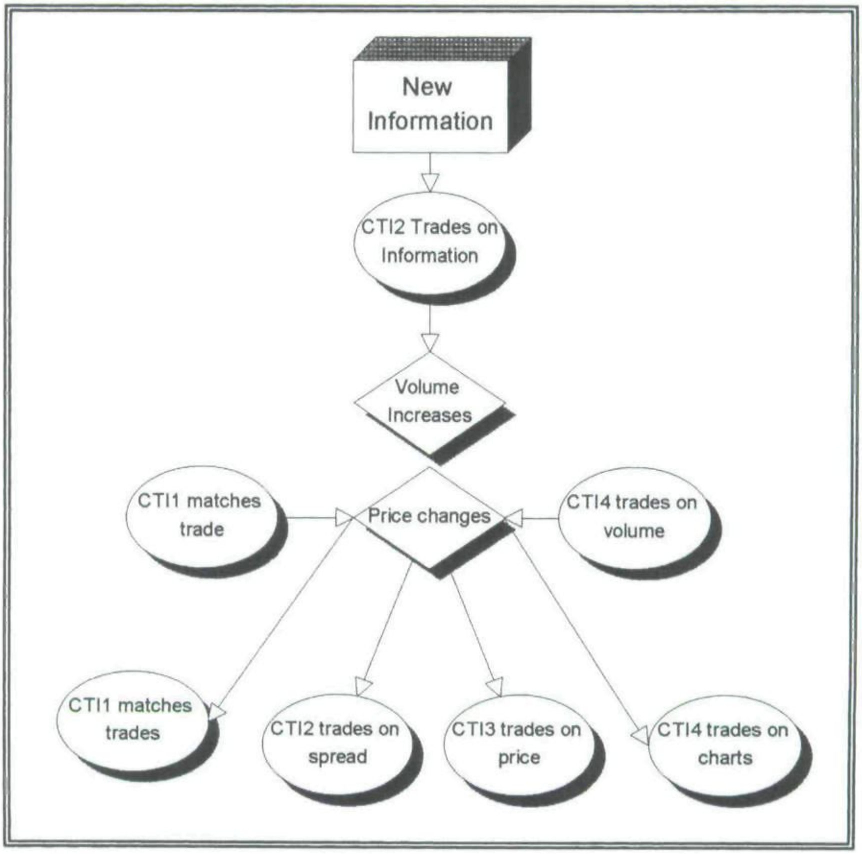

FIGURE 1
Hypothetical trading response to information release.

The volume data span 2 years for five financial futures contracts: silver, the MMI stock index, Muni bonds, 10-year T-notes, and T-bond contracts, all of which trade on the Chicago Board of Trade. Daily volume data are employed in the analysis by using the expiration month with the highest open interest in order to concentrate on the most active contract month.[1] Consequently, the interest rate contracts are rolled over near the first of the expiration month. The MMI contract is rolled over at expiration. The largest open interest for silver does not follow a nearby pattern,

[1]Using the contract with the largest *volume* as the selection criteria creates the unwanted feature of continually skipping from one expiration month to another for the less liquid futures contracts. Moreover, using the largest open interest on a daily basis avoids using a contract during its expiration period. Alternatively, lumping all expirations together could obscure the true relationships for the most important contract month. In any case, the expiration month with the largest open interest almost always equals the largest volume contract for the day in question.

because the December contract often has the largest open interest from summer until the end of November.

Individual Group Motivation

According to Kuserk and Locke (1993), scalpers make up the vast majority of the traders identified as CTI1. Scalpers trade on bid–ask spreads and hold positions for very short time intervals. Scalpers perform the important function of adding short-term liquidity to the market. Thus, when other groups trade, this group will increase its volume to accommodate the greater supply/demand of the market. Such trading is not motivated by fundamental information.

Commercial clearing members (CTI2) are primarily hedgers and fundamental traders, although they also take positions based on their knowledge of supply and demand of their customers. These traders have the resources to evaluate the underlying factors and information affecting the market and their impact on future prices. They have a *relatively* homogeneous set of beliefs and therefore trade within a relatively small range of prices. Information, especially information created by in-house analysis, influences their trading behavior to the extent their trading is not purely liquidity based or affected by the information gathered from client trading activities. As hedgers, they use futures as a means to rebalance their cash portfolios to reduce risk via a short hedge or to lock in the future price of a cash purchase via a long hedge. Hedgers' demands are based on a combination of changes in beliefs, risk aversion, and liquidity requirements. For example, if the commercial provides over-the-counter products to their customers, then futures typically are employed to dynamically hedge this position. In addition, commercial traders have fundamental information based on the supply and demand dynamics of the market garnered from trades of their customers, allowing commercials to make more informed decisions than speculators typically make. Hence, their trades are associated with superior analysis rather than with factual private macroeconomic knowledge, and they tend to take positions for longer time periods than other types of traders.

The motivations of CTI3 traders are driven by a mixture of several different types of trades. Those floor traders who are not in the pit, but who wish to trade, can act through another floor trader, and the resulting trade will be posted in the CTI3 category. This can occur when a day trader (short-term speculator) is not on the floor or is in another pit. In addition, spreaders between futures markets and arbitragers between options on futures and futures contracts will trade through colleagues in other pits, creating a CTI3 trade.

CTI4, the general public, often makes trading decisions based on the volume and price changes created by other groups. These speculators (including managed futures funds) attempt to profit by inferring when new information enters the market, which often is based on their interpretation from charts of past prices or from other technical trading models. However, according to Shalen (1993), these traders are likely to observe the liquidity trading of hedgers and scalpers and incorrectly assume that it is based on information.[2] Thus, CTI4 can be defined as primarily composed of speculators. Because of their approach to trading, these speculators tend to turn their positions over quickly.[3]

The motivations and trading behaviors attributed to the CTI categories here are consistent with the findings of Silber (1984) and Kuserk and Locke (1993), as well as earlier studies by Working (1967, 1977). However, they are not directly observable. For further support of these inferences concerning trading behavior, the number of days it takes for commercials and noncommercials to turn over their open interest positions is calculated in the next section.

Examining volume by the CTI categories provides information on the relative proportions of trades by group for each futures market and shows the differences in trading behavior of the four trader categories. In addition, statistical analysis of the relationships among the category volume series provides insights into the link between volume and the flow of information through the market. It is anticipated that volume differs across trading groups. The analytical results presented here are consistent with this hypothesis. Further, asynchronous changes in volume as traders enter and leave the market should be expected. If CTI4 traders (speculators) respond to the trades of the commercials (CTI2) then the changes in trading volume of speculators may lag those of other groups slightly. Arbitragers, an important part of the CTI3 group, should trade independently of other groups. There is some support for this conclusion.

[2]For a more in-depth discussion of the motivations and types of information possessed by the *CTI* traders see Daigler and Wiley (1997). They also show that the general public is the group who drives the volatility in the futures markets, which is consistent with noise generated by speculation. Such noise is consistent with the noise literature. For example, see Black (1986) and DeLong, Shleifer, Summers, and Waldmann (1990, 1991). In particular, DeLong et al (1990) examine how the unpredictability of noise traders' beliefs creates excess risk, causing prices to diverge significantly from fundamental values. However, DeLong et al claim that noise traders can earn higher expected returns than rational investors despite their negative influences.

[3]At times larger commercial hedgers may wish to hide their trades by funneling them through brokers, creating a CTI4 trade. However, evidence suggests this is done relatively infrequently.

TABLE I

Open Interest and Turnover of Futures Contracts by Type of Trader

Panel A: Open Interest Positions of Traders

		Percentage of Total Open Interest Held by Group		
	Total Open Interest	*Large Commercials*	*Large Noncommercials*	*Large Spreaders*
Silver	25,404	33.6	9.0	5.1
MMI	12,705	52.7	19.4	3.2
Munis	26,500	53.3	18.5	1.7
T-notes	137,697	70.4	8.7	2.4
T-bonds	564,759	57.1	7.3	4.8

Panel B. Turnover of Positions

	Average Daily Volume		*No. of Days until all Open Interest is Turned Over**	
	Commercials	*Noncommercials*	*Commercials*	*Noncommercials*
Silver	122	682	213.3	10.2
MMI	2,646	3,097	6.3	2.0
Munis	1,742	2,769	20.5	4.5
T-notes	6,350	8,373	36.2	3.4
T-bonds	47,040	86,808	17.9	1.2

*Nonreporting open interest is allocated to commercials and noncommercials based on the ratio of the large trader open interest. Open interest values are long plus short positions. Thus, it takes two trades (volume) for one open interest position to be turned over.

POSITION TURNOVER

Table I uses the Commodity Futures Trading Commission's (CFTC) "Commitments of Traders" to identify the commercial and noncommercial traders open interest, plus it uses the daily trading activity of the commercials (CTI2s) and general public (CTI4s) to calculate how quickly positions are turned over. The "Commitments of Traders" is a survey conducted monthly by the CFTC of the open interest positions of all large traders (those who have the minimum number of contracts for the given futures); holders of these contracts are required to identify position size, how many contracts are long and short for their positions, and whether they have a commercial position. It is likely that most commercial positions are related to hedging, whereas noncommercial positions are likely to be speculative positions.[4] Panel A in Table I shows the average monthly

[4]The CFTC and the volume data will not be exactly the same groups, because the CFTC open interest data only surveys large traders, and because the definitions of commercial vary somewhat between

open interest and the percentage of open interest controlled by commercials and noncommercials.[5] The average daily volume for the commercials and general public (from the CTI database) and the resultant number of days it takes to turn over the open interest are reported in Panel B. The turnover is reported by using the actual positions of large traders and then assigning the nonreporting positions in the same ratio as the large traders; the latter is a common procedure when allocating open interest positions.

Table I shows that on average, commercials keep their positions significantly longer than do the noncommercials. In particular, for the interest-rate contracts it takes 17.9–36.2 trading days for the commercials to turn over their open interest positions, whereas it only takes 1.2–4.5 days for the noncommercials to turn their positions over. The long average holding period for the commercials is consistent with hedging and/or fundamental positions, whereas the short holding period for the noncommercials is consistent with shorter-term speculative positions. Alternatively, one may view the trading behavior of commercials to be intrinsically different than the trading behavior of the general public.[6]

VOLUME RESULTS

Table II provides descriptive statistics concerning the mean, standard deviation, skewness, and kurtosis for each volume series of each futures contract. Tests for skewness and kurtosis are significant across all categories, indicating the distributions are nonnormal. The means and standard deviations are clearly different across trading groups within a single contract, as well as across different futures contracts.[7]

Table III shows summary statistics on the proportion of total volume traded for each CTI category for the five futures contracts. The relative importance of each CTI category and the differing proportions across contracts provide interesting results. Marketmaker (scalper) volume (CTI1) is 45% to 55% for all contracts. Kuserk and Locke (1993) found that on the Chicago Mercantile Exchange the average scalper volume was 40% of all volume, and the Manaster and Mann (1996) data show scalpers

the two types of data. However, they are much more similar than they are different, allowing a reasonable estimate of turnover of positions.

[5]It takes two contracts of volume to create and then close one side of an open interest position.

[6]For an additional discussion of these concepts see Witherspoon (1993, p. 487) and Black (1986).

[7]In order to determine whether the underlying volume categories possess different means, the nonparametric Mann–Whitney test is employed. Due to the nonnormality of the volume samples, this nonparametric test has greater validity than a t test. The Mann–Whitney test confirms that the observed differences in means are significant in every case.

TABLE II

Descriptive Statistics of Daily Volume by Type of Trader

Series	*Obs*	*Mean*	*Std Error*	*Skewness*	*Kurtosis*
			Panel A—Silver		
CTI1	502	852.5	700.5	1.53**	2.95*
CTI2	502	121.7	225.8	3.04**	10.69*
CTI3	502	198.4	350.6	3.46**	17.13*
CTI4	502	681.6	604.4	1.82**	4.62*
CTITOT	502	1,854.4	1,597.8	1.66**	3.95*
			Panel B—MMI		
CTI1	507	6,813.4	3,699.9	1.03**	1.59*
CTI2	507	2,645.8	1,438.6	1.03**	1.40*
CTI3	507	971.5	534.9	0.86**	0.42*
CTI4	507	3,097.2	2,075.9	1.35**	1.77**
CTITOT	507	13,528.1	7,327.6	1.05**	1.27**
			Panel C—Munis		
CTI1	507	4,722.5	2,643.3	1.01**	0.92**
CTI2	507	1,742.1	1,156.7	1.68**	3.35**
CTI3	507	130.8	138.8	2.12**	5.45**
CTI4	507	2,769.1	1,680.7	1.91**	5.71**
CTITOT	507	9,364.6	5,347.0	1.38**	2.44**
			Panel D—T-notes		
CTI1	507	14,356.8	7,023.7	1.54**	4.67**
CTI2	507	6,349.6	3,154.1	1.58**	5.76**
CTI3	507	2,180.6	1.456.1	2.33**	8.86**
CTI4	507	8,373.2	4,241.3	1.71**	5.46**
CTITOT	507	31,260.4	14,733.3	1.65**	5.49**
			Panel E—T-bonds		
CTI1	503	245,825.9	98,817.8	0.50**	0.84**
CTI2	503	59,142.3	24,794.7	0.72**	1.06**
CTI3	503	31,483.6	13,060.6	1.01**	2.08**
CTI4	503	106,539.2	44,279.1	0.74**	1.12**
CTITOT	503	442,991.1	177,086.8	0.59**	1.00**

**Indicates significantly different from 0 at the 0.01 level

TABLE III

Average Trader Category Volume as a Percentage of Total Volume

Series	*CTI1*	*CTI2*	*CTI3*	*CTI4*	*Total Avg. Volume*
Silver	45.98%	6.56%	10.70%	36.76%	1,854
MMI	50.37%	19.56%	7.18%	22.89%	13,528
Munis	50.43%	18.60%	1.40%	29.57%	9,364
T-notes	45.93%	20.31%	6.98%	26.79%	31,260
T-bonds	55.49%	13.35%	7.11%	24.05%	442,991

volume to be 47% of total volume. Thus, market makers participate in a large proportion of the trades with nonscalpers. Although market makers also trade among themselves in these contracts, such trading is not sufficient to artificially increase trading volume—as is sometimes suggested as the reason for the large volume in futures markets.

The less-liquid silver futures contract has lower CTI2 proportions than CTI3 proportions (which is the reverse of the more liquid futures contracts), and silver has the highest proportions of all contracts for the CTI3 and CTI4 categories. The other four futures contracts have a large proportion of commercial (CTI2) volume relative to CTI3 activity, although T-bond futures have a lower percentage of commercial volume than do the MMI, Munis, and T-note contracts. Finally, the general public (CTI4) accounts for a larger share of trading volume than commercial traders (CTI2) for all five futures contracts. The results in Table III are consistent with Grossman and Stiglitz (1980), whose work indicates that the relative importance of different types of traders will differ between low and high volume contracts.

Table IV presents the results for stationarity testing and the number of lags contributing significant information to an autoregressive model of each volume series. These tests are performed on each individual trader category for each of the futures contracts. The lag columns employ the Schwarz criterion to determine the optimal number of lags contributing information without overfitting the model. The results show that the typical lag length is 2–4 days. This suggests that important information does exist in the trading volume of recent past days; however, information in the volume series decays quickly. The importance of past volume shown by the optimal lag results is consistent with Shalen's dispersion of beliefs model, which says that current volume is related to the current and past dispersions of information or beliefs. These results also suggest that technical analysis using volume may be useful in determining near-term supply and demand.

Augmented Dickey–Fuller and Phillips–Perron (PP) tests are used to examine the stationarity of the volume series.[8] Stationarity implies a constant mean and finite variance over time. The null hypothesis of nonstationarity is rejected for every group in every futures contract. Thus, the series are stationary (after considering the deterministic time trend). Therefore, it is appropriate to examine the behavior of volume in levels rather than applying a differencing transformation.

Table V shows Pearson's product-moment correlation coefficients and Spearman's rho coefficients between category volume pairs. These

[8]The Phillips–Perron test has less stringent restrictions on the error terms.

TABLE IV

Augmented Dickey–Fuller and Phillips–Perron Tests for Volume Stationarity

	CTI1			CTI2			CTI3			CTI4			CTITOT		
Series	*Lags*	*ADF*	*PP*	*Lags*	*ADF*	*PP*	*Lags*	*ADF*	*PP*	*Lags*	*ADF*	*PP*	*Lags*	*ADF*	*PP*
Silver	1	−10.21	−13.02	9	−3.99	−16.70	1	−11.96	−15.70	4	−5.90	−14.30	1	−10.27	−13.62
MMI	5	−3.58	−7.10	2	−6.43	−10.11	5	−4.04	−9.63	3	−3.57	−5.92	3	−4.08	−6.71
Munis	4	−4.57	−11.56	4	−4.25	−9.90	4	−5.78	−17.75	4	−4.96	−11.71	4	−4.48	−10.80
T-note	4	−5.42	−14.00	4	−5.26	−14.71	4	−6.43	−16.03	4	−5.55	−14.59	4	−5.37	−14.12
T-bond	4	−5.42	−14.00	2	−8.80	−14.42	3	−7.15	−15.76	3	−6.60	−14.38	3	−6.33	−13.88

Augmented Dickey–Fuller (ADF) tests and Phillips–Perron (PP) tests for stationarity. All regressions include a deterministic trend and incorporate the number of lags determined to be significant by the Schwarz Bayesian Information Criterion. All results are significant at the 0.01 level, indicating stationarity.

TABLE V

Nonparametric Tests of Relationships between Trader Category Pairs

Series	*Test*	*CTI1/ CTI2*	*CTI1/ CTI3*	*CTI1/ CTI4*	*CTI2/ CTI3*	*CTI2/ CTI4*	*CTI3/ CTI4*
Silver	Pearson	0.8510	0.5948	0.9311	0.3994	0.8156	0.5500
	Spearman	0.5935	0.5600	0.9241	0.6870	0.5280	0.5538
MMI	Pearson	0.8519	0.8504	0.8834	0.7887	0.7404	0.7643
	Spearman	0.8835	0.8660	0.8528	0.8306	0.7284	0.7060
Munis	Pearson	0.8431	0.5998	0.9013	0.5571	0.8641	0.5971
	Spearman	0.8150	0.6261	0.9080	0.4927	0.7988	0.5609
T-notes	Pearson	0.8694	0.6947	0.8713	0.6065	0.7693	0.5572
	Spearman	0.8249	0.6500	0.8363	0.5503	0.6835	0.5361
T-bonds	Pearson	0.9564	0.8549	0.9560	0.8476	0.9286	0.8652
	Spearman	0.9474	0.8353	0.9544	0.8168	0.9173	0.8110

Two nonparametric tests of correlation and concordance between trader category pairs. Pearson's product moment correlation r is defined as

$$r = \frac{\sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y})}{\left(\sum_{i=1}^{n} (X_i - \bar{X})^2 \sum_{i=1}^{n} (Y_i - \bar{Y})^2\right)^{1/2}}$$

where $\bar{X}$ and $\bar{Y}$ are the sample means. Although there is no format test of significance for this statistic, positive correlations indicate a direct relationship between two trading categories. The closer the statistic is to 1.0, the stronger the relationship. Spearman's ρ is calculated with the use of the same formula as Pearson's product moment, but the values of X and Y are replaced by their relative ranks within each series, and $\bar{X}$ and $\bar{Y}$ are the means of the ranks. All statistics are significant at the 0.01 level (critical value 0.1145).

tests, robust to nonnormality are used to see whether trading volume is likely to increase simultaneously across pairs of trading categories, or whether their trading behavior is independent. Both types of correlation coefficients are calculated for each pair of trader categories for each futures contract. Six possible pairs are examined per correlation coefficient for each futures contract. If the Pearson correlation coefficient is close to 1.0 then one can infer that the category volumes move together. Close pairings may suggest that groups use information to reach similar conclusions, while coefficients substantially less than 1.0 suggest that traders are responding either to different sources of information or to the same source with alternative interpretations.

The results in Table V suggest that the relationship among trader categories is partly a *function of the contract being traded.* The strongest relationships among trader categories are observed in the T-bond contract, and the weakest relationships are for the CTI3 category with the other three groups for the silver, Muni, and T-note contracts. For all contracts, the strongest relationships among groups occur in the CTI1/

CTI2 and CTI1/CTI4 pairs, which are logical relationships because they involve marketmaker activity. The role of scalpers as liquidity providers seems clear from this test. Overall, for any single futures contract, the volumes for most trader categories are highly related, but group CTI3 appears to be influenced by different factors. The different effects related to CTI3 are logical, because this group includes spreads between different futures contracts and/or futures and options contracts.

Also shown in Table V are the results of Spearman's Rho, a test for rank concordance. For this test two pairs of observations are concordant if both members of one observation are larger than their respective members of the other observations, that is, both members of one observation possess the same rank. This is a stronger test of the relationship between two series than the correlation test.[9] In Table V all trader pairs are significantly related. Moreover, the relationships among trader categories are similar to those defined by the Pearson statistic. The important CTI2/CTI4 correlations vary from 0.528 (silver) to 0.917 (T-bonds). The other contracts are below 0.8, indicating a strong but imperfect relationship. Thus, consistent with Shalen and other models, speculators volume does exhibit a highly significant relationship with hedger volume. However, the correlations suggest that there may be some differences in information utilization across groups CTI2, CTI3, and CTI4.

CROSS-CORRELATION RELATIONSHIPS

For a better understanding of whether volume differences across trader groups are simultaneous or reactive, the cross correlations between paired groups over leading and lagging days are examined next. Figures 2–6 show the cross correlations between each pair of CTI volume categories for the five futures contracts, with the use of lags from -20 to $+20$ days. For example, the CTI1-2 relationship provides the cross correlations between CTI1 on day 0 and CTI2, with CTI2 measured from 20 days before (negative days) to 20 days after (positive days) the value of CTI1 on day 0. The cross correlations between CTI1 (scalpers) and the other CTI categories for day 0 generally are large and highly significant [as previously shown in Table IV and here via Figures 2–6(a)]. Within the CTI1 group, the strongest relationships to other CTI categories for day 0 are for the MMI, T-notes, and T-bonds (typically above 0.8); silver has substantially lower cross correlations for CTI1-2 and CTI1-3.[10] All of the cross cor-

[9]Kendall's tau is also employed as a measure of concordance. However, for sample sizes greater than 60 the two statistics produce nearly identical results.

[10]Except for silver, these parametric correlations for day 0 are almost identical to the nonparametric correlations in Table IV. The low liquidity for silver is the likely cause for the differences found between Table IV and Figure 2.

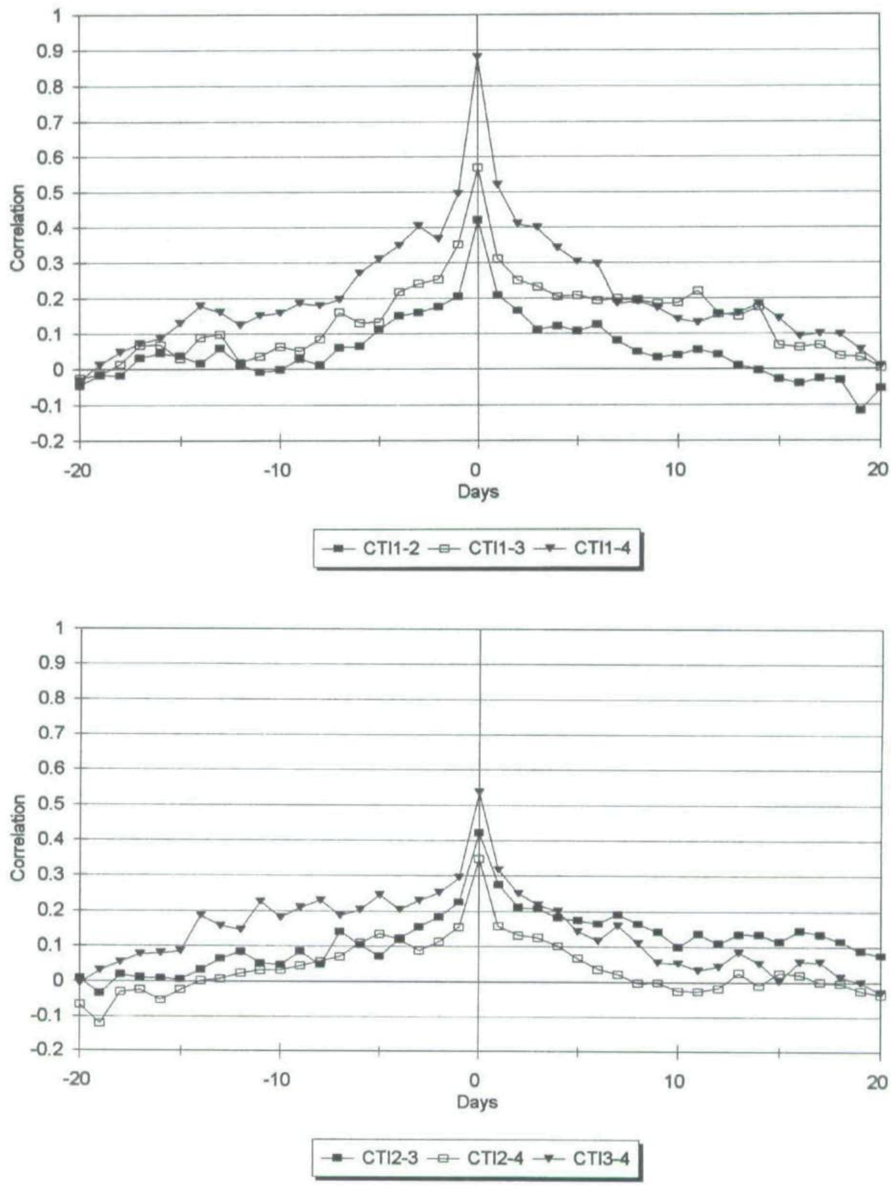

FIGURE 2
Cross correlations for (a) CTI1: Silver and (b) CTI2–CTI4: Silver.

relations *decline quickly* as one moves away from day 0, with the correlations falling below 0.5 after several days (*one* day for T-notes and T-bonds). By day ± 10 the correlations are near or below 0.3. Silver and T-notes eventually tend toward a correlation of 0, whereas while the cross

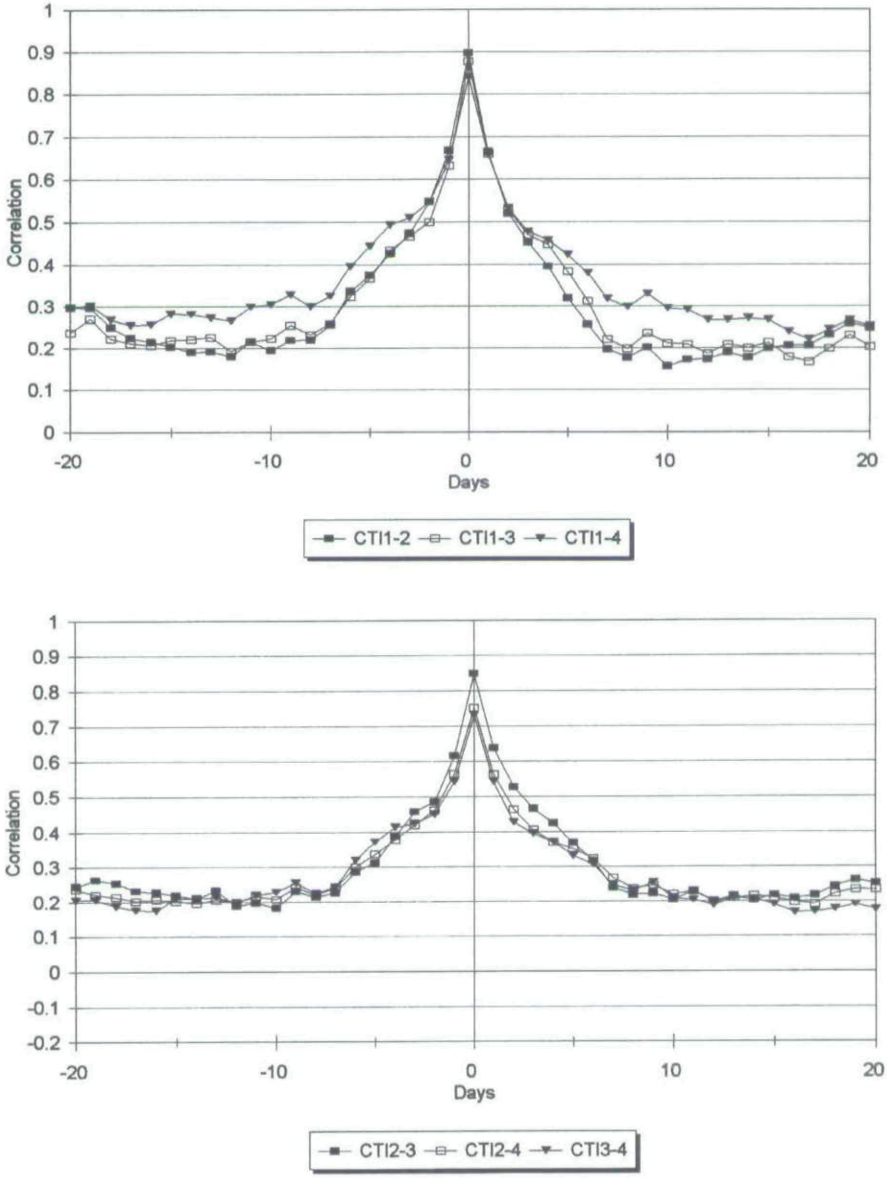

FIGURE 3
Cross correlations for (a) CTI1: MMI and (b) CTI2–CTI4: MMI.

correlations for the MMI and Munis do not completely damp out within the ±20 day range.

The cross correlations between the CTI2, CTI3, and CTI4 pairs [Figures 2(b)–6(b)] generally are lower than those with CTI1, although the correlations at day 0 are relatively large for the MMI, T-note, and T-bond

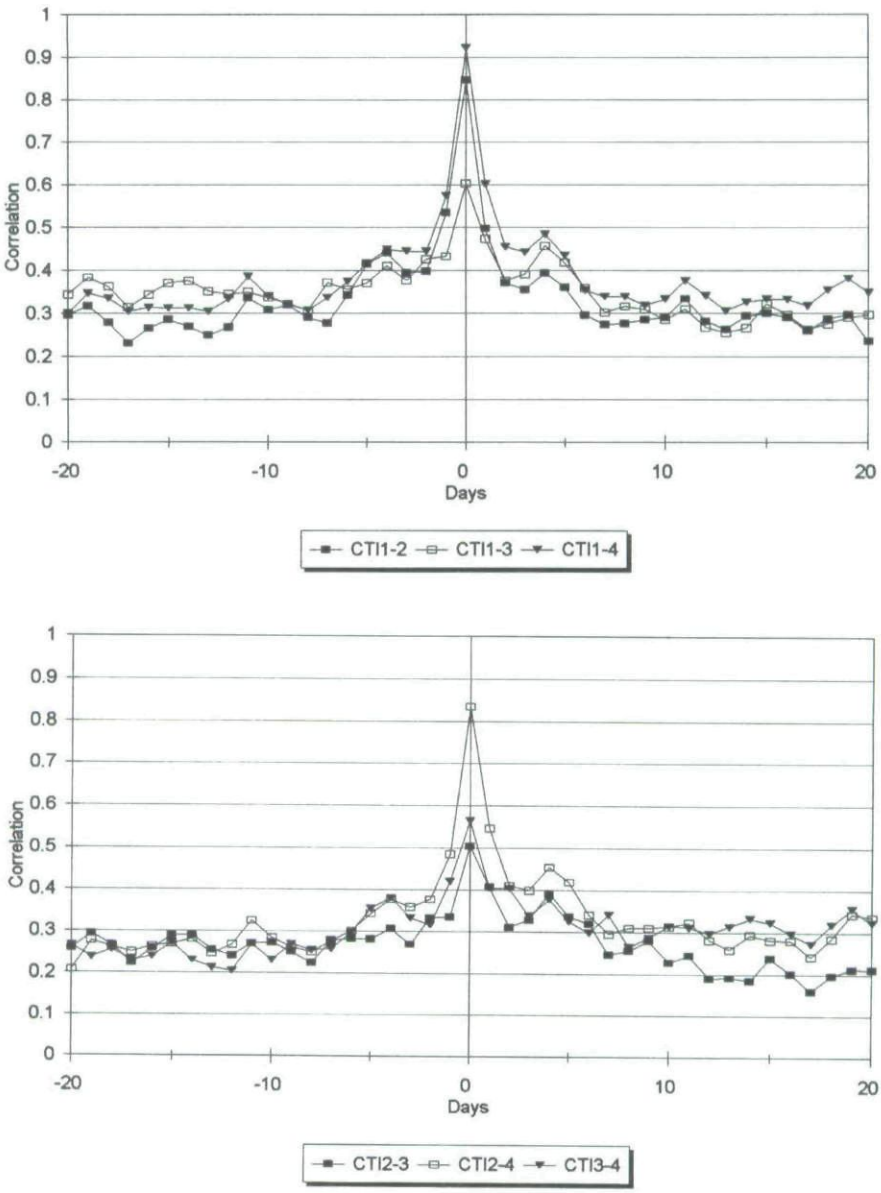

FIGURE 4
Cross correlations for (a) CTI1: munis and (b) CTI2–CTI4: munis.

contracts. These cross correlations have a similar pattern to those found for CTI1, but the correlation values typically are somewhat lower at equivalent lead/lag days. In general, the relatively high cross correlations for some nonzero leads suggests that a degree of predictability of category volume may be possible for some contracts, particularly 1 or 2 days ahead.

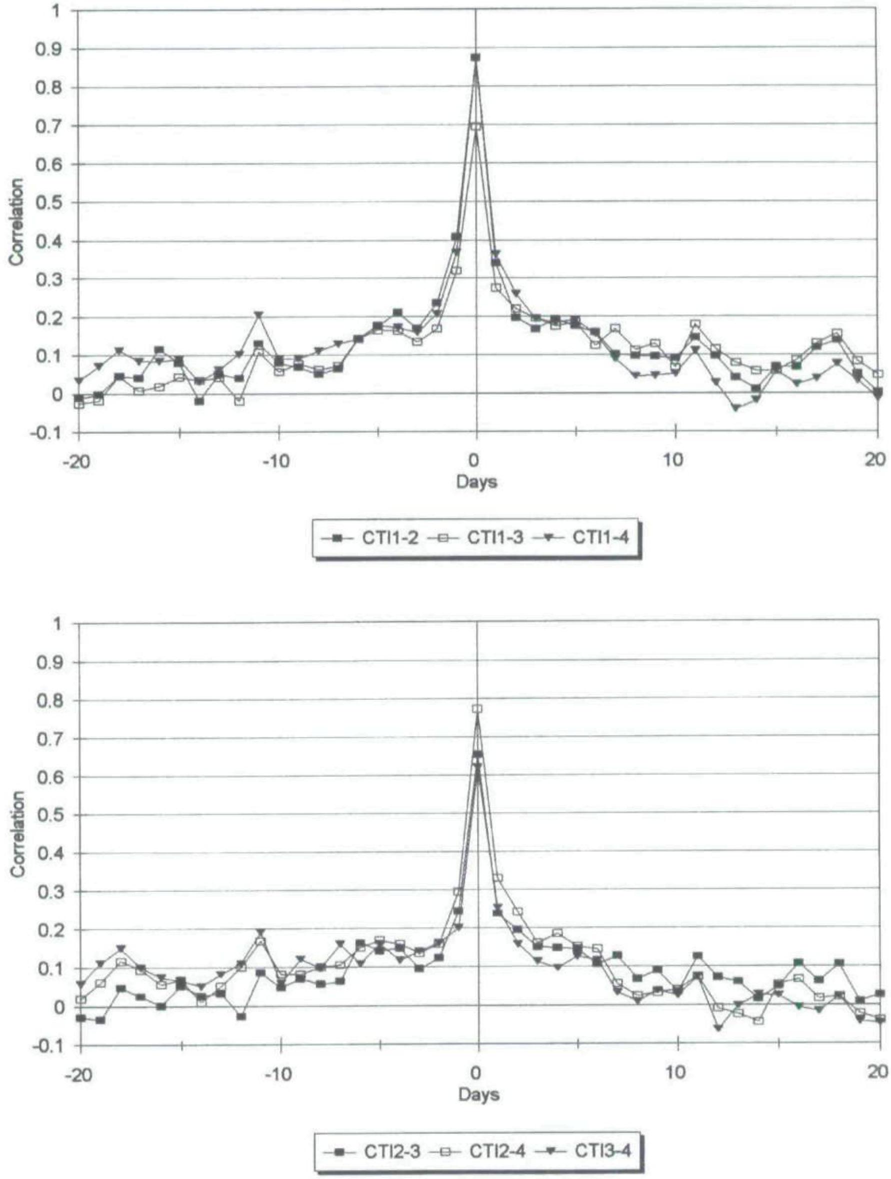

FIGURE 5
Cross correlations for (a) CTI1: T-notes and (b) CTI2–CTI4: T-notes.

Ljung–Box Q statistics are significant at the 0.001 level for all groups/all contracts for the 10- and 20-day windows. The significance of the cross correlations at nonzero lags implies that there may be reactive behavior across trading groups; that is, speculators may trade in response to the observed trades of hedgers.

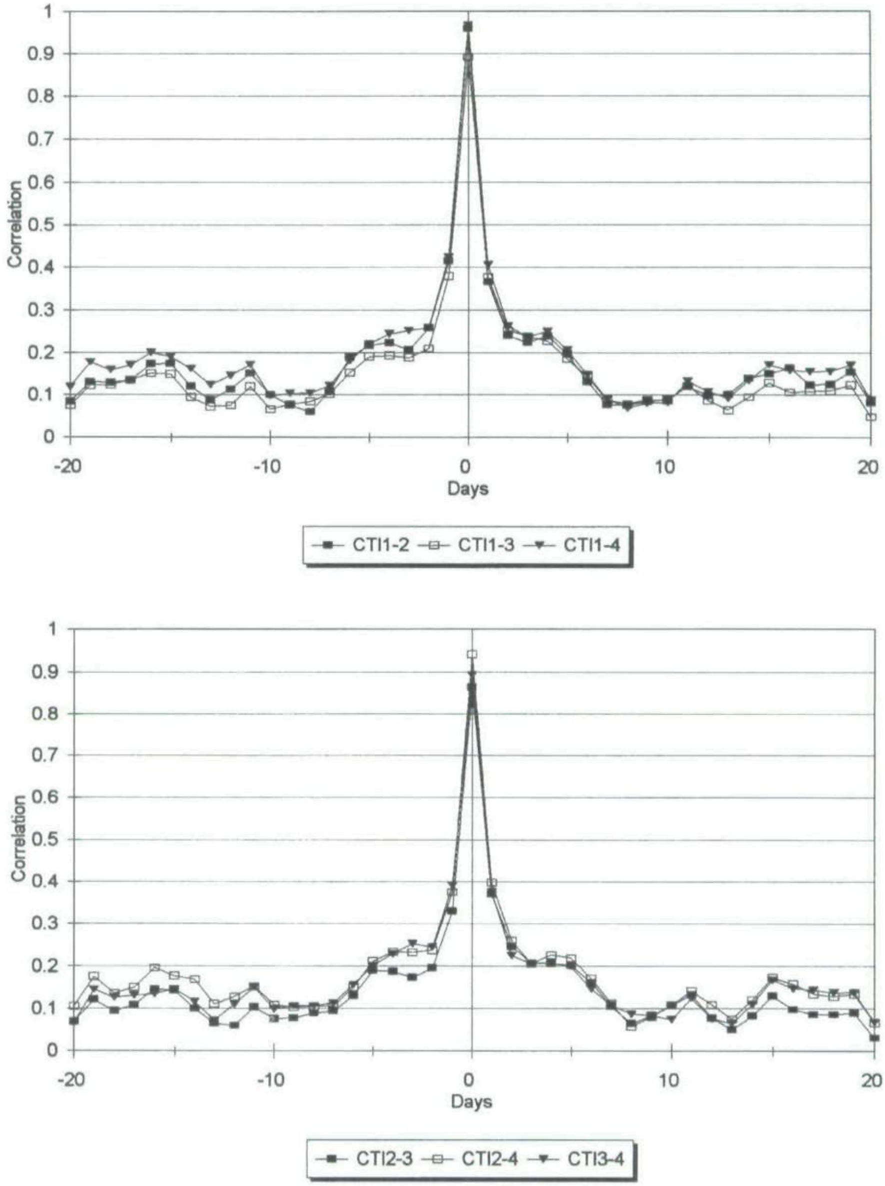

FIGURE 6
Cross correlations for (a) CTI1: T-bonds and (b) CTI2–CTI4: T-bonds.

The fast decay of these lead–lag correlations is consistent with the Schwarz criterion results in Table III. Thus, relationships among categories persist for several lags, and then often die out quickly. Most interesting is the slower-decaying function for the MMI and Muni contracts—especially for the CTI2/4 relationship—compared to the faster decay and lower cross correlations after 1 day for the more liquid T-note and T-bond contracts. This suggests that contract liquidity has an effect on the speed with which traders can trade in response to the observed trades of others.[11]

CONCLUSIONS AND IMPLICATIONS

The results of this study provide a unique view of (a) which group(s) dominate trading on the financial futures markets, (b) the characteristics of the volume series, and (c) the volume relationships among the types of traders. Scalpers provide the short-term liquidity for the markets, and the general public is more active than commercial traders. The group volume series are stationary, and serial correlation in volume generally persists for fewer than five days. The coincident relationships among groups are strong, but lagged cross correlations decay quickly, especially for the more liquid contracts. Thus, any information about prior days trading volumes, both within and across trader categories, typically is useful for only a few days. However, statistically significant cross correlations still exist between paired groups after several lags, especially for the MMI and Muni contracts. These results are consistent with the sequential arrival of information hypothesis; that is, that one group trades on information provided by another group.

The results shown here cannot prove who has information or whether the general public trades on the increased volume of commercials. On the other hand, the observed volume information and cross correlations are consistent with many of the aspects of Shalen's dispersion of beliefs model. Moreover, the volume characteristics of the four types of traders examined in this article suggest several interesting questions for future research. In particular, using volume by type of trader may provide insights as to whether each group has similar volume distributions, as to the existence of lead–lag relationships between paired group volumes (does one group obtain perceived information from another group), and as to the relationship between volume and volatility.

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[11]However, the very low volume silver contract has cross correlations below 0.10 after several days for the CTI2/4 category association.

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