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Intraday trading volume and return volatility of the DJIA stocks: A note

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Abstract

We examine the contemporaneous correlation as well as the lead–lag relation between trading volume and return volatility in all stocks comprising the Dow Jones industrial average (DJIA). We use 5-minute intraday data and measure return volatility by the exponential generalized autoregressive conditional heteroscedasticity method. Contrary to the mixture of distribution hypothesis, the vast majority of the DJIA stock shows no contemporaneous correlation between volume and volatility. However, we find evidence of significant lead–lag relations between the two variables in a large number of the DJIA stocks in accordance with the sequential information arrival hypothesis.

JEL classification: G12; G14
Keywords: DJIA; Trading volume; Return volatility; EGARCH; Pooled Granger-causality

1. Introduction

Movements in stock prices (returns) and trading volume are influenced by the flow of new information into the market. Prior research is not clear on the nature of the relationship between return volatility and trading volume. This paper revisits this debate using intraday data and a more refined measure of return volatility. We study both the contemporaneous and the causal relations between return volatility

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and trading volume for all 30 stocks comprising the Dow Jones industrial average (DJIA).

There are two theoretical explanations for the observed volume–volatility relations of stocks. These are the sequential information arrival hypothesis (SIAH) of Copeland (1976), Jennings et al. (1981), and Smirlock and Starks (1985); and the mixture of distribution hypothesis (MDH) advanced by Clark (1973), Harris (1987) and Andersen (1996). SIAH assumes that traders receive new information in a sequential, random fashion. From an initial position of equilibrium where all traders possess the same set of information, new information arrives in the market and traders revise their expectations accordingly. However, traders do not receive the information signals simultaneously. Reactions of different traders to information are parts of a series of incomplete equilibria. Once all traders have reacted to the information signal, a final equilibrium is reached. The sequential reaction to information in the SIAH suggests that lagged values of volatility may have the ability to predict current trading volume, and vice versa.

On the other hand, the MDH hypothesis implies an alternative volatility–volume nexus, in which the relation is critically dependent upon the rate of information flow into the market. The model assumes that the joint distribution of volume and volatility is bivariate normal conditional upon the arrival of information. All traders simultaneously receive the new price signals. As such, the shift to a new equilibrium is immediate and there will be no intermediate partial equilibrium. This is contrary to the SIAH, which assumes that there are intermediate equilibria en route to the final equilibrium. Thus, under the MDH, there should be no information content in past volatility data that can be used to forecast volume (or vice versa) since these variables contemporaneously change in response to the arrival of new information.

This study tests these two alternative explanations of the volume–volatility relation and contributes to the literature in several respects. First, we use intraday data to investigate the volume–volatility relation. Intraday observations seem particularly suitable for examining the volume–volatility relation. Since stock markets display high speeds of adjustment, empirical results reported in prior studies using longer time frequencies, such as daily or weekly observations, might fail to capture valuable information contained in intraday market movements. Second, we utilize the exponential generalized autoregressive conditional heteroscedasticity (EGARCH) model to measure return volatility. The proposed EGARCH model accounts for the time-varying volatility process with asymmetric responses to both positive and negative price changes. Third, we avoid the "large sample problem" in our intraday data by appropriately adjusting the critical values in the tests using a Bayesian approach.

2. Data and methodology

2.1. Data

Our sample consists of transaction prices and trading volumes from April 1, 1998 to June 30, 1998 on the 30 stocks of the DJIA. We obtain intraday transaction data (trades and quotes) from the NYSE Trade and Quote database. The DJIA stocks are very actively traded and typically experience the most frequent flow of information into the market. We divide each trading day into 78 successive 5-minute intervals when the market is open at 9:30 a.m. through 4:00 p.m., Eastern Standard Time. From the data, we compute 5-minute interval return and trading volumes. We generate the 5-minute return series for each stock by taking the log of the ratio of transaction prices in successive intervals. Because stock returns are computed within each day using only intraday prices, we exclude overnight returns from the series. Following Stoll and Whaley (1990), we exclude the first two 5-minute returns. They report that the average time to open for stocks in the S&P 500 Index (average time elapsed between the market opening and an opening transaction) is around 5–7 minutes. Prices during these intervals could reflect the stale closing price of the previous day. Therefore, disregarding the first two 5-minute return observations each day can mitigate the effects of stale price information.

2.2. Methodology

A typical characteristic of asset returns is volatility clustering where one period of high volatility is followed by more of the same and then successive periods of low volatility ensue (Bollerslev et al., 1992, 1994). Given this common characteristic, the literature has witnessed a growing interest in GARCH models, which parameterize time-varying conditional variances of stochastic processes (Glosten et al., 1993). Following Nelson (1991), we use the exponential version of GARCH (EGARCH) to measure return volatility for several reasons. The EGARCH approach is relatively novel for measuring intraday volatility of stock returns, and it is also superior to the more common GARCH model. Unlike GARCH, the EGARCH model imposes no positive constraints on estimated parameters and explicitly accounts for asymmetry in asset return volatility, thereby avoiding possible misspecification in the volatility process (Glosten et al., 1993). The EGARCH model also allows for a general probability density function (i.e., generalized error distribution, GED), which nests the normal distribution along with several other possible densities. As Bollerslev et al. (1992) note, imposing the normality assumption could bias the estimates.

The EGARCH model expresses the conditional variance of a given time series as a non-linear function of its own past values and the past values of standardized innovations. We allow the squared root of the conditional variance to enter the mean return equation, leading to an EGARCH-in-mean model (EGARCH-M). To allow for sufficient flexibility in the estimation, we use up to 12 autoregressive lags in the mean equation and specify the conditional variance as an EGARCH-M (1,1) process to obtain parsimonious estimations. The model can be written as

$$R_t = \psi + \sum_{i=1}^{12} \alpha_i R_{t-i} + \sqrt{h_t^2} + \varepsilon_t \tag{1}$$

where $\varepsilon_t \sim \mathrm{GED}(0, h_t^2)$,

$$h_t^2 = \exp\left\{\phi \ln(h_{t-1}^2) + \varphi\left[\gamma\left(\left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| - E\left(\left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right|\right)\right) + \theta\left(\left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right|\right)\right]\right\} \tag{2}$$

where R_t denotes stock returns; the ε_t's are innovations distributed as a GED with zero mean and conditional variance, h_t^2; and the coefficients ψ, α, ϕ, φ, γ, and θ are the estimated parameters. Eq. (1) represents dynamic changes in the first moment (mean) of returns, while Eq. (2) describes time variations in the conditional second moment (variance). We estimate the EGARCH-M system of equations (1) and (2) jointly using the predicted values of h_t^2 from Eq. (2) to represent the conditional variance. We apply the EGARCH-M (1,1) model for each of the 30 DJIA stock return series, and then extract the associated conditional variance to represent return volatility.

Having measured the intraday return volatility, we proceed to testing the MDH versus the SIAH hypotheses. Our first task is to investigate the contemporaneous correlation between return volatility and volume. We then examine the lead–lag relations between volume and volatility using appropriate Granger-causality tests.

Consider the following two equations:

$$h_t^2 = \gamma_1 + \sum_{k=1}^{p} a_k h_{t-k}^2 + \sum_{k=1}^{q} b_k V_{t-k} + \varepsilon_{1t}, \tag{3}$$

$$V_t = \gamma_2 + \sum_{k=1}^{m} c_k V_{t-k} + \sum_{k=1}^{n} d_k h_{t-k}^2 + \varepsilon_{2t}, \tag{4}$$

where ε_{1t} and ε_{2t} are disturbances reflecting variations in the variables over time beyond that attributable to past movements in both variables, h_t^2 is the conditional volatility, and V_t is the natural log of trading volume during time interval t. To account for possible contemporaneous correlations across equations, we estimate Eqs. (3) and (4) jointly using Zellner's seemingly unrelated regression technique. We compute likelihood ratio (LR) statistics to test the joint significance of lagged variables in each equation to distill Granger-causality inferences. We allow p, q, m and n in the above two equations to assume up to 12 lags.

Standard tests of significance can be misleading if the sample size is very large. The problem arises since extremely large samples, like ours, reduce the standard errors of the estimates, leading to the rejection of almost any null hypothesis. An appropriate approach for resolving this large-sample problem is to use Zellner (1984) Bayesian approach of posterior odds ratio statistics. We follow Zellner's approach and adjust the critical values of all tests in the paper (technical details are relegated to an appendix available upon request).

Based on the binomial test outlined by Gibbons (1985), we calculate a z-statistic to determine the probability that the actual number of stock-specific LR statistics that is significant at some predetermined levels would be observed if no causal relationship exists. The binomial z-test for the null of no causality takes the form:

$z = (S - 0.5 - N\theta_0)/(\sqrt{N\theta_0(1-\theta_0)})$, where θ_0 is the predetermined significance level (e.g., $\theta_0 = 5\%$); S is the number of stock-specific LR statistics that proved significant based on adjusted critical values derived from posterior odds ratios statistics, and N is the number of stocks in the sample.

The binomial z-distribution emphasizes extreme, rather than overall, tendencies across the sample. In order to investigate the general behavior across the sample, we employ a pooling procedure proposed by Cox and Hinkley (1974). This procedure examines systematic patterns in the data as a departure from the null. Under the null hypothesis of no causality, the probabilities (p_i) of observing particular LR statistics are distributed uniformly over an (0,1) interval. That is, the probability level of one stock-specific LR statistic is expected to be the same as the probability level of another under the null. Following Smirlock and Starks (1985), we test the average departure of p_i from the null using a LR test since $-2\sum_{i=1}^{N} \log p_i$ is distributed as a χ^2 with $2N$ degrees of freedom. Pooled Granger-causality tests have important implications for both the MDH and the SIAH. In particular, significant causal relations running in either direction between trading volume and return volatility suggest that the information arrival follows a sequential, rather than a simultaneous process.

3. Empirical results

We first obtain the conditional return variances (volatilities) of the 30 stocks in the DJIA from EGARCH-M (1,1) processes. Next, we test the statistical significance of contemporaneous correlations between return volatilities and trading volumes. Table 1 gives the contemporaneous correlations between volume and volatility, and the corresponding Bayesian-adjusted statistical significance for the DJIA stocks. As is clear from the table, only three stocks show a positive and significant contemporaneous correlation between trading volume and return volatility. The vast majority of the DJIA stocks (27) show no significant positive contemporaneous correlation between volume and volatility. Since the MDH argues for a positive contemporaneous correlation between the two variables, our results clearly fail to support the MDH.

Table 2 reports the sum of coefficients and the LR χ^2-statistics to test for Granger-causality between trading volume and return volatility. The tests are based on joint estimations of Eqs. (3) and (4) for each of the 30 stocks, and the critical values of χ^2 are also adjusted for the large-sample problem by using Zellner's posterior odds ratio approach. The results suggest that there exists significant causality flowing from trading volume to return volatility in at least 12 stocks. The calculated statistics for the reverse causality from volatility to volume are generally much smaller, but achieve statistical significance in two cases. Therefore, almost half of the DJIA stocks show robust evidence of significant causality between volume and volatility in one way or another (as suggested by the SIAH), compared to only three stocks that exhibit significant positive contemporaneous correlation (as required by the MDH).

Table 1
Contemporaneous correlations between return volatility and trading volume in the DJIA stocks

Stock symbols	Correlation coefficients	t-stats	Adj. CV's	Stock symbols	Correlation coefficients	t-stats	Adj. CV's
AA	0.0350	1.99	2.92	IP	0.0096	0.56	2.93
ALD	0.0223	1.31	2.93	JNJ	0.0031	0.19	2.94
AXP	0.0581*	3.64	2.96	JPM	−0.0075	0.47	2.96
BA	0.0088	0.51	2.93	MCD	−0.0280	1.62	2.93
CAT	−0.0031	0.18	2.93	MMM	0.0310	1.84	2.94
CCE	0.0065	0.35	2.91	MO	0.0221	1.25	2.92
CHV	0.0050	0.29	2.94	MRK	0.0095	0.61	2.96
DD	0.0270	1.69	2.96	PG	0.0051	0.32	2.95
DIS	−0.0556	3.52	2.96	S	−0.0110	0.65	2.94
EK	0.0033	0.20	2.94	T	0.0590*	3.51	2.94
GE	0.0005	0.03	2.95	TRV	0.0151	0.90	2.94
GM	0.0169	0.98	2.93	UK	0.0209	1.18	2.92
GT	−0.0386	2.19	2.92	UTX	0.0224	1.34	2.94
HWP	0.0577*	3.58	2.95	WMT	−0.0008	0.05	2.94
IBM	0.0460	2.92	2.96	XON	−0.0186	−1.13	2.95

Notes: The first column contains stock symbols, and these are: Aluminum Co. of America (AA), Allied Signal Inc. (ALD), American Express Co. (AXP), Boeing Co. (BA), Caterpillar Inc. (CAT), Coca-Cola Co. (CCE), Chevron Corp. (CHV), E.I. Du Pont de Nemours & Co. (DD), WALT Disney Co. (DIS), Eastman Kodak (EK), General Electric Co. (GE), General Motors (GM), Goodyear Tire & Rubber Co. (GT), Hewlett-Packard (HWP), International Business Machine (IBM), International Paper Co. (IP), Johnson & Johnson (JNJ), JP Morgan Chase (JPM), McDonalds Corp. (MCD), Minnesota Mining & Manufacturing Co. (MMM), Philip Morris (MO), Merck & Co. (MRK), Procter & Gamble (PG), Sears Roebuck (S), A T & T Corp. (T), Travelers Group Inc. (TRV), Union Carbide Co. (UK), United Technology (UTX), Wal-Mart Stores (WMT), Exxon Corp. (XON). The t-stats are the absolute values of the t-statistics. Adj. CV's are the corresponding critical values that are adjusted for the large-sample problem using Zellner (1984) posterior odds ratio procedure. An $*$ indicates a positive and significant correlation coefficient.

Finally, it may be useful to gauge the average (overall) causal relation between volume and volatility across the DJIA stocks as a group. We test for average causality using appropriate binomial-z and LR pooled statistics. We use the conventional 5% critical value to judge the significance of the pooled z-statistic since the large-sample problem is already resolved through using the Bayesian critical values before the pooled z-statistic was calculated. For the pooled LR statistics, we rely on a very conservative critical value that assumes 0.01% for the benchmark probability value for each stock. Therefore, the critical value of the pooled LR statistic is $-2\sum_{t=1}^{30}\log(0.0001) = 552.62$. Any computed statistic that is greater than 552.62 implies that the average probability of no-causality for a given stock is less than 0.01%.

Table 3 reports the results from the pooled causality tests. Both the z-test and the LR test easily reject the null that trading volume does not Granger-cause return volatility. Both test statistics for the reverse causality from return volatility to trading volume fail to achieve significance. This finding corroborates our earlier results from individual causality tests in support of the SIAH.

Table 2
Bayesian tests of Granger-causality hypotheses between return volatility (h^2) and trading volume (V) in the DJIA stocks

Stock symbols	Null: $V_t \nrightarrow h_t^2$ ($b_1 = b_2 = \cdots b_{12} = 0$)	Null: $h_t^2 \nrightarrow V_t$ ($d_1 = d_2 = \cdots d_{12} = 0$)	Bayesian adjusted CV's	Stock symbols	Null: $V_t \nrightarrow h_t^2$ ($b_1 = b_2 = \cdots b_{12} = 0$)	Null: $h_t^2 \nrightarrow V_t$ ($d_1 = d_2 = \cdots d_{12} = 0$)	Bayesian adjusted CV's
AA	31.67	4.94	48.46	IP	120.65*	16.58	48.80
ALD	52.38*	15.21	48.85	JNJ	49.16*	6.09	49.15
AXP	54.55*	12.04	49.64	JPM	52.56*	3.27	49.69
BA	9.61	7.45	48.69	MCD	10.57	11.43	48.67
CAT	66.09*	5.16	48.76	MMM	9.61	8.05	49.03
CCE	10.95	6.39	47.84	MO	56.49*	8.34	48.46
CHV	42.47	10.28	49.02	MRK	26.29	12.66	49.87
DD	8.32	8.10	49.65	PG	77.58*	13.29	49.56
DIS	50.58*	72.38*	49.75	S	27.17	7.66	49.03
EK	79.86*	8.76	48.93	T	50.79*	28.16	49.02
GE	24.65	15.33	49.50	TRV	38.07	4.97	49.12
GM	42.84	14.25	48.74	UK	14.54	10.95	48.47
GT	28.43	8.27	48.49	UTX	48.58	6.94	49.03
HWP	15.42	51.85*	49.51	WMT	24.96	8.72	48.92
IBM	99.94*	14.67	49.81	XON	43.31	10.26	49.29

Notes: See notes to Table 1. The first column contains the adjusted χ^2 critical values computed by the posterior odds ratio statistic described in Zellner (1984). An * indicates statistical significance.

Table 3
Pooled tests of average Granger-causality hypotheses between return volatility (h_t^2) and trading volume (V_t) in the DJIA stocks

Null hypotheses	No. of significant causality cases	Pooled z-stat.	Pooled χ^2-stat.
$V_t \nrightarrow h_t^2$ $[H_0 : b_1 = b_2 = \cdots b_{12} = 0]$	12	8.37*	681.41*
$h_t^2 \nrightarrow V_t$ $[H_0 : d_1 = d_2 = \cdots d_{12} = 0]$	2	0.00	115.01

Notes: This table displays the number of stocks whose LR statistics are significantly greater than the corresponding Bayesian critical values, the average of the sums of lagged coefficients in the respective equations, the pooled z-statistics, and the pooled χ^2-statistics which test the average null hypotheses across the DJIA stocks. The critical value of the z-statistic is the conventional 5% critical value of 1.96. The Bayesian critical value of the pooled χ^2-statistic is 552.62.

4. Concluding remarks

In this paper, we examine the contemporaneous correlations, as well as the lead–lag relations, between trading volumes and return volatility in all 30 stocks comprising the DJIA. We use intraday return volatility and trading volume, and use an EGARCH-M process to incorporate persistence in return volatility. We adjust our tests for the large-sample problem using posterior odds ratios, and examine the lead–lag relations between volume and volatility using individual and pooled Granger-causality tests.

Our results suggest that contemporaneous correlations are positive and statistically significant in only three of the 30 DJIA stocks. However, all remaining stocks of the DJIA (27) exhibit no significant positive correlation between trading volume and return volatility. Such weak evidence of contemporaneous correlations contradicts the prediction of the MDH in intraday data. The results support instead the SIAH since trading volume and return volatility are found to follow a clear lead–lag pattern in a large number of the DJIA stocks.

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Corrigendum

In the articles, "Do US stock prices deviate from their fundamental values? Some new evidence" [1] by Maosen Zhong, Ali F. Darrat and Dwight C. Anderson (Journal of Banking & Finance 27 (4) (2003), pp. 673–697), and "Intraday trading volume and return volatility of the DJIA stocks: A note" [2] by Ali F. Darrat, Shafiqur Rahman and Maosen Zhong (Journal of Banking & Finance, this issue, pp. 2035–2043), the current affiliation of the author Maosen Zhong was not mentioned. The current affiliation is

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