

Intraday Trading by Floor Traders and Customers in Futures Markets: Whose Trades Drive the Volatility-Volume Relation?

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The study tests the effect of trader types on the intraday volatility-volume relation in four futures markets. Each trade is identified by the trader type on both sides of a transaction. The results from a VAR model show that the dynamic volatility-volume relation depends on the trader types involved. The positive contemporaneous volatility-volume relation is driven mainly by volume from trading between floor traders and customers. Contemporaneous volatility is either not related or negatively related to volume from trading between floor traders, which is consistent with conventional wisdom that floor traders are informed traders. On the other hand, volatility is significantly positively related to volume from trading between customers only in the two agricultural markets but not in the two foreign exchange markets. After decomposing volume into expected and unexpected parts, contemporaneous volatility-volume relation is almost symmetric between expected and unexpected volume for three major types of trading.

Introduction

Under the mixture-of-distributions hypothesis in Clark (1973) and Tauchen and Pitts (1983), there exists a positive relation between prices and trading volume because both respond to the same underlying latent information. On the other hand, there is a considerable interest in the impact of trader type on volatility. Theoretic models such as De Long et al. (1990) and Campbell and Kyle (1993) show that trading by uninformed noise traders increases market volatility. Shalan (1993)

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reaches a similar conclusion that the least informed traders increase volatility, whereas informed trading reduces volatility by removing uncertainty in the marketplace. In addition, Harris and Raviv (1993) show that even in the absence of noise traders, traders with homogenous prior information but different processing procedure can result in a positive volatility-volume relation.¹

This paper aims to shed light on the question of whose trades drive the volatility-volume relation. Such a study presents an empirical test of the financial theories discussed earlier. In addition, the effect of trading parties on market volatility is an important public policy issue. For example, the advocates of throwing sand in the gear argue that transaction tax should be imposed to reduce volatility. One can argue that such a tax be imposed specifically on retail customers if only volume from trading by retail customers is positively related to price volatility.²

The paper makes four improvements over the previous studies. First, the unique transaction dataset in this study codes both parties for each trade, e.g., a floor trader against a retail customer. In contrast, data in previous studies such as Manaster and Mann (1996) and Wiley and Daigler (1998) contain trader type only for one of the two parties involved in a trade. The use of only one party in identification can hide the true impact of trader types on volatility. This paper is the most vigorous examination that reveals true pairings of parties and their effect on market volatility.

Second, minute-by-minute transaction data are used in this study, whereas previous studies use daily data. Given the speed of trading and price adjustments in future markets, studies with low frequency data easily can fail to capture the volatility-volume relation that is evident only in intraday data. Therefore, results from this study can complement and contrast with those from the previous studies to assess whether the volatility-volume relation is robust to market microstructures such as the frequency of data.

The third improvement comes from the fact that Hausman specification test is used to test the presence of simultaneity between volatility and volume. In the presence of simultaneity bias, ordinary least squares (OLS) method is replaced by the generalized method of moments (GMM) approach with instrumental variables to study the contemporaneous intraday volatility-volume relation. The removal of simultaneity bias makes the results in the paper more reliable.

Finally, in addition to using a vector-autoregressive (VAR) model to answer the question of which types of trading Granger-cause volatility, volume is decomposed into expected and unexpected parts using autoregressive integrated moving average (ARIMA) models to study the contemporaneous intraday volatility-volume relation.

¹ The informed trading models, such as Admati and Pfleiderer (1988) and Foster and Viswanathan (1990), show that both informed traders and liquidity traders trade during high liquidity periods. Liquidity traders are assumed to be noise traders in these models. Thus, trading by liquidity traders presumably increases price volatility during higher volume period.

² See, e.g., Stigleitz (1989), and Summers and Summers (1989).

Furthermore, a robustness check is done to examine whether results vary in different trading sessions, e.g., morning session versus afternoon session.

Related Studies

A positive volatility-volume relation in futures markets has been documented extensively in the literature. For example, Grammatikos and Saunders (1986) find that price variability and trading volume are positively correlated in all futures markets studied. Martell and Wolf (1987), Foster (1995), and Wang and Yau (2000) report evidence of a positive relation between trading volume and price volatility in various futures markets. Garcia, Leuthold, and Zapata (1986) use a VAR framework to document a lead-lag relationship between trading volume and price variability in five grain futures markets.

Using an ARIMA model, Bessembinder and Seguin (1993) find that unexpected volume shocks have a larger effect on volatility in futures markets than expected volume. Fujihara and Mougoue (1997) find a non-linear causal relation between volatility and volume in petroleum futures markets. Luu and Martens (2003) use realized volatility from intraday data and find a bi-directional causal relation between volatility and volume in the US stock index futures market.

On the other hand, Chang, Pinegar, and Schachter (1997) document a positive association between volatility and volume by large speculators in five futures markets. Daigler and Wiley (1999) report evidence that trading by the least-informed traders (i.e., retail customers as a group) is positively associated with volatility in five futures markets. In contrast, trading by floor traders, i.e., the most informed traders, is negatively associated with volatility.

In contrast, Irwin and Yoshimaru (1999) find that trading by large managed futures funds and pools does not increase market volatility. Similarly, Wang (2002) find that trading by large speculators actually stabilizes price volatility, whereas trading by hedgers is associated with increases in volatility. Presumably, these large commercial traders are better informed than small speculators. All these studies use daily data.

Data and Methodology

Data

The transaction data are audit data compiled by Commodity Futures Trading Commission (CFTC); see Sahin and Sarajoti (2005) and Locke and Mann (2005) for a detailed description of the data. The data contain every trade in 1995 for live cattle, frozen pork bellies, German mark, and Swiss franc futures contracts at the Chicago Mercantile Exchange (CME). As shown in Panel A of Table 1, regular trading session is longer for the two foreign exchange futures than for the two agricultural contracts. There was no after-hour electronic trading in 1995. Because each trade in

the dataset is timed to the nearest minute, there are usually multiple trades within a minute.

Table 1—Summary Statistics

Trading hour is Chicago time. Sample size is the number of 30-minute intervals during which the total number of contracts traded (Volume) is aggregated. Each trade involves two parties. The three most active are trading between floor traders and customers (Type 14), trading between customers (Type 44), and trading between floor traders (Type 11). Market volatility is measured by realized volatility, i.e., squared 5-minute returns. Similar to volume aggregation, volatility is also aggregated over the 30-minute interval and is scaled by a factor of 1,000. In parentheses are standard deviations

Panel A: Sample Size

	Live Cattle	Pork Bellies	Deutsch Mark	Swiss Franc
Trading Hours	9:10-13:00	9:10-13:00	7:20-14:00	7:20-14:00
Sample Size	2,246	1,996	3,481	3,481

Panel B: Composition of Volume by Three Major Types of Trading

Type 14	58.87%	60.79%	40.37%	48.68%
Type 44	24.92%	24.88%	14.84%	15.28%
Type 11	6.75%	7.82%	9.07%	7.86%

Panel C: Volume by Three Major Types, Mean and Standard Deviations

Type 14	839 (735)	169 (149)	718 (643)	544 (463)
Type 44	355 (370)	69 (89)	264 (349)	171 (170)
Type 11	97 (85)	22 (21)	162 (142)	88 (79)

Panel D: Mean Realized Volatility

	0.0343	0.0297	0.0217	0.0229
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The trading parties behind every trade are coded by four customer type indicators (CTI) defined by CFTC. They are CTI 1 - floor trader proprietary trading for own accounts; CTI 2 - the floor trader is trading for the trader's clearing member; CTI 3 - the floor trader is trading for another trader who is present on the floor (such as a futures options trader wishing to hedge); and CTI 4 - trading for off-the-floor customers. Each trade is recorded twice. For example, a trade between a floor trader and a customer is recorded as a Type 14 trade and also as a Type 41 trade. In this study, only trades from Types 11, 12, 13, 14, 22, 23, 24, 33, 34, and 44 are used.³

Following the approach in Bessembinder and Seguin (1993) and Luu and Martens (2003), volume from different maturities is aggregated over a 30-minute sampling interval to reach intraday trading volume (TV) in equation (1).⁴

³ In comparison, a small discrepancy does exist if trades from Types 44, 43, 42, 41, 34, 32, 31, 22, 21, and 11 are used—probably due to errors in the data. Also, Types 11, 22, 33, and 44 trades are adjusted so that there is no double-counting.

⁴ There are several contracts with different maturity months are traded simultaneously. Therefore, the total trading volumes are the sum of each contract month over the period of 30

$$TV_{t,t+k} = \sum_{i=1}^j \left(\sum_{k=1}^{30} volume_k \right) \quad (1)$$

where k indicates minute and i is for maturity month. As a result, there are more such 30-minute intervals for the foreign exchange contracts than for the two agricultural contracts. Trading for the two foreign exchange futures contracts is equally active, which results in identical sample size. In contrast, trading is more active for live cattle futures than for frozen pork bellies futures, which is reflected by a larger sample size for live cattle futures.

Panel B of Table 1 shows the composition of types of trading. The most active types of trading are trader-customer (Type 14). The next two active types of trading are customer-customer (Type 44) and trader-trader (Type 11). These three types of trading account for about 90 percent and 70 percent of all volume in the agricultural futures markets and the foreign exchange futures markets, respectively. These three types are the focus of the paper.

Panel C of Table 1 shows the mean and standard deviations of volume for each type of trading during the sampling interval of 30 minutes. Trading between traders and customers (Type 14) has the highest average trading volume as well as the highest standard deviations. Trading between floor traders has the lowest average volume and the smallest deviations.

Realized volatility, i.e., squared returns, is used widely with high frequency data. Because all trades are time-stamped to the nearest minute, the volume-weighted price is calculated to obtain the market price for each minute, see, e.g., Manaster and Mann (1996). As discussed by Andersen and Bollerslev (1998), realized volatility (V) should be calculated with 5-minute rather than 1-minute returns because the latter is more noisy due to market microstructure induced price bounces.⁵ Following this approach, realized volatility is calculated using the first prices from the two adjacent 5-minute intervals.

$$r_t = \log(p_t) - \log(p_{t-5}) \quad (2)$$

where r_t and p_t are return and volume-weighted price, respectively. Similar to the calculation of trading volume, realized volatility from each contract month is summed up to reach realized volatility within the 30-minute sampling interval.

$$V_t = \sum_{i=1}^j \left(\sum_{s=1}^6 r_s^2 \right) \quad (3)$$

minutes. Notice that the last interval does not always have 30 minutes depending the opening minute and closing time specific to the day and contracts. The main results remain unchanged when a 15-minute or a 60-minute sampling interval is used.

⁵ Some researchers even suggest the use of one-hour interval; see for example, Corsi, Zumbach, Muller, and Dacorogna (2001).

As in Luu and Martens (2003), overnight returns are calculated using today's first price and the last price from the previous day. Panel D of Table 1 reports the average realized volatility. Notice that volatility is higher for the agricultural futures contracts than for the foreign exchange contracts.

Table 2 presents Pearson correlation coefficients between volatility and volume for the three major types of trading. Consistent with the findings in Grammatikos and Saunders (1986), correlation between volatility and volume is positive and statistically significant at the 1 percent level. Volatility is more correlated with Type 14 and Type 44 volume, whereas volatility is least correlated with Type 11 volume, i.e., trading between floor traders. Type 14 trading is correlated more with Type 44 trading than with Type 11 trading in the two agricultural markets. Trading between floor traders, however, is correlated more with Type 14 than with Type 44 in the two foreign exchange markets. Comparing with the results in Wiley and Daigler (1998), Pearson coefficients between the types of volume are much smaller. This is due to further decomposition of volume according to both parties involved in a trade, rather than based on CTI alone. Table 2 provides some anecdotal evidence for the importance of customer trading in relation to volatility.

Table 2—Correlations between Volatility and Three Major Types of Volume

The table presents Pearson correlation coefficients between volatility and trading volume for each of the three major types of trading, i.e., trading between floor traders and customers (Type 14), trading between customers (Type 44), and trading between floor traders (Type 11). The null hypothesis is that there is no correlation between the two variables

	Volume 11	Volume 14	Volume 44
Panel A. Live Cattle			
Volatility	0.42***	0.53***	0.51***
Volume 11		0.79***	0.63***
Volume 14			0.89***
Panel B. Pork Bellies			
Volatility	0.32***	0.54***	0.57***
Volume 11		0.65***	0.41***
Volume 14			0.76***
Panel C. Deutsch Mark			
Volatility	0.18***	0.29***	0.23***
Volume 11		0.78***	0.48***
Volume 14			0.73***
Panel D. Swiss Franc			
Volatility	0.22***	0.33***	0.27***
Volume 11		0.83***	0.53***
Volume 14			0.72***

*** indicates statistical significance at 1 percent level.

Hypotheses and Methodology

Of course, correlation does not imply causality. For example, Chang, Chou, and Nelling (2000) show that hedgers increase trading in response to the increase in market volatility. For public policy debate, it is necessary to show that individual types of volume Granger cause price volatility. It is hypothesized that there exists no Granger causality relation between volatility and any of the three major types of volume.

HO1: There is no Granger-causality between price volatility and each of the three individual trading types.

The VAR approach provides a framework for testing Granger causality and has been used widely in the literature, e.g., Garcia, Leuthold, and Zapata (1986), Fujihara and Mougoue (1997), and Luu and Martens (2003). VAR modeling requires that all time series be stationary. Both the augmented Dickey-Fuller test and the Phillips-Perron test are conducted for up to 12 lags for three cases: zero mean, single mean, and deterministic trend. Although not reported in the paper, the null hypothesis of nonstationarity is rejected in all cases, which is consistent with the results in many previous studies, e.g., Wiley and Daigler (1998), and Wang and Yau (2000).

As a result, the following VAR (p) model is estimated, in which the Schwarz Bayesian information criterion is used to determine the optimal lag length (p) in the model with a maximum lag of 5.

$$\Omega_t = \alpha + \sum_{k=1}^p \lambda_k \Omega_{t-k} + \varepsilon_t \quad (4)$$

where Ω is a vector for volatility and trading volume from the three major types of trading. Given the VAR model above, there are two tests for each of the three major types of trading. Hence, six tests are conducted to shed light on the Granger-causality between price volatility and volume from the three main types of trading.

In addition to Granger-causality testing, contemporaneous volatility-volume relation is also of interest. Equation (5) is used to represent the contemporaneous volatility-volume relation.

$$V_t = \alpha + \beta_1 TV_{11,t} + \beta_2 TV_{14,t} + \beta_3 TV_{44,t} + \psi \text{Monday} + \varepsilon_t \quad (5)$$

where TV_{11} , TV_{14} , and TV_{44} are trading volume from trading between floor traders, trading between floor traders and customers, and trading between customers, respectively. The dummy variable Monday accounts for the well-known Monday effect. Chang, Pinegar, and Schachter (1997) and Han, Kling, and Sell (1999) report evidence for the Monday effect. The following hypothesis is tested.

HO2: There is no contemporaneous relation between price volatility and each of the three major types of trading volume.

It is important to account for possible simultaneity between contemporaneous volatility and volume. As discussed above, both the mixture-of-distributions hypothesis and the informed trading models predict that volume and volatility are jointly determined. Empirical evidences in Koch (1993), Foster (1995), and Wang and Yau (2000) find that simultaneity bias is present. Therefore, Hausman's specification test is conducted to test the null hypothesis that volume is exogenous to volatility. Under the null hypothesis of no simultaneity, OLS estimates are consistent and efficient. Under the alternative hypothesis of simultaneity, however, OLS estimates are inconsistent but efficient. After obtaining a consistent estimate under the alternative hypothesis, e.g., a two-stage least squares estimator (2SLS), one can apply Hausman m-statistic to test the null hypothesis of no simultaneity.⁶

If the null hypothesis of no simultaneity cannot be rejected, equation (5) is estimated by GMM. GMM imposes weaker distribution assumptions and is especially suitable due to positive serial correlation in squared returns. On the other hand, if simultaneity exists, GMM is used with lagged values as instrumental variables for volume.

Bessembinder and Seguin (1993) decompose volume into expected and unexpected parts to test informational effects of volume on volatility. It is likely, under the rational expectation theory, that the effect from expected and unexpected parts can be asymmetric. As in Bessembinder and Seguin (1993), ARIMA models are used to decompose volume into expected and unexpected parts. Because all time series are stationary, the following ARIMA(p,0,q) model is estimated.

$$TV_t = \theta + \sum_{i=1}^p \alpha_i TV_{t-i} + \sum_{j=0}^q \beta_j \varepsilon_{t-j} \quad (6)$$

The Schwarz Bayesian information criterion is used to determine the orders of the autoregressive and moving average parts in the ARIMA models. Equation (7) is used to test the effects of expected and unexpected volume on contemporaneous volatility.

$$V_t = \alpha + \sum_1^3 \phi_i E(TV_{i,t}) + \sum_1^3 \lambda_i U(TV_{i,t}) + \psi \text{Monday} + \varepsilon_t \quad (7)$$

where V and TV are for volatility and trading volume, respectively. E(TV) is expected volume, which is the fitted value from the corresponding ARIMA models.

⁶ See Maddala (1992), pp. 506-508 for a discussion of the Hausman m-statistic and its application.

U(TV) is unexpected volume, which is the residual of the corresponding ARIMA models. Equation (7) also is estimated by GMM.

Results

VAR Model

Table 3 presents the results from the Granger-causality test for volatility and volume. In the two agricultural markets, a bi-directional causality is found between volatility and each of the three major types of trading volume, which is consistent with the findings in Luu and Martens (2003). In the two foreign exchange futures markets, volume from trading between traders and customers does not Granger-cause price volatility, but volume from trading between customers Granger-causes price volatility. There is a Granger-causal relation from volume to volatility for trading between floor traders in Swiss franc futures market but not in German mark futures market. Overall, the results in Table 3 show that the dynamic relation between volatility and volume depends on trader types involved on both sides of the transactions.

Table 3—Granger Causality Test for the Volatility-Volume Relation

The χ^2 statistics tests the null hypothesis of no Granger-causality from volume to ($\rightarrow$) volatility or from volatility to volume. Schwarz Bayesian Information Criterion is used to determine the optimal lag length (p) with up to 5 lags in the model. In parentheses are the p-values

	Live Cattle	Pork Bellies	Deutsch Mark	Swiss Franc
Optimal Lag Length	2	2	2	2
Panel A. Trader-Trader Volume				
Volume $\rightarrow$ Volatility	14.97 (0.00)	8.58 (0.01)	4.57 (0.10)	6.35 (0.04)
Volatility $\rightarrow$ Volume	5.94 (0.05)	16.12 (0.00)	2.28 (0.32)	18.63 (0.00)
Panel B. Trader-Customer Volume				
Volume $\rightarrow$ Volatility	32.75 (0.00)	6.80 (0.03)	1.84 (0.40)	0.16 (0.92)
Volatility $\rightarrow$ Volume	21.09 (0.00)	19.71 (0.00)	1.49 (0.47)	7.01 (0.03)
Panel C. Customer-Customer Volume				
Volume $\rightarrow$ Volatility	29.68 (0.00)	15.48 (0.00)	11.32 (0.00)	26.26 (0.00)
Volatility $\rightarrow$ Volume	10.22 (0.01)	40.33 (0.00)	18.87 (0.00)	7.58 (0.02)

Contemporaneous Volatility-Volume Relation – Total Volume

The volatility-volume relation at the aggregate level is established before testing the impacts of volume from three major types of trading. Panel A of Table 4 presents the results from Hausman's specification test. Except for frozen pork bellies futures market, Hausman's m-statistic is not significant and thus the null hypothesis

that volume is exogenous to volatility is not rejected. As a result, GMM with lagged values as instrumental variables is used for frozen pork bellies contract and OLS is used for all other three futures contracts in the estimation of equation (5).

Table 4—Contemporaneous Volatility and Total Volume

The regression model is $V_t = \alpha + \beta TV + \psi \text{Monday} + e_t$. The dependent variable is intraday volatility (V). The independent variables are trading volume (TV) and dummy variable Monday for the Monday effect. In Panel A, Hausman's m-statistic tests the null hypothesis that volume is exogenous to volatility. If the null hypothesis of no simultaneity is rejected, GMM with lagged values as instrumental variables in the estimation. Panel B presents the estimation results of the same model. Coefficients for volume and the dummy variable are adjusted by a factor of 1,000. In parentheses are t -statistics with autocorrelation and heteroskedasticity consistent standard errors

	Live Cattle	Pork Bellies	Deutsch Mark	Swiss Franc
Panel A. Hausman Specification Test for Simultaneity between Volatility and Volume				
Hausman m-statistic	8.67	34.96	7.06	2.02
(p-value)	(0.12)	(0.00)	(0.07)	(0.57)
Panel B. Contemporaneous Volatility-Volume Relation – Three Types of Trading				
α	-0.01 (-2.36**)	0.08 (1.15)	-0.03 (-3.58***)	-0.02 (-3.38***)
β	0.03 (6.85***)	0.74 (3.19***)	0.03 (5.92***)	0.04 (5.68***)
ψ	6.40 (2.19**)	81.77 (1.68)	14.66 (1.43)	2.80 (0.49)
N	2,246	1,995	3,481	3,481
Adj. R^2	0.29	0.25	0.08	0.10

*** and ** indicate statistical significance at 1 percent level and 5 percent level, respectively

As shown in Panel B of Table 4, the coefficient for total volume is positive and significant in all markets, which is consistent with those in Foster (1995) and Wang and Yau (2000) as well as other studies surveyed in Karpoff (1987). Because a positive relation generally is found between intraday volatility and intraday aggregate volume, the results in the paper support both the mixture-of-distributions hypothesis and the informed trading models.

Notice that the coefficient for the dummy variable Monday is not significant in all markets except for the live cattle futures market, in which it is significantly positive. Therefore, there is no evidence that volatility decreases on Mondays, as found in Chang, Pinegar, and Schachter (1997) and Han, Kling, and Sell (1999).

Whose Trades Drive the Contemporaneous Volatility-Volume Relation – Individual Volume

Table 5 presents results of contemporaneous relation between volatility and the three major individual types of trading. Again, there is no evidence that volatility tends to decrease on Monday. For trading between floor traders, volatility is significantly negatively related to volume in the two foreign exchange markets and is not

correlated to volume in the agricultural markets. Therefore, the results are consistent with conventional wisdom that professional floor traders are informed traders. Floor traders have at least some access to information circulating on the floor including the level of communication between brokers and the phone desks. Thus, trading between them probably is motivated by position adjustments and injects little noise into the price, which in return will not increase price volatility. The results are also consistent with those in Daigler and Wiley (1999).

Table 5—Contemporaneous Volatility-Volume Relation – Three Types of Trading

The regression model is $V_t = \alpha + \beta_1 TV_{11,t} + \beta_2 TV_{14,t} + \beta_3 TV_{44,t} + \psi \text{Monday} + e_t$. The dependent variable is intraday volatility (V). The types of trading volume (TV) are: trading between floor traders and customers (Type 14), trading between customers (Type 44), and trading between floor traders (Type 11). Monday is a dummy variable for the Monday effect. GMM with lagged values as instrumental variables is used in the estimation for frozen pork bellies futures market. Coefficients for volume and the dummy variable are adjusted by a factor of 1,000. In parentheses are t-statistics with autocorrelation and heteroskedasticity consistent standard errors

	Live Cattle	Pork Bellies	Deutsch Mark	Swiss Franc
A	-0.01 (-2.32***)	0.12 (1.90)	-0.02 (-4.06***)	-0.02 (-3.31***)
β_1	0.03 (1.02)	-2.59 (-0.66)	-0.11 (-2.50***)	-0.24 (-2.60***)
β_2	0.03 (5.05***)	0.39 (0.47)	0.08 (5.39***)	0.11 (4.82***)
β_3	0.04 (2.67**)	2.27 (2.24**)	0.01 (0.45)	0.04 (1.21)
Ψ	6.35 (2.14**)	82.72 (1.74)	14.77 (1.46)	2.71 (0.56)
N	2,246	1,995	3,481	3,481
Adj. R^2	0.29	0.27	0.09	0.12

*** and ** indicate statistical significance at 1 percent level and 5 percent level, respectively

For trading between floor traders and customers, volatility is significantly positively related to volume in all markets except for the frozen pork bellies futures market. In the frozen pork bellies futures market, volatility is not related to volume. For trading between customers, volatility is significantly related to volume in the agricultural markets but not in the foreign exchange markets. Therefore, evidence supports the empirical results in Daigler and Wiley (1999) that retail customers are noise traders only in the agricultural markets. It is clear that two types of trading, trading between customers and trading between floor traders and customers, drive the positive volatility-volume relation.

Notice the differences in both data and methodology between this study and that by Daigler and Wiley (1999), i.e., intraday data versus daily data and identifying a trade by both parties versus by only one of the two parties involved. Nevertheless, the results from this study are more consistent than contradicting with those in Daigler and Wiley (1999). For example, the results on volume from trading between floor traders are consistent with their results. On the other hand, this study also pro-

vides support that retail customers, at least in the agricultural futures markets, are noise traders.

Volatility and Expected and Unexpected Volume

Panel A of Table 6 shows the orders of the autoregressive and moving average parts in the ARIMA models, which is determined by the Schwarz Bayesian information criterion. Panel B of Table 6 reports the results of regressing volatility on expected and unexpected parts of volume from three major types of trading.

Table 6—Contemporaneous Volatility and Volume – Expected versus Unexpected Volume

The dependent variable is intraday volatility. The independent variables are expected, unexpected parts of volume, and a Monday dummy variable. Volume is decomposed into expected (E) and unexpected (U) parts using ARIMA models. Schwarz Bayesian Information Criterion is used to determine the orders of autoregressive and moving average in the model, i.e., ARIMA(p,d,q). The types of trading volume are: trading between floor traders and customers (Type 14), trading between customers (Type 44), and trading between floor traders (Type 11). GMM is used in the estimation. Coefficients for volume and the dummy variable are adjusted by a factor of 1,000. In parentheses are t-statistics with autocorrelation and heteroskedasticity consistent standard errors

	Live Cattle	Pork Bellies	Deutsch Mark	Swiss Franc
Panel A. ARIMA(p,d,q) Specifications				
Volume 11	(2,0,1)	(2,0,1)	(5,0,5)	(5,0,5)
Volume 14	(3,0,2)	(5,0,5)	(5,0,5)	(5,0,5)
Volume 44	(3,0,3)	(2,0,2)	(1,0,5)	(5,0,5)
Panel B. Regression Results				
Constant	-0.03 (-2.78***)	0.06 (1.28)	0.002 (0.28)	0.021 (1.29)
E(volume ₁₁)	-0.11 (-1.37)	-5.49 (-1.88)	-0.12 (-3.88***)	-0.45 (-4.86***)
U(volume ₁₁)	0.03 (1.09)	0.18 (0.15)	-0.05 (-0.84)	-0.09 (-1.10)
E(volume ₁₄)	0.04 (4.19***)	1.51 (2.99***)	0.04 (3.19***)	0.10 (5.01***)
U(volume ₁₄)	0.04 (5.21***)	0.94 (2.29**)	0.08 (5.01***)	0.11 (4.73***)
E(volume ₄₄)	0.10 (4.62***)	1.27 (2.34**)	0.02 (1.28)	0.02 (0.57)
U(volume ₄₄)	0.03 (2.18**)	3.11 (2.79***)	0.01 (0.56)	0.04 (1.08)
Monday	6.11 (2.07**)	80.55 (1.78)	13.65 (1.35)	2.27 (0.41)
N	2,246	1,996	3,481	3,481
Adj. R ²	0.29	0.36	0.10	0.13

*** and ** indicate statistical significance at 1 percent level and 5 percent level, respectively

There is almost symmetric volatility-volume relation between expected and unexpected volume, which is consistent with the results in Bessembinder and Seguin (1993). The only exception is for trading between floor traders in the two foreign

exchange markets. In this special case, expected volume is negatively related to price volatility and unexpected volume is not related to volatility.

By decomposing volume into expected and unexpected parts, it is more evident that trading between customers and floor traders becomes the main driving force behind the positive volatility-volume relation. For example, volatility is related to both expected and unexpected volume from trading between customers and floor traders in all markets. Overall, the results in Table 6 are consistent with the results in Table 5. Therefore, the conclusions in Table 5 are not affected by the decomposition of volume into expected and unexpected components.

Robustness Check – Different Sessions during the Day

It is well known that there is a U-shaped pattern in both intraday volume and volatility see, e.g., Chan, Chan, and Karolyi (1991) and Daigler (1997). It is of interest if the observed volatility-volume relation is present only during certain trading sessions. As a robustness check, each trading day is divided into four sessions: opening (the first 30 minutes), morning (after the opening but before 11:30am Chicago time), afternoon before closing, and closing session of last 30 minutes of trading. Table 7 presents estimation results during the four different sessions.

Overall, Table 7 shows that opening and closing sessions are not the only two periods that observe a positive volatility-volume pattern as in Table 6. For example, for trading between floor traders and customers, a significantly positive volatility-volume relation is present more during opening, morning, and afternoon sessions than during closing sessions in all markets. For frozen pork bellies contracts, it is only during the afternoon session that volatility is positively related to volume.

For trading between customers, the effects from both unexpected volume and expected volume are more or less present in all four sessions. For trading among floor traders, a negative volatility-volume relation is more likely to be observed during opening and closing sessions than during morning and afternoon sessions. There is no evidence that a single trading session drives the results in Table 6. In summary, U-shaped volatility and volume patterns do not affect the volatility-volume relation severely.

Summary and Conclusion

This study analyzes the impact of trading parties on the intraday volatility-volume relation in four futures markets. Three types of most active engagements are trader-customer, customer-customer, and trader-trader. These three types of trading account for an average of 80 percent of all volume in these markets. Conventional wisdom is that floor traders are the most informed due to their presence in the trading floor, whereas outside retail customers are the least informed.

Table 7—Volatility, Expected Volume, and Unexpected Volume -- Robustness Check with Different Sessions During the Day

The dependent variable is intraday volatility and independent variables are Monday dummy variable and expected and unexpected parts of volume, which is decomposed into expected (E) and unexpected (U) parts using ARIMA models. The types of trading volume are: trading between floor traders and customers (Type 14), trading between customers (Type 44), and trading between floor traders (Type 11). Each trading day is divided into four sessions: opening session of the first half hour of trading; morning session from open to 11:30 am; closing for the last half hour; and afternoon session. Coefficients for volume and the dummy variable are adjusted by a factor of 1,000. In parentheses are t-statistics with autocorrelation and heteroskedasticity consistent standard errors

Panel A: Opening and Morning Sessions

	Live Cattle		Pork Bellies		Deutsch Mark		Swiss Franc	
	Opening	Morning	Opening	Morning	Opening	Morning	Opening	Morning
Constant	-0.12 (-0.84)	-0.01 (-0.99)	0.18 (0.35)	0.02 (0.55)	-0.10 (-0.56)	-0.002 (-0.71)	-0.05 (-0.37)	-0.001 (-0.49)
E(Volume ₁₁)	-0.51 (-0.51)	-0.10 (-1.41)	-20.53 (-1.15)	0.29 (0.16)	0.74 (0.78)	-0.09 (-5.05***)	-1.78 (-0.89)	-0.05 (-2.14**)
U(Volume ₁₁)	0.23 (2.10**)	-0.03 (-0.75)	-0.44 (-0.13)	-0.21 (-0.33)	-0.56 (-1.67)	-0.06 (-4.63***)	-1.45 (-2.55**)	-0.01 (-0.48)
E(Volume ₁₄)	0.07 (0.88)	0.03 (3.75***)	3.46 (1.25)	0.27 (0.79)	-0.20 (-1.00)	0.03 (4.97***)	0.48 (2.16**)	0.02 (3.09***)
U(Volume ₁₄)	0.05 (2.10**)	0.04 (4.28***)	1.44 (1.50)	0.19 (0.39)	0.08 (1.57)	0.03 (5.57***)	0.38 (4.20***)	0.02 (3.83***)
E(Volume ₄₄)	0.02 (1.57)	0.06 (3.44***)	-3.02 (-1.14)	2.20 (2.84***)	0.93 (2.70***)	0.02 (2.10**)	0.12 (0.20)	0.03 (1.21)
U(Volume ₄₄)	0.06 (2.10**)	0.02 (1.24)	4.27 (1.94**)	2.57 (2.00**)	0.28 (1.88)	-0.01 (-1.59)	0.15 (0.82)	-0.001 (-0.01)
Monday	27.49 (1.73)	4.52 (1.22)	405.01 (1.60)	62.15 (1.50)	165.30 (1.39)	-2.95 (-1.91)	39.70 (0.54)	-4.59 (-3.17***)
N	252	748	252	756	252	1,764	252	1,784
Adj. R ²	0.22	0.32	0.26	0.31	0.19	0.22	0.22	0.11

Panel B: Afternoon and Closing Sessions

	Live Cattle		Pork Bellies		Deutsch Mark		Swiss Franc	
	Afternoon	Closing	Afternoon	Closing	Afternoon	Closing	Opening	Closing
Constant	-0.04 (-2.63***)	-0.02 (-1.24)	0.42 (1.13)	-0.02 (-0.27)	-0.01 (-1.46)	-0.003 (-1.38)	-0.004 (-1.61)	-0.0003 (-0.16)
E(Volume ₁₁)	0.20 (1.19)	0.31 (2.22**)	-1.45 (-0.82)	-0.23 (-0.08)	-0.04 (-0.77)	0.03 (0.84)	0.06 (0.67)	-0.06 (-0.58)
U(Volume ₁₁)	0.02 (1.89)	0.02 (0.21)	0.50 (1.03)	2.37 (1.98**)	-0.04 (-1.24)	0.02 (0.59)	0.08 (1.04)	-0.02 (-0.56)
E(Volume ₁₄)	0.02 (1.71)	-0.02 (-0.89)	0.24 (1.34)	0.67 (1.58)	0.04 (2.03**)	-0.01 (-0.86)	0.04 (3.53***)	0.02 (0.76)
U(Volume ₁₄)	0.03 (2.51***)	-0.02 (-0.56)	0.53 (3.97***)	0.36 (1.66)	0.03 (4.37***)	-0.03 (-0.65)	0.03 (3.04***)	-0.01 (-0.97)
E(Volume ₄₄)	0.09 (3.29***)	0.02 (0.27)	2.11 (6.27***)	1.45 (3.06***)	0.02 (1.12)	0.04 (1.74)	-0.01 (-1.07)	-0.02 (-0.48)
U(Volume ₄₄)	-0.01 (-0.46)	0.002 (-0.04)	0.66 (2.91***)	0.64 (1.16)	-0.01 (-0.73)	-0.01 (-0.21)	-0.03 (-2.21**)	-0.01 (-1.69)
Monday	1.88 (0.52)	4.52 (1.22)	14.20 (0.76)	-43.34 (-1.78)	-2.05 (-0.99)	-2.04 (-1.46)	-0.18 (-0.11)	-1.31 (-1.02)
N	978	252	730	252	1,213	252	1,213	252
Adj. R ²	0.24	0.04	0.27	0.31	0.10	0.07	0.19	0.00

*** and ** indicate statistical significance at 1 percent level and 5 percent level, respectively

The dynamic relation between volatility and volume is first examined in a VAR model. A bi-directional causal relation is found generally. On the other hand, the results also show that trading party does have an impact on market volatility. Volume from trading between floor traders—the most informed ones—is associated with either no change or a reduction in volatility. Volatility is positively related to volume from trading between floor traders and customers. Only partially consistent with the noise trading models and common perception, however, trading between customers is significantly positively related to volatility only in two of the four markets. Using ARIMA models to decompose volume into expected and unexpected parts, it is more evident that trading between customers and floor traders drives the observed positive volatility-volume relation.

The results in the paper raise questions on two issues. First, are retail customers the least-informed traders in all markets? Second, will trading by customers, even if they are less informed, always increase market volatility? This study highlights that caution is needed against the perception that trading by retail customers increases market volatility in all markets.

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