The Journal of Financial Research • Vol. XXXI, No. 3 • Pages 247–270 • Fall 2008

INFORMATION AND NOISE IN FINANCIAL MARKETS: EVIDENCE FROM THE E-MINI INDEX FUTURES

Alexander Kurov
West Virginia University

Abstract

I examine the informational contributions and effects on transitory volatility of trades initiated by different types of traders in three actively traded index futures markets. The results show that trades initiated by exchange member firms account for more than 60% of price discovery during the trading day. These institutional trades appear to be more informative than trades of individual exchange members or off-exchange traders. I also find that off-exchange traders introduce more noise into the prices than do exchange members. My findings provide new evidence on the role of different types of traders in the price formation process.

JEL Classification: G10, G14

I. Introduction

I examine the roles of different types of traders in the price discovery process and their effect on transitory volatility in index futures markets. First, I analyze the relative information content of trades initiated by individual exchange members, exchange member firms, and off-exchange traders in three E-mini index futures markets. Kurov and Lasser (2004) use Hasbrouck's (1995) information share approach to show that individual exchange members make larger informational contributions than off-exchange traders or clearing member firms. Consistent with Kurov and Lasser, I find that the informational contributions of off-exchange traders are relatively small. However, the results also show that exchange member firms contribute significantly more to price discovery than do individual members or off-exchange traders. Trades of exchange member firms appear to be more informative than trades of other traders. These results show that institutional traders now play a dominant informational role in electronic index futures markets.

I thank Lou Abarcar, Arabinda Basistha, Robert Daigler (the referee), Upinder Dhillon, Grigori Erenburg, Gerald Gay (the editor), Andrew Harvey, Dennis Lasser, Peter Locke, Stephen Satchell, and Robert Webb for helpful comments and suggestions. Special thanks to Alessio Sancetta for many helpful discussions. I am also grateful to the staff of the Commodity Futures Trading Commission for their help in obtaining the data. Any remaining errors are my own.

Second, I analyze the effect of trading activity initiated by different types of futures traders on transitory volatility. I find that trades initiated by off-exchange traders are positively related to transitory volatility, whereas the similar relation for individual and institutional exchange member trades is negative. This finding, supported by results from a decomposition of transitory volatility, shows that off-exchange traders introduce more noise into the prices than do exchange members.

My analysis of transitory volatility extends the work of Daigler and Wiley (1999), who show that the positive volume–volatility relation is determined by off-exchange traders, whereas trading volumes of exchange clearing members tend to have a negative relation with volatility. They conclude that off-exchange traders are more likely to trade on noise and cause excess volatility than exchange members, who are more informed. However, when returns are sampled at daily intervals, as in Daigler and Wiley, the estimated volatility may be dominated by information flow.[1] Therefore, the results of Daigler and Wiley may be explained by differential contributions of trader types to the price discovery process rather than by noise trading. My results are broadly consistent with theirs but provide direct evidence on the relation between noise volatility and trading activity classified by trader type.

I consider the S&P 500, NASDAQ-100, and Russell 2000 E-mini index futures markets for several reasons. First, the trader type classifications available in futures trade data allow studying the effects of proprietary trading by exchange member firms. Such institutional traders play an important intermediary role on many securities exchanges. Second, the E-mini contracts trade on an electronic limit order market that is similar to the trading systems that now account for most of the securities trading around the world. Therefore, my results can be generalized to other electronic markets. Finally, an analysis of the E-mini markets allows examining the after-hours trading period, when the major stock markets are closed.

Overall, my findings contribute to a better understanding of the roles of different types of traders in price formation. I find that off-exchange traders account for a disproportional share of noise, whereas institutional traders introduce less noise and bring more information to the market. Institutional traders are better able to exploit their informational advantages in anonymous electronic trading than in traditional floor markets. Therefore, given the continuing transition to electronic trading in the U.S. securities markets, we can expect an increasing informational dominance of institutions across a variety of markets.

[1]Speight, McMillan, and Ap Gwilym (2000) examine the component structure of volatility in the FTSE 100 index futures market. They show that the transitory component dominates the volatility process over intraday frequencies, whereas the long-run component dominates over daily and lower frequencies. They argue that the long-run volatility component is determined by information flow, and the transitory component may be induced by trading activity.

II. Literature Review

Price Formation and Noise Trading

Price information is perhaps the single most important product of financial markets. Informative prices reflect the underlying asset values and contribute to efficient allocation of resources in the economy. French and Roll (1986) provide evidence that private information, which is reflected in the prices through the trading of informed traders, accounts for most of the information affecting stock prices. Security prices contain information, but they also contain noise induced by market frictions and noise trading. Grossman and Stiglitz (1980) and Kyle (1985) offer a theoretical rationale for existence of noise trading by showing that noise is necessary for informed traders to profit from their information. Noise traders facilitate the price-discovery process by providing camouflage to informed traders. As a result, both information and noise end up reflected in the security prices.

The interplay between informed and noise traders in the price formation process has been extensively studied theoretically but remains underexplored in empirical work. One difficulty in addressing this issue empirically is that, as Black (1986) notes, it is unclear who is informed and who is a noise trader. Information about the type of trader behind a particular transaction is generally not publicly available. Existing equity market research (e.g., Chakravarty 2001) provides evidence that institutions, as opposed to retail traders, are informed traders. The apparent informational advantage of institutional traders may stem from their superior analytical resources or privileged access to information. Kurov and Lasser (2004) and Anand and Subrahmanyam (2008) analyze how trading activity of different types of financial traders affects the price formation. My article contributes to this strand of literature.

Information Asymmetry in Futures Markets

I examine informational contributions of different trader types in index futures markets. Therefore, it is important to consider the possible nature of information asymmetry in the context of my study. Microstructure theories usually assume that informed traders are insiders with private information about the firm's cash flows. Security-specific private information is unlikely to be an important source of information asymmetry in index futures markets because such information becomes diversified in broad market indexes (e.g., Subrahmanyam 1991). However, Chan (1992) argues that index futures represent a low-cost instrument for trading on marketwide information. Some traders are likely to be better than others at interpreting public information or simply able to react to macroeconomic information faster than other traders. For example, Erenburg, Kurov, and Lasser (2006) show that exchange locals trading the E-mini S&P 500 index futures make profitable trades immediately after scheduled macroeconomic announcements.

Existing research shows that trading based on heterogeneous interpretation of public information plays an important role in price discovery in markets where private information in its common sense does not exist. For example, Evans and Lyons (2002) and Brandt and Kavajecz (2004) find that order flow contains information that determines foreign exchange rates and U.S. Treasury bond yields. Studies of futures markets by Kurov and Lasser (2004) and Locke and Onayev (2007) show that access to customer order flow ensures that exchange locals have an informational advantage over off-floor traders.

Volume–Volatility Relation

Numerous empirical studies document a positive contemporaneous correlation between trading volume and price volatility. Several theories explain the volume-volatility relation. The mixture of distributions hypothesis (MDH) was originally proposed by Clark (1973) and extended by Epps and Epps (1976) and Tauchen and Pitts (1983). According to MDH, both price volatility and trading volume are driven by the unobserved information arrival process.

In the strategic trading model of Admati and Pfleiderer (1988), contemporaneous correlation between volume and volatility arises from behavior of liquidity traders who bunch their trades in time to reduce their losses to informed traders. Informed traders find it optimal to trade more in intervals of high uninformed trading activity because this activity allows them to hide their trades. Their private information is impounded into the prices, leading to higher price volatility during periods of high trading activity.

I do not test a particular theoretical model. However, the model most closely related to my research is the noisy rational expectations model of a futures market developed by Shalen (1993). In this model hedgers trade for liquidity reasons and speculators attempt to extract information from observed price changes but are unable to distinguish between price changes caused by information and price changes caused by trades of hedgers. This confusion increases dispersion of expectations, leading to excess price volatility, increased trading volume, and contemporaneous correlation between volume and volatility. Daigler and Wiley (1999) provide empirical evidence supporting this model by showing that the volume–volatility relation in futures markets is driven by off-exchange traders.

III. Background and Hypotheses

Futures markets offer an excellent environment to analyze the effects of trader heterogeneity on price formation because of availability of data with trader type classifications. The three major types of traders identified in such data include individual exchange members, also called “locals”; exchange member firms making proprietary trades; and off-exchange traders. Exchange members act as intermediaries and de facto market makers (e.g., Chang and Locke 1996). They enjoy exclusive access to open outcry trading, as well as substantially lower trading and clearing fees. Such trading privileges are commonly justified by the role of these traders in providing liquidity.

The E-mini futures contracts trade on the GLOBEX electronic trading system operated by the Chicago Mercantile Exchange (CME). These contracts are sized at one-fifth of the respective floor-traded contracts. With combined average daily trading volumes exceeding 1 million contracts, the E-minis are perhaps the most successful contracts in the CME's history. CME local traders actively trade the E-mini futures. Some of these trades are made from GLOBEX terminals located in the equity quadrant on the CME floor. Kurov and Lasser (2004) show that trades initiated by locals are more informative than off-exchange initiated trades. They find that locals make well-timed trades in GLOBEX around large floor trades, suggesting that locals are able to use their access to the order flow information from the open outcry floor to take positions in the simultaneous electronic market. Kurov and Lasser argue that the resulting transfer of information from the floor to GLOBEX may contribute to the informational dominance of the E-mini futures documented by Hasbrouck (2003).

My analysis of GLOBEX transactions data shows that CME's member firms account for a large proportion of the E-mini trading activity. These large institutions trade primarily for hedging and speculative reasons. Information generated by in-house analysis, as well as analysis of the order flow of their customers, affects the trading strategies of these proprietary traders. Member firms have substantial analytical resources, a real-time access to information about the cash market, knowledge of customer order flow, and access to the trading floor. Large institutional traders also have the resources to develop and maintain algorithmic trading systems, which generate a growing share of trading activity in index futures markets.[2] Algorithmic trading systems reduce execution costs by minimizing the price impact of trades and can respond to electronic information from newswires much faster than human traders. These advantages are likely to ensure that exchange member firms are better informed relative to most off-exchange traders and individual exchange members.

Off-exchange traders are smaller institutions and retail customers of brokerage firms. These traders do not have direct access to the trading floor, have limited analytical resources, and often make trading decisions based on technical analysis (i.e., interpretation of recent price patterns and trading activity). Given their informational advantages, exchange members are likely to induce less

[2]Futures exchanges have been experiencing rapid growth in algorithmic trading. Algorithmic trading systems give institutional traders an advantage over retail traders ("Small traders face losing calculus," *Wall Street Journal,* February 21, 2007, p. E5).

transitory volatility and make larger contributions to price discovery than off-exchange traders. These considerations lead to the following hypotheses:

H1: Trades initiated by off-exchange traders are associated with higher transitory volatility and lower informational volatility than trades initiated by exchange members.

H2: Trades initiated by exchange members contribute more to price discovery than do off-exchange initiated trades.

IV. Data and Descriptive Statistics

I use transactions data obtained from the Commodity Futures Trading Commission (CFTC). For both sides of each trade, the data contain the trade date, order submission time and trade time to the nearest second, the contract month, buy/sell code, number of contracts traded, trade price, and customer type indicator (CTI). CTI ranges from 1 to 4 as follows: CTI 1 are local trades (i.e., trades initiated and executed by an individual member for his or her own account), CTI 2 are trades executed for a proprietary account of a member firm, CTI 3 are trades executed for a personal account of another individual member, and CTI 4 are trades executed for an account of any other trader.[3] CTI 4 trades originate from off-exchange traders. CTI 3 trades account for less than 2% of the trading activity and I combine them with CTI 1 trades into a single category for individual exchange members. My usage of the term "exchange members" refers to individual exchange members and member firms.

I examine 250 trading days from January 3, 2005, to December 30, 2005 and consider only the most actively traded expiration in each market for every trading day. Shortened preholiday days are removed from the sample. The summary statistics of my sample are given in Table 1. Trading in the E-mini futures is extremely active, with several trade executions per second on average. The open interest in the E-mini contracts is comparable to the daily trading volume, suggesting that most of the volume is generated by intraday speculative trading activity. Table 1 also shows trading activity statistics for after-hours trading.[4] The overall level of trading activity after hours is relatively low.

[3]In 2004, the U.S. futures exchanges adopted a harmonized set of CTI code definitions. Before this change in code definitions, CTI 2 was used only for proprietary accounts of clearing member firms. Based on the new definitions, which applied in 2005, orders of non-clearing-member firms, previously coded as CTI 4, were reclassified as CTI 2. Therefore, the new CTI code definitions allow a more accurate identification of institutional trades.

[4]After-hours trading starts at 4:30 p.m. and continues until 9:30 a.m. ET the following day. GLOBEX closes at 5:30 p.m. for a 30-minute maintenance period. I omit the 4:30–5:30 p.m. period to prevent the possible effect of the trading halt on model estimates.

TABLE 1. Summary Statistics.

	E-Mini S&P 500	E-Mini NASDAQ-100	E-Mini Russell 2000
Regular trading hours			
Mean number of trade executions per minute	235.3	124.2	140.9
Mean daily trading volume (contracts)	737,424	264,821	105,696
Mean execution size (contracts)	7.74	5.26	1.85
Median execution size (contracts)	2	2	1
After-hours trading			
Mean number of trade executions per minute	9.7	3.1	0.56
Mean daily trading volume (contracts)	49,059	13,243	1,017
Mean execution size (contracts)	5.42	4.54	1.96
Median execution size (contracts)	2	2	1
Mean open interest (contracts)	1,015,239	339,362	213,665

Note: The regular trading hours are from 9:30 a.m. to 4:15 p.m. ET. The after-hours period is from 6:00 p.m. to 9:30 a.m. ET the following day. The sample period is from January 3, 2005, to December 30, 2005.

I analyze trades initiated by individual exchange members, member firms, and off-exchange traders. Using initiated trades allows me to assign each trade to a specific trader type rather than to both counterparties in the trade, an approach used by Daigler and Wiley (1999). It is more appropriate to examine transitory volatility using initiated trades, which represent liquidity demands. Given that limit orders account for a significant proportion of order flow, a positive relation between the total trading volume of a particular trader type and volatility is also consistent with those traders supplying liquidity to other traders in high-volatility periods. Using initiated trades eliminates the potential for this alternative explanation of the results.

GLOBEX is a limit order market. Incoming market orders are executed immediately against the standing limit orders. My data set includes the order submission times for both sides of each trade. Because aggressive orders are executed immediately and limit orders tend to spend some time waiting for execution, comparing the submission times for the two sides of each trade allows identifying the initiating side. Specifically, I identify the initiating side by assuming that the order with the later submission time initiated the trade. About 99% of nonzero tick trades are classified identically by the order submission times and the tick rule, showing that the submission times can be used to classify trades accurately. When the submission times for both sides of the trade are the same, the trade is signed using the tick rule. More than 80% of all trades are zero-tick trades. Finucane (2000) shows that the tick rule is relatively inaccurate for zero-tick trades. Therefore, I remove trades that occurred on a zero tick and have the same reported submission times for both sides. These trades account for less than 14% of the total number of trades.

Table 2 shows proportions of the total trading volume and the total number of trades initiated by different trader types for both trading periods. During the

TABLE 2. Trading Activity Statistics for Trades Initiated by Individual Exchange Members (CTI 1 and 3), Exchange Member Firms (CTI 2), and Off-Exchange Traders (CTI 4).

	Regular Trading Hours			After-Hours Trading		
	CTI 1 & 3	CTI 2	CTI 4	CTI 1 & 3	CTI 2	CTI 4
E-mini S&P 500						
Distribution of number of trades						
Overall	17.4%	45.0%	37.5%	24.6%	29.9%	45.5%
Nonzero tick trades	12.2%	29.9%	58.0%	17.8%	22.9%	59.3%
Zero-tick trades	18.3%	47.6%	34.0%	25.4%	30.9%	43.7%
Distribution of trading volume	20.0%	48.7%	31.3%	24.4%	33.2%	42.4%
Average execution size (contracts)	8.88	8.38	6.47	5.39	6.01	5.05
E-mini NASDAQ-100						
Distribution of number of trades						
Overall	17.1%	57.1%	25.8%	23.5%	35.5%	41.1%
Nonzero tick trades	13.0%	43.6%	43.4%	20.3%	27.0%	52.7%
Zero-tick trades	17.5%	58.5%	24.0%	24.0%	37.0%	39.0%
Distribution of trading volume	18.8%	54.5%	26.7%	24.0%	37.1%	38.9%
Average execution size (contracts)	5.98	5.18	5.62	4.65	4.77	4.31
E-mini Russell 2000						
Distribution of number of trades						
Overall	11.4%	48.5%	40.1%	16.7%	28.6%	54.7%
Nonzero tick trades	10.0%	41.0%	49.0%	14.8%	25.1%	60.1%
Zero-tick trades	11.7%	50.5%	37.7%	18.2%	31.3%	50.5%
Distribution of trading volume	12.4%	50.1%	37.5%	18.3%	33.6%	48.1%
Average execution size (contracts)	2.04	1.93	1.75	2.15	2.30	1.72

Note: The regular trading hours are from 9:30 a.m. to 4:15 p.m. ET. The after-hours trading period is from 6:00 p.m. to 9:30 a.m. ET the following day. The sample period is from January 3, 2005, to December 30, 2005. Trades are classified by type of initiator using the reported GLOBEX order submission times. Trades with equal submission times for both sides are classified using the tick rule. Nonclassifiable trades (i.e., trades that occurred on a zero tick and have the same reported submission times for both sides) are removed.

trading day, trades for proprietary accounts of exchange member firms account for about half of the trading activity in all three E-mini markets. Exchange member firms account for a much lower percentage of the after-hours trading activity, with their share of trades ranging from about 29% for the E-mini Russell 2000 futures to about 35% in the E-mini NASDAQ-100 market. The lower proportion of trading activity generated by member firms after hours is consistent with existence of an institutional trading day tied to the normal exchange trading hours (e.g., Ferguson, Mann, and Schneck 1998). Individual exchange members and off-exchange traders also trade actively in both trading periods. In after-hours trading, off-exchange traders account for the largest share of trading activity.

Table 2 also reports the distribution of the number of zero-tick and non-zero-tick trades initiated by different trader types. In all three markets, individual and institutional exchange members account for a larger proportion of zero-tick trades than of price-changing trades. The relatively small proportions of price-changing trades initiated by exchange members show that exchange members use trading strategies that reduce the temporary price effect of their trades.

V. Empirical Tests and Results

Effect of Trading Activity on Transitory and Informational Volatility

To test my hypotheses, I use two complementary approaches: regression analysis and variance decomposition techniques. This subsection discusses the regression results for informational and transitory volatility. In subsections that follow I use variance decomposition techniques that directly attribute components of the informational and transitory volatility to trades initiated by different types of traders. This approach alleviates possible concerns about reverse causality in the volume–volatility relation. The two approaches provide consistent results.

Daigler and Wiley (1999) argue that their results are consistent with the notion that noise trading leads to excess volatility. However, the positive relation of the trading volume of off-exchange traders with volatility documented in their study is also consistent with a significant contribution of off-exchange traders to the price discovery process, that is, impounding new information into the prices. To distinguish between the effects of trading on informational and noise volatility, I look at the relation between these two distinct types of volatility and trading activity aggregated by type of trader. The high trading activity in the E-mini markets allows me to estimate informational and transitory volatility in intraday intervals using the Hasbrouck (1993) approach. I then regress these volatility estimates on trading activity variables to test Hypothesis 1. The security price is represented as:

$$p_t = m_t + s_t, \tag{1}$$

$$m_t = m_{t-1} + w_t, \tag{2}$$

where m_t is a random walk component or "efficient price" that is a conditional expectation of the security's terminal value, w_t are random walk innovations that reflect new information arrivals, and s_t is a stationary component that represents the pricing error (i.e., the difference between the actual trade price and the efficient price). The variance of the pricing error is a natural measure of transitory volatility, whereas the efficient price variance represents informational volatility.

Hasbrouck (1993) shows that the variance of the pricing error and the efficient price variance can be estimated using a vector autoregression (VAR) of returns and trades. The intuition for this approach is that it allows separating transitory effects of trades and price changes from permanent informational effects using impulse responses. I follow Hasbrouck's approach to estimate the variance of the pricing error and the efficient price variance for the regression tests. I begin by estimating a VAR using trade-by-trade data in each 15-minute interval. With extremely active trading in the E-mini markets, each 15-minute interval contains a sufficient number of observations to estimate the VAR, specified as follows:

$$\begin{bmatrix} r_t \\ \mathbf{x}_t \end{bmatrix} = \sum_{j=1}^{n} A_j \begin{bmatrix} r_{t-j} \\ \mathbf{x}_{t-j} \end{bmatrix} + \begin{bmatrix} v_{rt} \\ \mathbf{v}_{xt} \end{bmatrix}, \tag{3}$$

where r_t are trade-by-trade returns and $\mathbf{x}_t$ is a vector of three variables: (1) a signed trade variable (1 for buys and -1 for sells), (2) signed trade volume, and (3) signed square root of the trade volume. Therefore, the VAR includes four equations: an equation for transactions returns and three equations for signed trade variables. A_i are coefficient matrices and v_t are random disturbances with a covariance matrix cov(v).[5]

Hasbrouck (1993) shows that the pricing error in equation (1) can be represented as:

$$s_t = \sum_{j=0}^{\infty} \alpha_j v_{r,t-j} + \sum_{i=1}^{3} \sum_{j=0}^{\infty} \beta_{ij} v_{i,t-j}, \tag{4}$$

where the α and β coefficients are calculated using the vector moving average (VMA) coefficients, which are obtained using impulse responses, that is, by forecasting the VAR after a unit shock in one of the variables. Transitory volatility is estimated as:

$$\sigma_s^2 = \sum_{j=0}^{\infty} [\alpha_j \quad \beta_j] \operatorname{cov}(v) \begin{bmatrix} \alpha_j \\ \beta_j' \end{bmatrix}, \tag{5}$$

where β_j are 1×3 row matrices.

The variance of the random walk component (informational volatility) is estimated as:

$$\sigma_w^2 = \left[\sum a_j^* \quad \sum b_j^* \right] \operatorname{cov}(v) \begin{bmatrix} \sum a_j^* \\ \sum b_j^{*\prime} \end{bmatrix}, \tag{6}$$

where a_j^* and b_j^* are VMA coefficients.

[5] I use 15 lags for the E-mini S&P 500 market and 10 lags for the E-mini NASDAQ-100 and E-mini Russell 2000 futures. The different numbers of lags are used to account for differences in trading activity. The regression results discussed in the text are not affected qualitatively by the number of lags in the VAR.

After estimating transitory and informational volatility for each 15-minute intraday interval, I test Hypothesis 1 by estimating the following regression using 15-minute data:

$$\sigma_t^2 = \alpha + \beta_0 AV_t + \sum_{i=1}^{3} \beta_i NT_{i,t} + \tau Trend + \sum_{j=1}^{5} \rho_j \sigma_{t-j}^2 + \sum_{k=1}^{26} \gamma_k D_{k,t} + \varepsilon_t, \quad (7)$$

where σ_t^2 is the estimate of transitory or informational volatility (σ_s^2 or σ_w^2) in 15-minute interval *t*, AV_t is the average trade size, $NT_{i,t}$ is the number of trades initiated by trader type *i*, *Trend* is a linear time trend, and $D_{k,t}$ are interval dummy variables. The interval dummies are used to control for the intraday seasonality in volatility. Lagged volatility and trend are included to control for autocorrelation and a possible time trend in volatility.[6] Average trade size is included to test whether the overall trading volume has additional explanatory power after controlling for the number of trades classified by type of trader.[7] To simplify comparison of the coefficients, I divide the numbers of trades by their sample standard deviations. The overall specification of the model is similar to the one used by Jones, Kaul, and Lipson (1994), although they use a different measure of volatility. Equation (7) is estimated using ordinary least squares with Newey and West (1987) standard errors.

The estimation results for transitory volatility presented in Panel A of Table 3 follow a similar pattern for all three contract markets. The coefficients of the number of trades initiated by off-exchange traders are significantly positive in all cases. The similar coefficients for individual exchange members and member firms are negative and generally statistically significant, showing that trading activity of exchange members is associated with lower transitory volatility. Supporting Hypothesis 1, these results show that off-exchange traders induce more transitory volatility than do exchange members. The results are also consistent with the distribution of zero-tick and non-zero-tick trades reported in Table 2.

The results for informational volatility presented in Panel B of Table 3 are also consistent with Hypothesis 1. Trading activity of exchange member firms has a strong positive relation with informational volatility in all three E-mini markets. The similar relation for trades of off-exchange traders is negative in the S&P 500 and NASDAQ-100 E-mini markets, and insignificant in the E-mini Russell 2000 market. The informational volatility regression results for individual exchange members and off-exchange traders are generally consistent with Kurov and Lasser (2004),

[6]Five lags of volatility are included in the regression based on the Schwartz information criterion. The model uses all twenty-seven 15-minute intervals. Omitting the first five 15-minute intervals from estimation to avoid using volatility lags from the previous day has no significant effect on the results.

[7]Including separate average trade size variables for each trader type has little effect on the coefficients of interest.

TABLE 3. Estimates of the Effect of Trades on Informational and Transitory Volatility.

	E-Mini S&P 500		E-Mini NASDAQ-100		E-Mini Russell 2000	
Panel A. Transitory Volatility						
Number of trades						
Individual members (CTI 1 and 3)	−0.49	(5.75)***	−0.51	(1.94)*	−0.07	(0.40)
Member firms (CTI 2)	−1.54	(11.75)***	−1.00	(2.89)***	−0.91	(2.78)***
Off-exchange traders (CTI 4)	2.49	(19.14)***	1.54	(4.80)***	1.24	(4.82)***
Average trade size	−0.31	(4.67)***	−0.48	(2.00)**	1.12	(1.00)
Trend	−1.81	(6.85)***	−6.27	(9.59)***	−1.45	(2.90)***
Sum of 5 lagged volatilities	0.58	(700.7)***	0.47	(184.0)***	0.32	(45.5)***
Adjusted R^2	0.473		0.343		0.136	
Durbin-Watson d-statistic	1.998		2.000		2.003	
Panel B. Informational Volatility						
Number of trades						
Individual members (CTI 1 and 3)	0.07	(3.31)***	0.15	(1.17)	−0.11	(0.90)
Member firms (CTI 2)	0.26	(9.14)***	0.62	(4.87)***	0.42	(2.84)***
Off-exchange traders (CTI 4)	−0.25	(8.43)***	−0.54	(4.67)***	0.01	(0.09)
Average trade size	−0.03	(2.43)**	−0.04	(0.42)	−2.10	(4.37)
Trend	−0.12	(2.85)***	−0.86	(3.62)***	−1.22	(4.31)***
Sum of 5 lagged volatilities	0.75	(2627.9)***	0.67	(748.44)***	0.68	(516.88)***
Adjusted R^2	0.428		0.297		0.342	
Durbin-Watson d-statistic	1.979		2.007		2.008	

Note: The estimated coefficients are for the following regression:

$$\sigma_t^2 = \alpha + \beta_0 AV_t + \sum_{i=1}^{3} \beta_i NT_{i,t} + \tau Trend + \sum_{j=1}^{5} \rho_j \sigma_{t-j}^2 + \sum_{k=1}^{26} \gamma_k D_{k,t} + \varepsilon_t,$$

where σ_t^2 is the estimate of transitory or informational volatility in 15-minute interval t, AV_t is the average trade size, $NT_{i,t}$ is the number of trades initiated by trader type i, *Trend* is a linear time trend, and $D_{k,t}$ are interval dummy variables. The trend variable is calculated as the ordinal number of a given 15-minute interval divided by the total number of such intervals in the sample. The regression is estimated over regular trading hours from 9:30 a.m. to 4:15 p.m. ET using ordinary least squares. The sample period is from January 3, 2005, to December 30, 2005. The numbers of trades are standardized by dividing them by their standard deviations. All coefficients, except those for lagged volatilities, are multiplied by 10^6. Absolute values of t-statistics are given in parentheses. The t-statistics are computed using Newey and West (1987) standard errors. Test statistics for lagged volatilities are Wald statistics for the hypothesis that the sum of five coefficients is zero.

***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

who use Hasbrouck's (1995) information share methodology. Overall, the results in Table 3 are consistent with exchange member firms playing an important role in price discovery and off-exchange-initiated trades being a major source of transitory volatility.

In all three E-mini markets, the trend coefficients show a decline in both transitory and informational volatility during the sample period, perhaps driven by increasing liquidity of these markets. The results also show evidence of persistence in transitory volatility, with volatility lags strongly significant. This finding is consistent with Speight, McMillan, and Ap Gwilym (2000), who show that shocks to the transitory volatility component are persistent at intraday frequencies. These shocks completely decay in several hours, whereas shocks to the permanent volatility component persist much longer. Similarly, my regression estimates show stronger persistence in informational volatility.

The usual caveat applies that correlation does not imply causality. Given that transitory volatility by definition is created by trading, it is reasonable to expect causality running from the trading activity to transitory volatility. In the subsections that follow, I use variance decomposition techniques to directly examine contributions of different types of traders to transitory and informational volatility.

Relative Contributions of Trades to Transitory Volatility

I examine the determinants of transitory volatility using a two-stage approach, first estimating transitory volatility using a VAR model and then regressing it on the trading activity variables. An alternative approach is to introduce trades classified by trader type directly in the VAR used to estimate transitory volatility. This approach allows decomposing the transitory volatility into components representing the relative contributions of the different trader types into the variance of the pricing error. The VAR model is specified as follows:

$$r_t = \sum_{j=1}^{n} a_j r_{t-j} + \sum_{i=1}^{3} \sum_{j=0}^{n} b_{ij} x_{i,t-j} + v_{rt},$$

$$x_{it} = \sum_{j=1}^{n} c_{ij} r_{t-j} + \sum_{i=1}^{3} \sum_{j=1}^{n} d_{ij} x_{i,t-j} + v_{it}, \quad i = 1, 2, 3. \tag{8}$$

The model consists of four equations: a return equation and three signed trade equations. Each of the trade equations represents trading activity by a given type of traders as a function of lagged trades and price changes. The signed trade variable for a particular trader type i is set to 1 for buys, -1 for sells, and 0 if a given trade was initiated by one of the other types of traders. I use 15 lags of all variables in the VAR model and 30 lags in the VMA representation. Similar to the VAR model in (3), this model uses trade price changes.

In contrast to the VAR model in (3), this model includes contemporaneous trade variables in the return equation. E-mini futures prices tend to fluctuate in a one-tick range. Therefore, most trade price changes are bid–ask bounce. Price changes between the bid and ask quotes are caused by incoming market orders. Furthermore, all orders are executed automatically, without negotiation. Therefore, the contemporaneous causality runs from trades to transaction price changes. Including the contemporaneous trade variables in the return equation accounts for the contemporaneous effect of trades on transaction prices and dramatically improves the fit of the equation without affecting the estimated transitory volatility. The main benefit of this modification of the model is that the covariance matrix of the disturbances becomes block-diagonal, allowing a clean decomposition of the transitory volatility into trade-related and trade-unrelated components. Specifically, the variance of the pricing error can be represented as:

$$\sigma_s^2 = \sum_{j=0}^{\infty} \alpha_j^2 \sigma_{vr}^2 + \sum_{j=0}^{\infty} \beta_j \Omega \beta_j', \tag{9}$$

where $\sigma_{vr}^2 = \text{var}(v_{r,t})$ and Ω is the covariance matrix of the trade disturbances. The α and β coefficients are calculated using the VMA coefficients following Hasbrouck (1993). The first term in equation (9) represents the component of the pricing error variance contributed by return innovations. The second term is the trade-related component of the transitory volatility. Ω is generally not diagonal. Therefore, the components of the pricing error variance attributable to each of the three trader types, or "noise shares," can be computed after transforming Ω into a lower triangular matrix F by the Cholesky factorization, $\Omega = FF'$, as follows:

$$S_i = \frac{\sum_{j=0}^{\infty} ([\beta_j F]_i)^2}{\sigma_s^2}, \tag{10}$$

where $[\beta_j F]_i$ is the ith element of the row matrix $\beta_j F$. The result of this variance decomposition depends on ordering of the trade variables in the model. Similar to Hasbrouck's (1995) calculation of information shares, the upper and lower bounds of the noise shares can be computed by permuting the order of the trade variables in Ω and β_j.

The estimated noise shares are reported in Panel A of Table 4. For all three markets, trades initiated by off-exchange traders account for the largest percentage of the pricing error variance. The midpoints of the upper and lower bounds of the noise shares range from about 44% in the E-mini Russell 2000 market to about 65% in the E-mini S&P 500 market. The corresponding contributions of individual and institutional exchange members are much smaller despite the fact that exchange member firms account for a larger share of the trading activity.

To simplify comparison of the noise shares across the trader types, I compute the ratios of the noise share midpoints to the percentage of trades initiated by a particular trader type. The ratios reported in Panel B of Table 4 show that, controlling for the amount of trading activity, trades initiated by off-exchange traders are associated with at least twice as much transitory volatility as trades initiated by

TABLE 4. Noise Share Statistics.

Panel A. Noise Shares of Trades Initiated by Individual Exchange Members (CTI 1 and 3), Exchange Member Firms (CTI 2), and Off-Exchange Traders (CTI 4)

	Upper Bound			Lower Bound			Midpoint of Upper and Lower Bounds		
	CTI 1 & 3	CTI 2	CTI 4	CTI 1 & 3	CTI 2	CTI 4	CTI 1 & 3	CTI 2	CTI 4
E-mini S&P 500 futures									
Median	11.0%	21.7%	69.3%	4.7%	13.2%	60.3%	7.8%	17.4%	64.8%
Mean	11.1%	21.8%	69.7%	4.6%	13.2%	60.6%	7.8%	17.6%	65.1%
Std. error of mean	0.11%	0.17%	0.20%	0.06%	0.14%	0.17%	0.08%	0.15%	0.18%
E-mini NASDAQ-100 futures									
Median	8.1%	23.1%	51.7%	2.9%	14.5%	45.1%	5.5%	18.8%	48.4%
Mean	8.0%	22.6%	52.0%	2.7%	14.0%	45.5%	5.4%	18.3%	48.8%
Std. error of mean	0.11%	0.21%	0.47%	0.07%	0.18%	0.45%	0.08%	0.19%	0.45%
E-mini Russell 2000 futures									
Median	4.7%	25.0%	44.6%	3.2%	23.6%	43.6%	3.9%	24.3%	44.1%
Mean	4.6%	24.4%	44.4%	3.0%	23.1%	43.6%	3.8%	23.7%	44.0%
Std. error of mean	0.11%	0.47%	0.32%	0.09%	0.46%	0.32%	0.10%	0.46%	0.32%

Panel B. Noise Shares—Controlling for Proportion of Trades

	Individual Members (CTI 1 and 3)	Member Firms (CTI 2)	Off-Exchange Traders (CTI 4)
E-mini S&P 500	0.47 (0.007)	0.39 (0.003)	1.74 (0.007)
E-mini NASDAQ-100	0.33 (0.006)	0.33 (0.003)	1.90 (0.022)
E-mini Russell 2000	0.34 (0.008)	0.50 (0.010)	1.12 (0.011)

Note: The statistics are for regular trading hours from 9:30 a.m. to 4:15 p.m. ET. The sample period is from January 3, 2005, to December 30, 2005. Panel A reports "noise shares," that is, proportional contributions of trades initiated by different trader types to the pricing error variance. The noise shares are estimated separately for each day in the sample. The average contributions of return innovations to the pricing error variance in the S&P 500, NASDAQ-100, and Russell 2000 E-mini markets are 10.6%, 28.0%, and 27.8%, respectively. Panel B presents the mean ratios of the noise share midpoint to the proportion of trades initiated by the particular trader type on a given day. Standard errors of means are shown in parentheses. All ratios reported in the table are significantly different from 1 at the 1% level.

exchange members. The difference between exchange members and off-exchange traders is especially pronounced in the E-mini NASDAQ-100 market, where off-exchange-initiated trades are associated with about six times as much transitory volatility as exchange member trades. Overall, the results in Table 4 are consistent with the regression results presented in Table 3 and provide additional support to Hypothesis 1.

I have also estimated the "noise shares" for the after-hours trading. The results are qualitatively similar to the results for the regular trading hours reported in Table 4, with off-exchange traders contributing a disproportionately large share of transitory volatility.[8] Because the information share results discussed in the next section show that no trader type is clearly more informed in after-hours trading, the

[8]The noise shares for after-hours trading are not tabulated to conserve space but are available upon request.

differential effects of trader types on transitory volatility are likely to be explained by different trading strategies rather than by informational differences.

Informational Contributions

To test Hypothesis 2 relating to the relative information content of trades, I examine informational contributions of the three types of traders using Hasbrouck's (1995) model. This model estimates "information shares" as relative contributions of several cointegrated price series in the efficient price variance. The information shares are estimated using a vector error correction model (VECM).[9] Hasbrouck's model produces estimates of the upper and lower bounds of the information shares. These bounds may diverge substantially when the price innovations are correlated across the VECM equations. Using higher frequency price series reduces the correlation of innovations across the VECM equations and allows for a more precise identification of the information shares. As input data for the VECM analysis, I use a matched trade-by-trade price series of trades initiated by the three trader types.[10] To synchronize the price series, for each trade initiated by a given type of trader I use the last available trade prices for the other trader types. This matching procedure allows preserving the exact sequence of trades in the data.[11] Information shares are calculated separately for the regular trading hours and after-hours trading for each day in the sample and then averaged across days.

In addition to the analysis of the regular exchange trading hours, I look at after-hours trading to shed some light on the possible reasons for the informational differences among trader types. After-hours trading is different from trading during the regular hours in two important respects. First, the CME trading floor is closed and exchange members are unable to use their exclusive access to floor trading. Second, the major stock markets are also closed, although a small amount of trading takes place on electronic communication networks (ECNs) from 4:00 p.m. to 8:00 p.m. and from 7:00 a.m. to 9:30 a.m. Large institutional traders (exchange member firms) have better access to real-time information about stock prices than do individual traders or smaller institutions. Such information is generally unavailable after hours.

The estimated information shares are shown in Table 5. During the trading day, exchange member firms contribute most of the information in all three

[9]Detailed discussion of Hasbrouck's (1995) methodology is omitted for brevity.

[10]I employ 100 lags in the VECM for all three markets when the model is estimated during regular trading hours. During the after-hours trading period, I use 30 lags for the E-mini S&P 500, 15 lags for the E-mini NASDAQ-100, and 5 lags for the E-mini Russell 2000 futures, respectively, to account for different levels of trading activity.

[11]Kurov and Lasser (2004) use a one-second equally spaced price series in the VECM. That approach eliminates a large number of trades and does not preserve the sequence of trades that occurred within the same second. My trade matching procedure preserves the exact sequence of trades and significantly reduces the residual correlation in the VECM, allowing for a more accurate identification of the information shares.

TABLE 5. Information Share Statistics of Trades Initiated by Individual Exchange Members (CTI 1 and 3), Exchange Member Firms (CTI 2), and Off-Exchange Traders (CTI 4).

	Upper Bound			Lower Bound			Midpoint of Upper and Lower Bounds		
	CTI 1 & 3	CTI 2	CTI 4	CTI 1 & 3	CTI 2	CTI 4	CTI 1 & 3	CTI 2	CTI 4
Panel A. Regular Trading Hours									
E-mini S&P 500 futures									
Median	11.3%	63.4%	27.4%	10.3%	61.0%	25.0%	10.9%	62.2%	26.2%
Mean	12.8%	62.1%	28.0%	11.8%	59.7%	25.7%	12.3%	60.9%	26.9%
Std. error of mean	0.40%	0.59%	0.41%	0.38%	0.59%	0.40%	0.39%	0.59%	0.40%
E-mini NASDAQ-100 futures									
Median	10.4%	75.7%	15.6%	9.5%	73.4%	13.9%	9.9%	74.6%	14.7%
Mean	10.9%	75.0%	16.5%	10.0%	72.7%	14.9%	10.4%	73.9%	15.7%
Std. error of mean	0.32%	0.51%	0.46%	0.31%	0.52%	0.44%	0.31%	0.51%	0.45%
E-mini Russell 2000 futures									
Median	4.4%	72.3%	26.7%	4.1%	69.1%	23.8%	4.2%	70.7%	25.3%
Mean	5.1%	70.2%	27.8%	4.8%	67.2%	24.9%	4.9%	68.7%	26.4%
Std. error of mean	0.21%	0.63%	0.63%	0.20%	0.65%	0.60%	0.21%	0.64%	0.62%
Panel B. After-Hours Trading									
E-mini S&P 500 futures									
Median	21.7%	25.9%	52.4%	19.8%	24.0%	49.3%	20.8%	24.9%	50.9%
Mean	23.2%	27.8%	52.4%	21.2%	26.0%	49.4%	22.2%	26.9%	50.9%
Std. error of mean	0.76%	1.02%	0.96%	0.73%	0.98%	0.96%	0.74%	1.00%	0.96%
E-mini NASDAQ-100 futures									
Median	13.6%	37.7%	43.6%	12.3%	35.1%	40.4%	13.0%	36.4%	42.0%
Mean	19.5%	38.0%	45.8%	18.0%	35.6%	43.0%	18.8%	36.8%	44.4%
Std. error of mean	1.18%	1.64%	1.61%	1.13%	1.60%	1.59%	1.15%	1.62%	1.60%
E-mini Russell 2000 futures									
Median	13.4%	13.6%	63.3%	11.8%	11.5%	59.0%	12.9%	12.7%	60.7%
Mean	21.5%	22.7%	59.2%	19.8%	20.8%	56.0%	20.6%	21.8%	57.6%
Std. error of mean	1.42%	1.54%	1.74%	1.36%	1.49%	1.75%	1.39%	1.51%	1.75%

Note: The regular trading hours are from 9:30 a.m. to 4:15 p.m. ET. The after-hours trading period is from 6:00 p.m. to 9:30 a.m. ET the following day. The sample period is from January 3, 2005, to December 30, 2005. Information shares are calculated separately for each day in the sample and then averaged across days.

markets. The average midpoints of information shares for trades initiated by exchange member firms range from about 61% for the E-mini S&P 500 futures to about 74% for the E-mini NASDAQ-100 futures. The information shares of trades initiated by individual exchange members are modest, with mean information share midpoints ranging from about 5% in the E-mini Russell 2000 market to about 12%

in the E-mini S&P 500 market. Finally, the information share midpoints of off-exchange-initiated trades range from about 16% to about 27% and exceed those of the individual members' trades in all three markets. In contrast, off-exchange traders have the largest information shares in after-hours trading, consistent with their larger share in the trading activity.

Using a four-month sample period from early May to early September 2001, Kurov and Lasser (2004) report trivial information shares for clearing member trades. Although the CTI 2 category is now somewhat more inclusive than it was in 2001, comparing my information share results with those of Kurov and Lasser shows a significant change in the relative informational contributions of different trader types in recent years. Far from being uninformed hedgers, exchange member firms now appear to play a key role in price discovery in the E-mini index futures markets.[12] A possible reason for the growing informational role of institutional traders is their increased use of algorithmic trading systems, allowing them to exploit short-lived arbitrage opportunities and trade on electronically disseminated news faster than other traders.

To control for the proportion of trading activity initiated by different trader types, I calculate the ratios of the information share midpoints to the percentage of trades initiated by a given trader category. The ratios are calculated on a daily basis and reported in Panel A of Table 6. During the trading day, the ratios of the information share midpoint to the percentage of all trades are significantly higher than one for trades initiated by exchange member firms. This result shows that the member firms' trades are the more informative than trades of other traders. The information shares of trades initiated by other traders are significantly below their respective proportions of initiated trades. During after-hours trading, however, the ratio is greater than one for off-exchange traders and less than one for exchange member firms.

Information shares represent the proportional contributions of price innovations originating from a particular category of trades to the innovations in the common efficient price. Therefore, it is interesting to examine the relation between information shares and the percentages of price-setting trades initiated by different trader types. I define price-setting trades as buy trades with a higher price than the price of the previous buy trade or sell trades with a lower price than the price of the previous sell trade. Coval and Shumway (2005) use a similar approach to identify price-setting trades.

The ratios of information shares to percentages of price-setting trades initiated by a given trader type are reported in Panel B of Table 6. In all three markets,

[12]I also estimated information shares for the three trader types using my trade-matching procedure and the sample period of Kurov and Lasser (2004). The results were qualitatively similar to their results. Therefore, the differences between my information share results and theirs are not due to different trade-matching procedures.

TABLE 6. Information Shares—Controlling for Proportion of Trades Initiated by Individual Exchange Members (CTI 1 and 3), Exchange Member Firms (CTI 2), and Off-Exchange Traders (CTI 4).

	Regular Trading Hours			After-Hours Trading		
	CTI 1 and 3	CTI 2	CTI 4	CTI 1 and 3	CTI 2	CTI 4
Panel A. Information Share/Proportion of All Trades						
E-mini S&P 500	0.68 (0.02)***,a	1.34 (0.01)***,a	0.72 (0.01)***,a	0.90 (0.03)***,a	0.89 (0.03)***,a	1.09 (0.02)***,a
E-mini NASDAQ-100	0.61 (0.02)***,a	1.29 (0.01)***,a	0.59 (0.01)***,a	0.92 (0.04)***,a	0.91 (0.03)***,a	1.09 (0.03)***,a
E-mini Russell 2000	0.42 (0.01)***,a	1.41 (0.01)***,a	0.65 (0.01)***,a	1.04 (0.09)	0.66 (0.05)***,a	1.20 (0.03)***,a
Panel B. Information Share/Proportion of Price-Setting Trades						
E-mini S&P 500	1.13 (0.03)***,a	1.74 (0.02)***,a	0.49 (0.01)***,a	1.33 (0.05)***,a	1.10 (0.04)***,a	0.86 (0.01)***,a
E-mini NASDAQ-100	0.92 (0.03)***,a	1.58 (0.01)***,a	0.38 (0.01)***,a	1.16 (0.05)***,a	1.20 (0.05)***,a	0.84 (0.02)***,a
E-mini Russell 2000	0.50 (0.02)***,a	1.75 (0.01)***,a	0.51 (0.01)***,a	1.22 (0.12)	0.81 (0.07)***,a	1.11 (0.03)***,a

Note: The table presents the mean ratios of the information share midpoint to the proportion of all trades or price-setting trades initiated by the particular trader type on a given day. Price-setting trades are buy trades with a higher price than the price of the previous buy trade or sell trades with a lower price than the price of the previous sell trade. The regular trading hours are from 9:30 a.m. to 4:15 p.m. ET. The after-hours trading period is from 6:00 p.m. to 9:30 a.m. ET the following day. The sample period is from January 3, 2005, to December 30, 2005. Standard errors of means are shown in parentheses. ***, **, and * indicate that the *t*-test of the hypothesis that the mean of the ratio is equal to 1 is significant at the 1%, 5%, and 10% levels, respectively; a, b, and c indicate that the Wilcoxon signed-rank test of the hypothesis that the median of the ratio is equal to 1 is significant at the 1%, 5%, and 10% levels, respectively.

these ratios increase for trades initiated by exchange member firms and individual exchange members compared to the ratios based on the total number of initiated trades. Trades of exchange member firms still appear to be the most informed during the regular trading hours. In the S&P 500 and NASDAQ-100 E-mini markets, the price-setting trades initiated by individual members are more informative than off-exchange-initiated trades. For off-exchange traders during the regular trading hours, the ratios of information shares to the proportion of price-setting trades are much lower than one, indicating that these traders initiate a disproportionately high percentage of price-setting trades that have relatively little long-term effect on the prices.

To provide an additional test of the relative information content of trades initiated by the three types of traders, I calculate the cumulative impulse response functions by forecasting the VECM after a unit shock to one of the trade price series. Figure I shows the impulse responses for the regular trading hours. For

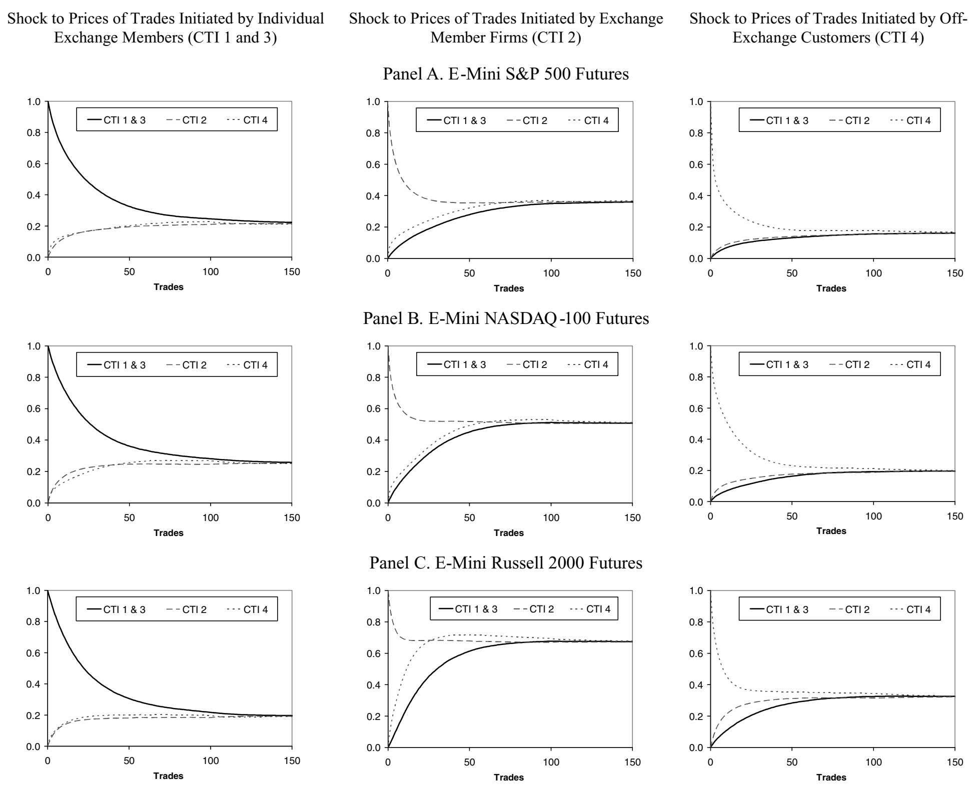

Figure I. Cumulative Impulse Response (Price Impact) Functions. Impulse responses are calculated separately for the regular trading hours of each day in the sample and then averaged across days. CTI 1 and 3 are individual exchange members, CTI 2 are exchange member firms, and CTI 4 are off-exchange customers.

TABLE 7. Coefficients of the Efficient Price (Long-Run Cumulative Price Effects) for Trades Initiated by Individual Exchange Members (CTI 1 and 3), Exchange Member Firms (CTI 2), and Off-Exchange Traders (CTI 4).

	Regular Trading Hours			After-Hours Trading		
	CTI 1 and 3	CTI 2	CTI 4	CTI 1 and 3	CTI 2	CTI 4
E-mini S&P 500 futures						
Mean	0.215	0.363	0.164	0.339	0.331	0.334
Std. error of mean	0.003	0.003	0.002	0.007	0.009	0.004
E-mini NASDAQ-100 futures						
Mean	0.253	0.508	0.199	0.348	0.399	0.407
Std. error of mean	0.004	0.003	0.003	0.011	0.012	0.007
E-mini Russell 2000 futures						
Mean	0.193	0.675	0.326	0.326	0.275	0.541
Std. error of mean	0.005	0.004	0.005	0.021	0.021	0.015

Note: The regular trading hours are from 9:30 a.m. to 4:15 p.m. ET. The after-hours trading period is from 6:00 p.m. to 9:30 a.m. ET the following day. The sample period is from January 3, 2005, to December 30, 2005. The long-run cumulative price effects are measured 500 trades after the price shocks to allow forecasted prices to fully converge. Coefficients of the efficient price are calculated separately for each day in the sample and then averaged across days.

all three markets, the long-run values of the cumulative impulse responses are much larger for unit shocks to the prices of trades initiated by exchange member firms than for similar innovations initiated by individual exchange members or off-exchange traders. For the S&P 500 and NASDAQ-100 E-mini futures, individual member trades are more informative than trades of off-exchange traders, whereas in the E-mini Russell 2000 market off-exchange-initiated trades are somewhat more informative. In all three markets, there is a small initial overreaction of off-exchange traders to price shocks initiated by other trader types.

Table 7 reports the coefficients of the efficient price, which are identical to the long-run values of the cumulative impulse responses. The cumulative impulse responses provide additional support to the information share results, showing that exchange member firms contribute more to price discovery than other traders during the regular trading hours. Overall, the results for the trading day reported in Tables 5, 6, and 7 are consistent with expectations expressed in Hypothesis 2.

Based on the cumulative impulse responses, trades of individual exchange members and off-exchange traders are more informative after hours than during the trading day. The increased information content of after-hours trades is consistent with Barclay and Hendershott (2003). Because the information content of trades initiated by individual exchange members increases after hours, access to the trading floor is unlikely to be a key factor influencing their trading. Table 7 shows that the permanent price effects in the S&P 500 and NASDAQ-100 E-mini markets are similar across the trader types in after-hours trading. In the E-mini Russell 2000 market, off-exchange-initiated trades are the most informative. Furthermore, the information content of institutional member trades declines in after-hours trading relative to the trading day. This result shows that exchange member firms no longer have an informational advantage after hours. The key difference between the two trading periods is lack of active trading in the underlying stocks after hours. Therefore, real-time access to the underlying stock prices is likely to be an important source of informational advantage that exchange member firms have during the trading day.

Daigler and Wiley (1999) argue that off-exchange traders fit the description of noise traders, and my results confirm that these traders introduce noise into the prices. However, the information share results show that their trades are also a source of information, especially in after-hours trading. Although this conclusion may appear counterintuitive, it is not inconsistent with microstructure theory. For example, Hasbrouck (1993, p. 199) specifies a structure of the efficient price innovation and the pricing error that implies that a trade can contain information and simultaneously push the security price away from the fundamental value.

VI. Conclusion

I examine the effects on transitory volatility and informational contributions of trades initiated by different types of traders in three E-mini index futures markets. The empirical results show a strong positive relation between transitory volatility estimated using the Hasbrouck (1993) model and trading activity initiated by off-exchange traders. Trading activity initiated by exchange members tends to be negatively related to transitory volatility. These results, supported by results from a VAR-based decomposition of transitory volatility, show that trades initiated by off-exchange traders induce more transitory volatility than trades initiated by exchange members. Although this conclusion is broadly consistent with Daigler and Wiley (1999), I provide direct evidence on the effect of different trader types on transitory volatility.

Exchange locals are usually viewed as better informed traders who play an important role in price formation (e.g., Kurov and Lasser 2004). My results confirm that trades initiated by local traders contain information and contribute to price discovery. I also find, however, that exchange member firms appear to be more informed and contribute more to price discovery than individual exchange members or off-exchange traders. During the trading day, trades of member firms account for between 61% and 74% of price discovery. These information shares exceed the proportions of trading activity generated by member firms. Taken together, the results show that institutional traders are more informed than other types of traders in anonymous electronic trading. I also find that the informational advantage of institutional traders disappears in after-hours trading when they do not have access to real-time information about the underlying stock prices. My findings are important because they contribute to better understanding of the effects of trader heterogeneity on price formation.

Trading is a zero sum game, with informed traders making profits at the expense of the uninformed. It would be interesting to see if the apparent informational advantage of institutions translates into trading profits. I considered estimating trading profits assuming that all trades are closed out at the settlement price. However, profit estimates based on this assumption are likely to be very imprecise. Because my data set does not allow tracking positions for each trader's account, I leave the analysis of trading profits across trader types for future research.

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