Effects of trading volume and transaction frequency on the intraday volatility of the Korean bond futures market

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Abstract

This study investigates the relationship between return volatility and trading volume (or transaction frequency) as a proxy variable for information arrival. For this purpose, we employ 30-minute intraday data from different time segments in the Korean treasury bond (KTB) futures market. Including trading volume in the GARCH model reduces the persistence of conditional variances, suggesting that trading volume is a useful innovation for explaining the persistence of return volatility in the KTB Futures market. This finding provides support for the mixture of distributions hypothesis that return volatility and trading volume are influenced by the same underlying flow of latent information to markets. In particular, we find that transaction frequency is a good substitute variable for explaining the persistence of return volatility as a proxy for information arrival for the KTB Futures market.

Keywords: Information arrival; Intraday volatility; Mixture of distributions hypothesis; Persistence; Transaction frequency; Trading volume

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1. Introduction

In recent years, there has been a growing interest in the role of trading volume in explaining return volatility dynamics in the fields of economics and finance. The mixture of distributions hypothesis (MDH) posits that return volatility and trading volume are influenced by the same underlying flow of latent information to markets and thus that they are positively correlated. When a proxy for information arrival is included, the persistence of conditional variances can be explained by information arrival (Karpoff, 1987; Clark, 1973; Epps and Epps, 1976; Tauchen and Pitts, 1983; Harris, 1987).

Following the MDH, Lamoureux and Lastrapes (1990) are the first to employ daily trading volume as a proxy for information arrival in the generalized autoregressive conditional heteroskedasticity (GARCH) model. Since their work, a large number of studies have documented the relationship between return volatility and trading volume but provided inconsistent findings (Najand and Yung, 1991; Gallo and Pacini, 2000; Omran and Mckenzie, 2000; Pyun, Lee and Nam, 2000; Chen, Firth and Rui, 2001; Miyakoshi, 2002; Bohl and Henke, 2003; Wang, Wang and Liu, 2005; Avramov, Chordia and Goyal, 2006; Fleming, Kirby and Ostdiek, 2006; Alsubaie and Najand, 2009).

Because market information is quickly reflected in financial time series, previous studies using low-frequency data, particularly daily or weekly observations, may not capture the real-time information flow in intraday market movements. Recent studies have indicated that intraday observations are particularly suitable for examining volatility-volume relationships (Huang and Yang, 2001; Darrat, Rahman and Zhong, 2003; Hodgson, Masih and Masih, 2006; Puri and Philippatos, 2008).

The main purpose of the present paper is to examine the relationship between intraday return volatility and trading volume in the Korean treasury bond (hereafter "KTB") futures market by using the GARCH model. Despite the obvious importance of the volatility-volume relationship, few studies have addressed this topic in the context of futures markets. For this reason, we narrow this gap by examining the validity of the MDH in the unique KTB Futures market.

We also consider 30-minute intraday data from different time segments. It is well known that return volatility and trading volume vary according to time intervals throughout any given trading day. Thus, segmenting daily transactions into various subintervals can lead to insightful findings with valuable implications for academicians and practitioners.

Also using the MDH, this study examines the role of transaction frequency as a proxy for information arrival. In technical analysis, market analysts can use information on changes in intraday transaction frequency for evaluating return volatility. Thus, it should be worthwhile to explore the effects of transaction frequency on return volatility.

The rest of the paper is organized as follows. Section 2 provides descriptive statistics for 30-minute KTB Futures data, including trading volume and transaction frequency. Section 3 reviews the GARCH model used in the study. Section 4 presents the empirical results, and Section 5 concludes.

2. Data and descriptive statistics

We use 30-minute data on price, trading volume, and transaction frequency for KTB Futures traded on the Korea Exchange (KRX). The 30-minute data set (January 2, 2003-August 31, 2005) are obtained from the KRX. Figure 1 shows the dynamics of 30-minute KTB Futures prices. These prices consist of 12 intervals per day from 9 a.m. to 3 p.m., covering 7,932 data points for 662 trading days.

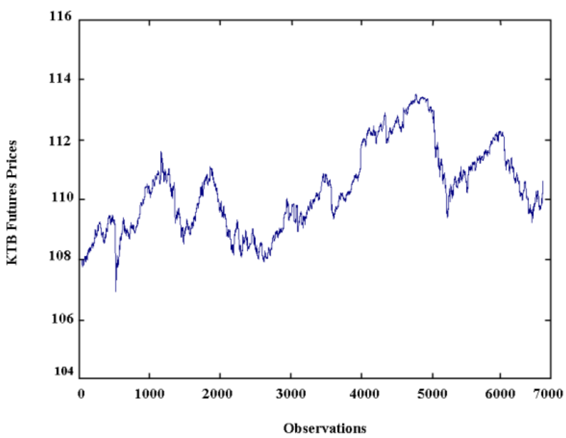

Figure 1. Dynamics of 30-minute KTB Futures prices

Table 1 presents the main features of KTB Futures contracts. KTB Futures prices are based on a three-year Korean treasury bond with a coupon rate of 8% and a semi-annual payment schedule; the bond is available on a quarterly basis (March, June, September, and December). Every 30-minute interval each day produces 12 series each for price, trading volume, and transaction frequency.

Table 1. Summary of KTB Futures contracts

Underlying assets	Three-year Korean treasury bond with a coupon rate of 8% and a semi-annual payment schedule
Contract size	KRW 100 million
Contract months	The first two consecutive months of each quarterly cycle (March, June, September, and December)
Trading hours	09:00~15:15 (09:00~11:30 on the last trading day) [1]
Tick size and value	0.01 point represents KRW 10,000
Last trading day	The third Tuesday of the contract month
Final settlement day	The day after the last trading day
Final settlement	Cash

Source: The Korea Exchange (http://www.krx.co.kr).

The 30-minute prices are converted into the percentage logarithmic returns by using the following formula:

$$r_{t,n} = \ln\left[\frac{P_{t,n}}{P_{t-1,n}}\right]\times 100, \quad t = 1, 2, \ldots, 662 \text{ and } n = 1, 2, \ldots, 12, \tag{1}$$

where t is the number of trading days; n is the number of 30-minute time intervals in the sample period; $P_{t,n}$ is the price of KTB Futures in n^{th} time segment (30-minute) of t^{th} trading day. In addition, trading volume and transaction frequency at the n^{th} transaction time on day t are expressed as

$V_{t,n} = trading\ volume_{t,n}$,

$T_{t,n} = transaction\ \ frequency_{t,n}$.

[1] Data from the last 15 minutes of each trading day are excluded to prevent problems associated with missing data.

Table 2 reports the descriptive statistics and the results of the unit root test for the 30-minute return series. As shown in Panel A of Table 2, each time interval consists of 661 observations (except for the 12:00 time period: 649 observations). The means and standard deviations of the return series are similar for each time period. The negative skewness and excess kurtosis of all the 30-minute returns indicate a substantial departure from normality. Similarly, the Jarque-Bera (J-B) test results indicate that the null hypothesis of normality is rejected at the 5% level of significance.

In addition, Panel B of Table 2 provides the results of two unit root tests for each sample return: the augmented Dickey-Fuller (ADF) test (the null hypothesis of a unit root) and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test (the null hypothesis of stationarity). As shown in Table 2, the ADF test rejects the null hypothesis of a unit root, whereas the KPSS test does not reject the null hypothesis of stationarity at the 1% level. Thus, we conclude that all 30-minute return series reflect stationary processes.

Figures 2 and 3 show the means and standard deviations for trading volume and transaction frequency, respectively, for each time period. Both figures show similar patterns for both the means and standard deviations: a U-shaped pattern indicating higher trading volume and transaction frequency around the opening time (9:00) and the closing time (14:30). Traders may be more active around these hours because of the intraday behavior of traders. For example, higher trading volume and transaction frequency are often seen during the first 30 minutes because traders use information from the previous night and from the morning before the market opens. In addition, trading volume and transaction frequency also increase before the end of the day because traders are likely to close or hedge their open positions. Similar behavior has been reported by Jain and Joh (1998), Huang (2002), Bertram (2004), and Puri and Philippatos (2008).

Table 3 shows the autocorrelation up to five lags and the Ljung-Box $Q(12)$ statistic of the 30-minute time series for trading volume and transaction frequency. The calculated values of autocorrelation indicate that all the trading volume and transaction frequency series exhibit strong serial correlation. In addition, the significance of the Ljung-Box test statistics confirms the presence of serial correlation in the trading volume and transaction frequency data. This implies that the rate of information arrival is serially correlated when it is measured with a proxy for the 30-minute trading volume or transaction frequency.

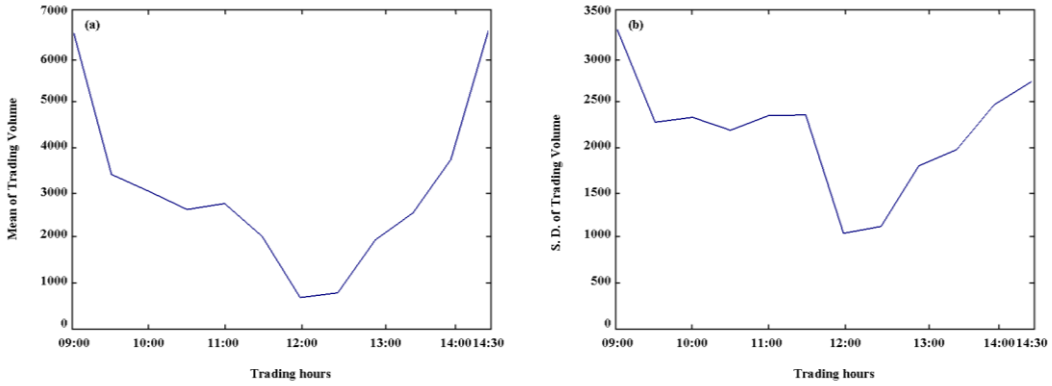

Figure 2. Intraday means and standard deviations for trading volume: (a) means and (b) standard deviations

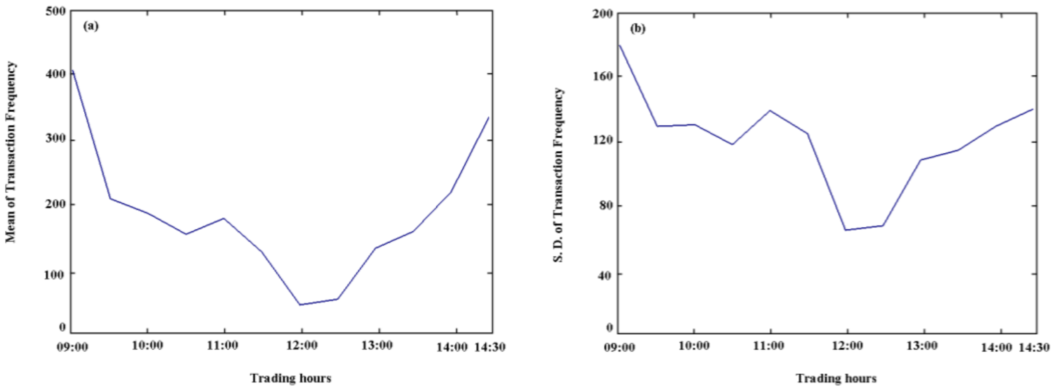

Figure 3. Intraday means and standard deviations for transaction frequency: (a) means and (b) standard deviations

Table 2. Summary of descriptive statistics and results of the unit root test for 30-minute KTB Futures returns

Time period	09:00	09:30	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30
Panel A: Descriptive statistics												
Mean (%)	0.0037	0.0038	0.0037	0.0036	0.0037	0.0037	0.0038	0.0037	0.0038	0.0038	0.0036	0.0035
Std. Dev.	0.186	0.188	0.183	0.179	0.176	0.177	0.179	0.181	0.182	0.181	0.179	0.177
Skewness	-1.389	-1.146	-0.827	-0.825	-0.739	-0.828	-0.720	-0.753	-0.724	-0.716	-0.906	-1.398
Kurtosis	14.71	10.21	6.516	7.099	6.750	6.761	6.696	6.765	6.625	5.933	6.748	11.71
J-B	3988**	1575**	415.8**	537.8**	447.6**	465.1**	425.5**	452.9**	419.9**	293.4**	477.3**	2306**
Panel B: Results of the unit root test												
ADF	-19.9**	-25.6**	-25.1**	-24.9**	-24.5**	-23.8**	-23.5**	-24.4**	-24.1**	-24.3**	-24.2**	-23.5**
KPSS	0.108	0.109	0.106	0.105	0.103	0.100	0.096	0.097	0.095	0.094	0.096	0.104

Notes: The Jarque-Bera (J-B) test (the null hypothesis of normality in the distribution of sample returns). The critical values for the ADF and KPSS tests are –3.435 and 0.739, respectively, at the 1% level. ** denotes the rejection of the null hypothesis at the 1% level.

Table 3. Autocorrelation (up to five lags) and $Q(12)$ for trading volume and transaction frequency

Time period	09:00	09:30	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30
Trading volume												
1 lag	0.345**	0.273**	0.213**	0.248**	0.093*	0.135**	0.111**	0.114**	0.161**	0.198**	0.179**	0.322**
2 lags	0.278**	0.208**	0.231**	0.124**	0.165**	0.128**	0.076	0.052	0.079*	0.221**	0.092*	0.243**
3 lags	0.257**	0.192**	0.193**	0.133**	0.111**	0.136**	0.070	0.089*	0.114**	0.104**	0.137**	0.207**
4 lags	0.276**	0.216**	0.163**	0.144**	0.088*	0.064	0.124**	0.188**	0.096*	0.101**	0.115**	0.216**
5 lags	0.245**	0.143**	0.224**	0.212**	0.096*	0.104**	0.038	0.029	0.102**	0.136**	0.107*	0.197**
$Q(12)$	431.17 [0.000]	230.53 [0.000]	256.99 [0.000]	158.1 [0.000]	66.74 [0.000]	70.10 [0.000]	32.97 [0.001]	55.86 [0.000]	66.00 [0.000]	154.4 [0.000]	81.12 [0.000]	293.90 [0.000]
Transaction frequency												
1 lag	0.539**	0.341**	0.274**	0.318**	0.206**	0.211**	0.151**	0.140**	0.209**	0.241**	0.289**	0.401**
2 lags	0.472**	0.292**	0.311**	0.181**	0.226**	0.196**	0.138**	0.092*	0.133**	0.254**	0.198**	0.327**
3 lags	0.460**	0.223**	0.246**	0.220**	0.183**	0.196**	0.119**	0.135**	0.158**	0.172**	0.166**	0.313**
4 lags	0.478**	0.273**	0.250**	0.224**	0.163**	0.137**	0.144**	0.228**	0.170**	0.169**	0.224**	0.317**
5 lags	0.417**	0.229**	0.275**	0.238**	0.201**	0.206**	0.080*	0.080*	0.113**	0.182**	0.201**	0.313**
$Q(12)$	1341.1 [0.000]	424.4 [0.000]	404.1 [0.000]	301.7 [0.000]	215.1 [0.000]	196.4 [0.000]	66.17 [0.000]	110.9 [0.000]	161.9 [0.000]	271.9 [0.000]	292.7 [0.000]	636.0 [0.000]

Notes: Autocorrelation contains up to five lags. The Ljung-Box $Q(12)$ statistic tests serial correlation up to the 12^{th} lag length. * and ** denote significance at the 5% and 1% levels, respectively.

3. Methodology

Following Lamoureux and Lastrapes (1990), we re-examine the relationship between return volatility and trading volume. If information arrival leads to volatility clustering, which is commonly observed in return series, then we can capture this feature by using the GARCH model of Bollerslev (1986), which includes trading volume as a proxy for information arrival. This specification can be expressed as follows:

$$r_{t,n} = \mu + \varepsilon_t, \tag{2}$$

$$\varepsilon_{t,n} \mid (V_{t,n}, \varepsilon_{t-1,n}, \varepsilon_{t-2,n}, \ldots) \sim N\left(0, h_{t,n}\right), \tag{3}$$

$$h_{t,n} = \alpha_0 + \alpha_1 \varepsilon_{t-1,n}^2 + \alpha_2 h_{t-1,n} + \alpha_3 V_{t,n}, \qquad \alpha_0 > 0,\ \alpha_1, \alpha_2, \alpha_3 \geq 0, \tag{4}$$

where $r_{t,n}$ is the 30-minute return series of KTB Futures; μ denotes the mean of returns; $V_{t,n}$ is the 30-minute time series of trading volume, which is used as a proxy for information arrival for the KTB Futures market.

In the case of $\alpha_3 = 0$, the above equation represents the GARCH (1,1) model, ignoring the volume effect of conditional variances. In the GARCH model, the persistence of conditional variances is measured by the sum $(\alpha_1 + \alpha_2)$. The greater this sum, the greater the persistence of shocks to return volatility is. If trading volume is considered a proxy for information arrival, then it is expected that $\alpha_3 > 0$. In this case, the sum $(\alpha_1 + \alpha_2)$ will be less than that when trading volume is excluded, and α_1 or α_2 may be insignificant.

We also examine the relationship between return volatility and transaction frequency as follows:

$$h_{t,n} = \alpha_0 + \alpha_1 \varepsilon_{t-1,n}^2 + \alpha_2 h_{t-1,n} + \alpha_3 T_{t,n}, \tag{5}$$

where $T_{t,n}$ is the transaction frequency series at each 30-minute interval and is an alternative proxy for information arrival. All the parameters of Equations (4) and (5) can be estimated by using the Brendt, Hall, Hall, and Hausman (BHHH) algorithm technique and assuming conditional Gaussian errors. The log-likelihood of the Gaussian or normal distribution $\left(L_{Norm}\right)$ can be expressed as

$$\log\left(L_{Norm}\right) = -\frac{1}{2}T\log\left(2\pi\right) - \frac{1}{2}\sum_{t=1}^{T}\left[\log\left(h_{t,n}\right) + \frac{\varepsilon_{t,n}^{2}}{h_{t,n}}\right]. \tag{6}$$

4. Empirical results

Table 4 presents the parameter estimates for the simple GARCH (1,1) model without trading volume (i.e. under the assumption of $\alpha_3 = 0$). The second and third columns show the estimates for the ARCH effect term $\left(\varepsilon_{t-1,n}^{2}\right)$ and the GARCH effect term $\left(h_{t-1,n}\right)$, respectively, in the conditional variance equation. The estimated coefficients α_1 and α_2 are highly significant, and the sum of these coefficients $(\alpha_1 + \alpha_2)$ range from 0.665 to 0.900, implying that every 30-miutue return series shows high persistence in the conditional variance.

Tables 5 and 6 report the estimates for the ARCH and GARCH parameters, respectively, in the GARCH (1,1) model, including trading volume and transaction frequency. The two tables show similar results. When trading volume and transaction frequency are included in the GARCH (1,1) model, the coefficient for the trading volume or transaction frequency effect, α_3, for all intraday series is positive and significant at the 1% level.

In addition, it is evident that the sum of α_1 and α_2 shown in Table 5 (the GARCH model with trading volume) and in Table 6 (the GARCH model with transaction frequency) is less than that in Table 4 (the GARCH model with neither trading volume nor transaction frequency). This indicates that including trading volume or transaction frequency in the simple GARCH (1,1) model dramatically reduces the degree of persistence. This provides support for the MDH that a serially correlated mixing variable measuring the rate at which information arrives in market can explain the GARCH effect. Thus, we conclude that both trading volume and transaction frequency are good proxies for information arrival in explaining the volatility persistence in 30-minute return series.

Table 4. Results for the GARCH $(1,1)$ model

Model: $h_{t,n} = \alpha_0 + \alpha_1 \varepsilon^2_{t-1,n} + \alpha_2 h_{t-1,n}$.

Time period	α_1	α_2	$\alpha_1 + \alpha_2$	$Q_2(12)$	ARCH(5)
09:00	0.308 (0.025)**	0.540 (0.005)**	0.848	4.425 [0.956]	0.392 [0.950]
09:30	0.216 (0.030)**	0.664 (0.048)**	0.880	9.231 [0.601]	1.181 [0.317]
10:00	0.127 (0.021)**	0.758 (0.050)**	0.885	5.967 [0.876]	0.405 [0.845]
10:30	0.065 (0.017)**	0.817 (0.049)**	0.882	2.731 [0.994]	0.205 [0.960]
11:00	0.058 (0.026)*	0.842 (0.063)**	0.900	2.427 [0.996]	0.256 [0.937]
11:30	0.066 (0.025)*	0.814 (0.069)**	0.880	2.557 [0.995]	0.203 [0.961]
12:00	0.058 (0.024)*	0.834 (0.061)**	0.892	3.771 [0.976]	0.257 [0.934]
12:30	0.082 (0.024)**	0.796 (0.054)**	0.878	5.003 [0.931]	0.312 [0.906]
13:00	0.093 (0.027)**	0.769 (0.062)**	0.862	6.125 [0.865]	0.374 [0.867]
13:30	0.132 (0.034)**	0.728 (0.067)**	0.860	5.750 [0.889]	0.497 [0.778]
14:00	0.169 (0.041)**	0.611 (0.070)**	0.780	5.067 [0.928]	0.387 [0.858]
14:30	0.148 (0.053)**	0.517 (0.106)**	0.665	1.496 [0.999]	0.151 [0.979]

Notes: Standard errors are in parentheses, and p-values are in brackets. The Ljung-Box $Q_2(12)$ test statistic checks for serial correlation up to 12th lag length in the squared standardized returns. The ARCH (5) test statistic checks the remaining ARCH effects in the 5th order lagged squared residuals. * and ** denote significance at the 5% and 1% levels, respectively.

Table 5. Results for the GARCH $(1,1)$ model with trading volume

Model: $h_{t,n} = \alpha_0 + \alpha_1 \varepsilon_{t-1,n}^2 + \alpha_2 h_{t-1,n} + \alpha_3 V_{t,n}$.

Time period	α_1	α_2	$\alpha_1 + \alpha_2$	$\alpha_3 \times 10^5$	$Q_2(12)$	ARCH(5)
09:00	0.155 (0.040)*	0.030 (0.066)	0.185	0.389 (0.034)**	4.636 [0.947]	0.410 [0.942]
09:30	0.207 (0.043)**	0.002 (0.044)	0.209	0.814 (0.072)**	13.19 [0.281]	1.124 [0.346]
10:00	0.088 (0.049)	0.024 (0.051)	0.112	0.832 (0.092)**	13.55 [0.259]	0.475 [0.795]
10:30	0.115 (0.040)**	0.078 (0.063)	0.193	1.050 (0.090)**	5.636 [0.896]	0.266 [0.931]
11:00	0.041 (0.038)	0.019 (0.039)	0.060	0.850 (0.073)**	11.63 [0.392]	0.368 [0.870]
11:30	0.024 (0.033)	0.123 (0.060)*	0.147	1.190 (0.120)**	22.19 [0.023]	1.443 [0.207]
12:00	0.057 (0.024)*	0.709 (0.050)**	0.766	1.030 (0.182)**	10.36 [0.498]	0.225 [0.952]
12:30	0.006 (0.024)	0.408 (0.049)**	0.414	2.360 (0.316)**	15.46 [0.162]	0.112 [0.989]
13:00	0.033 (0.025)	0.128 (0.085)	0.061	1.150 (0.211)**	7.525 [0.756]	0.265 [0.932]
13:30	0.071 (0.028)*	0.011 (0.041)	0.082	1.030 (0.089)**	7.628 [0.773]	0.415 [0.838]
14:00	0.120 (0.035)**	0.084 (0.043)	0.204	0.775 (0.058)**	17.44 [0.095]	0.603 [0.697]
14:30	0.058 (0.043)	0.059 (0.540)	0.117	0.547 (0.006)**	8.592 [0.659]	1.377 [0.231]

Note: See Table 4.

Table 6. Results for the GARCH $(1,1)$ model with transaction frequency

Model: $h_{t,n} = \alpha_0 + \alpha_1 \varepsilon^2_{t-1,n} + \alpha_2 h_{t-1,n} + \alpha_3 T_{t,n}$.

Time period	α_1	α_2	$\alpha_1 + \alpha_2$	$\alpha_3 \times 10^4$	$Q_2(12)$	ARCH(5)
09:00	0.183 (0.038)**	0.097 (0.040)*	0.280	5.750 (0.427)**	3.326 [0.986]	0.573 [0.722]
09:30	0.188 (0.039)**	0.043 (0.038)	0.231	1.490 (0.120)**	14.68 [0.197]	1.126 [0.345]
10:00	0.073 (0.049)	0.033 (0.053)	0.106	1.390 (0.138)**	15.20 [0.173]	0.326 [0.897]
10:30	0.114 (0.039)**	0.030 (0.045)	0.144	2.000 (0.116)**	3.522 [0.982]	0.205 [0.960]
11:00	0.034 (0.037)	0.021 (0.049)	0.055	1.360 (0.119)**	7.279 [0.776]	0.508 [0.770]
11:30	0.030 (0.033)	0.152 (0.075)**	0.182	1.730 (0.183)**	17.49 [0.094]	1.261 [0.279]
12:00	0.0151 (0.025)	0.503 (0.091)**	0.518	2.120 (0.454)**	6.093 [0.867]	0.177 [0.971]
12:30	0.012 (0.017)	0.737 (0.042)**	0.749	1.360 (0.203)**	4.428 [0.956]	0.163 [0.976]
13:00	0.013 (0.021)	0.129 (0.031)**	0.142	1.800 (0.183)**	8.603 [0.658]	0.208 [0.959]
13:30	0.061 (0.028)*	0.043 (0.056)	0.104	1.790 (0.142)	21.10 [0.032]	0.640 [0.669]
14:00	0.081 (0.057)	0.254 (0.010)**	0.335	1.660 (0.200)**	10.28 [0.505]	1.749 [0.121]
14:30	0.120 (0.034)**	0.039 (0.051)	0.159	0.762 (0.047)**	6.208 [0.859]	1.039 [0.394]

Note: See Table 4.

Finally, we examine the accuracy of model specifications by using the Ljung-Box $Q_s(12)$ and ARCH (5) tests (Tables 5 and 6). Due to the insignificance of both diagnostic tests at the 1% level, we conclude that the GARCH $(1,1)$ model with trading volume and transaction frequency is sufficiently specified in the measurement of information arrival for the KTB Futures market.

5. Conclusions

Following Lamoureux and Lastrapes (1990), we re-examine the relationship between return volatility and trading volume (or transaction frequency) as proxies for information arrival. For this purpose, we employ 30-minute intraday data from different time segments in the KTB Futures market. Including trading volume in the GARCH model reduces the persistence of conditional variances, suggesting that trading volume is a useful indicator of the persistence of return volatility in the KTB Futures market. This finding provides support for the MDH that return volatility and trading volume are influenced by the same underlying flow of latent information to markets. In particular, we find that transaction frequency is a good substitute variable for explaining the persistence of return volatility as a proxy for information arrival for the KTB Futures market. This finding implies that transaction frequency and trading volume have very similar contents of market information.

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