Trading volume and volatility of stock market returns: High-frequency evidence from Indonesia

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Abstract

We examine the relationship between market-wide realized volatility and trading volume of emerging market equities. This study contributes to the literature by using high-frequency data to investigate trading volume-volatility relations in the Indonesian equity market, thereby enhancing understanding of Indonesian market microstructure before, during and after the 2008 global financial crisis. Consistent with the literature, we find different patterns of trading volume and volatility during intraday. We also find mixed results on the significance and directions of volume-volatility relations. While we find no Granger-causality relations between trading volume and volatility during the full sample period, there is evidence of bi-directional causality relationships when observations are decomposed into subsample periods and days of the week.

1. Introduction

There is a growing number of studies on the patterns of volatility, particularly in emerging market settings. Recent studies include Hanousek, Kočenda, and Kutan (2009), Kim and Singal (2000), and Engle, Ghysels, and Sohn (2013). However, despite its significance, little research has been undertaken to uncover the relationship between volatility patterns and trading activities in emerging equity markets, particularly during periods when the volatility is unusually high.

Previous studies such as Admati and Pfleiderer (1988), Pisedtasalasai and Gunasekarage (2007) and Shahzad et al. (2014) show that trading volume and volatility move together with information arrivals and, to some extent, create a similar U-shaped pattern. Therefore, trading volume may indicate the flows and dissemination level of information into the market in a similar way to price, returns and volatility data.

This study aims to investigate the causal and dynamic relations between the trading volume and volatility of Indonesian equities. This study contributes to the literature in several ways. First, as suggested by Karpoff (1987), this study will enhance the understanding of trading volume-volatility relations conditioning on the rate of information flow to the market, dissemination of information, market size, or short-sales restriction. Second, although trading volume-volatility relations have been studied previously, to the authors' knowledge, this study is the first in the context of the Indonesian stock market using high-frequency data. Third, trading volume patterns might be applied as a measure, additional to volatility, to identify markets in a financial crisis.

Consistent with the literature, we find that both trading volume and volatility increase before and during the global financial crisis (GFC). The jump in trading volume is reported during August and November whilst that of volatility is recorded during October-November. Furthermore, there are different patterns of trading volume and volatility during intraday, both by subsample periods and days of the week. Before and after the GFC, the volatility of LQ45 returns forms a U shape. During the GFC, the intraday volatility creates a reverse J-shaped pattern.

Similar to volatility, trading volume shows a U-shaped pattern in pre-GFC period. During the GFC, trading volume fluctuates during intraday and reaches peaks during opening and closing hours. In post-GFC period, trading volume increases gradually until midday before it finally decreases until the end of day.

Furthermore, the volatility creates a U-shaped intraday pattern throughout the year, except between September and November. This finding is in contrast to the patterns of trading volume which are not significantly different between months of the year. Moreover, we also find a U-shaped intraday pattern for all days of the week except on Friday. The intraday pattern of trading volume is also similar over days of the week except on Friday.

We find a positive relationship between trading volume and volatility, particularly before and during the GFC. However after the GFC, the trading volume and volatility are negatively correlated. This finding is supported by previous studies that the volume-volatility relations are mixed and affected by a number of factors such as the level of information efficiency, behaviour of informed traders and liquidity traders, and foreign trading activities.

Prior to the GFC, trading volume Granger-causes volatility in the first lag level. Consistent with previous studies, trading volume Granger-causes volatility with higher impact during the GFC than in other periods. During the full sample period, volatility does not Granger-cause trading volume. The volatility Granger-causes trading volume only during pre-GFC and from Monday-Thursday. During the GFC, volatility has negative impact on both trading volume and during Monday-Thursday. However, there is no predictive power of volatility on trading volume for trading in Friday during GFC and since then.

The paper is organized as follows: in the following section our topic is placed into the context of the literature. Section 3 presents the data and methodology. In Section 4, we report and discuss the results and Section 5 is the conclusion.

2. Literature review

Research into equity return volatility has largely focussed on risk management, asset price modelling and portfolio selection (Andersen, Bollerslev, and Das 2001; Andersen et al. 2003), monetary policy making (Poon and Granger 2003; Kalev et al. 2004), warning of potential crises (Schwert 1989), and identifying price manipulation (Bekaert and Harvey 2000; Aggarwal and Wu 2006). However, there is a dearth of studies focussing on the relationship between volatility and trading volume.

Studies in the market microstructure literature such as Admati and Pfleiderer (1988) and Foster and Viswanathan (1994) support the importance of trading volume in the price discovery process. Trading volume can explain the price variability in the market by showing the role of informed traders and liquidity traders, and concentration of trading.

According to Admati and Pfleiderer (1988), the relationship between volume and volatility depends on strategic trading behaviour of informed and liquidity traders. The more informed traders go into the market and observe the same piece of information, the more informative the asset prices and the lower the price variance. As a result, more liquidity traders join to trade and trading activity increases. If the informed traders who go into the market observe a diverse piece of information, the price variance increases since the market is more filled with various information although trading activity increases.

Nevertheless, Foster & Viswanathan (1994) argue that high trading activity can occur in a less liquid market since the better-informed traders tend to trade more intensively on the information that is similar to that of lesser-informed traders but less intensively on their additional information to disguise their strategy from other traders. Other studies argue that shocks in trading volume are not necessarily due to information asymmetry but due to pressures from liquidity traders (Darrat, Zhong, and Cheng 2007; Kalev et al. 2004; Gropp and Kadareja 2012).

Patterns of volatility and trading volume during intraday

Empirical studies reveal that both returns and volatility draw particular patterns during the day. The intraday pattern of volatility is typically U-shaped due to high trading activities surrounding the opening and closing of the market, but low during mid-day (Admati and Pfleiderer 1988; Ozenbas, Pagano, and Scwartz 2010; Andersen, Bollerslev, and Cai 2000). Furthermore, based on a study on the Tokyo Stock Exchange, using 5-minute Nikkei 225 index returns, Andersen, Bollerslev, and Cai (2000) suggest that the U-shape pattern of intraday volatility is due to strategic interactions among informed traders during opening hours as a reaction to information accumulated overnight and to anticipate information arriving after market closing. Similar pattern is also evidenced in studies looking at markets and products which are structurally different such as in the U.S. markets (Admati and Pfleiderer 1988), London Stock Exchange (Ozenbas, Pagano, and Scwartz 2010), and in foreign exchange, warrants and options markets (e.g. Segara and Sagara 2007; Andersen, Bollerslev, and Das 2001).

Admati and Pfleiderer (1988) argue that the U-shaped pattern of intraday volatility is caused by the concentration of trading conducted by liquidity traders and informed traders. The rate of information arrival in the stock market is high just after the opening and before the closing of the market, and the number of informed traders increases during these periods. Furthermore, the more competition amongst informed trader increases, the more private information prevails in the market, which attracts liquidity traders to trade. As a result, trading cost reduces, price variance decreases and trading activities intensify, which results in high trading volume and increased liquidity. However, Foster and Viswanathan (1994) suggest that in a market where information is asymmetrically distributed, trading volume can be high although the market is less liquid.

Similar to Admati and Pfleiderer (1988), Andersen, Bollerslev, and Cai (2000) argue that the U-shaped pattern of intraday volatility is due to traders' responses to a number of items of information which have been accumulated during previous non-trading periods. Trading activities subsequently cool down during mid-day when all information has been fully captured in prices. Furthermore, traders tend to increase trading before market closing to avoid risks caused by new information arriving after market closes. Thus, the level of trading volume and frequency is usually different across trading hours.

Furthermore, a similar U-shaped pattern of trading volume is also found during intraday. Using the New York Stock Exchange hourly data, Jain and Joh (1988) assert that trading volume follows a U-shaped intraday pattern due to heavy transactions at the beginning and end of the trading day, but only light during midday. Jain and Joh (1988) also find that the average volume of shares traded is significantly different across trading hours of the day and across days of the week. Furthermore, they find that the volume-relations are much steeper for positive returns and for negative returns. Stephan and Whaley (1990) find similar results using data of CBOE call options and their underlying stocks.

Day of the week and seasonality effects

A great number of studies in efficient market hypothesis literature have included calendar effects to investigate whether stock returns have regularities from which investors can predict and gain abnormal returns. For example, the average rate of stock returns in January is commonly higher than other months of the year. Furthermore, the different returns between days of the week have also been of interest in empirical finance since the study by Cross (1973) who examines different stock price behaviour on Fridays and Mondays. Using three different types of return measurements: intraday returns, interday returns and overnight returns, McInish and Wood (1985), for example, find that interday returns are positive for Friday but negative for Monday. Similar patterns are also reported for intraday returns, but not for overnight. The results that intraday returns for Fridays are higher than Mondays are robust when they are decomposed by actively traded and smaller-size stocks.

The dynamic relationships of volume-volatility

We further extend the examination of the joint patterns of trading volume and volatility in the literature by looking at their dynamic and causal relationships. For example, Darrat, Zhong, and Cheng (2007) find bi-directional relationships between trading volume and volatility of the NYSE stocks returns during the period with public news. However during the period without public news, they find that volume causes more volatility. Furthermore, they find that volatility is higher in the period with public news whilst trading volume is higher in the period without public news.

In the context of emerging stock markets, a study by Pisedtasalasai and Gunasekarage (2007) shows that trading volume has a negative impact on stock returns but does not Granger-cause. However, the returns of emerging stock markets Granger-cause and positively lead to trading volume. This finding is consistent with Girard and Biswas (2007) who find a negative relation between expected trading volume and volatility in 27 emerging markets, which is mostly due to the informational inefficiency.

3. Data and methodology

This study attempts to investigate the dynamic relations between trading volume and volatility using five-minute data. We use data of the Jakarta LQ45 index[2] which is the weighted value of 45 most liquid stocks and represents almost two-third of total Indonesian stock market capitalization (Indonesia Stock Exchange, 2012). Data of five-minute trading

[2] There are 12 stock price-related indices and one government bond index listed on the Indonesian Stock Exchange (IDX). Full explanation of the calculation method and most recent names of the indices are available from the IDX's Fact Books (Indonesia Stock Exchange 2013, 2012).

volume and price used in this study is from January 2, 2006 to December 28, 2012, or a total of 1707 trading days. The data is available from the Thomson-Reuter's Tick History database of SIRCA[3].

We use five-minute interval data in this study because it measures volatility with minimum error and less microstructure noise (Corsi et al. cited in Dacorogna et al., 2001; Hansen and Lunde, 2006). Moreover, during the sample period, there is the time when the Global Financial Crisis (GFC) occurred. In this case, we follow Smales (2013) in determining the cut-off times of the crisis. Smales (2013) suggests that the GFC starts from July 2007 when the U.S. Bear Stearns went bankrupt and initiated the global financial crisis. To capture the impact of the GFC, the sampling period in this study is divided into three sub-samples: (i) pre-GFC (January 2006 - July 2007), (ii) during GFC (August 2007 - December 2009), and (iii) post-GFC (January 2010 – December 2012).

3.1 Trading volume

Prior to examining the dynamic relations between trading volume and intraday volatility of returns, we first determine variables used in this study and how to measure them, as follows; trading volume, returns and volatility.

Brailsford (1996) suggests three measures of trading volume to examine the relationship between trading volume, returns and volatility in the Australian stock market from 24 April 1989 to 31 December 1994: (i) as the daily number of transactions, (ii) as the daily number of shares traded, and (iii) as the daily total dollar value of shares traded. However, Pisedtasalasai and Gunasekarage (2007) simply use daily trading volume data from January 1991 to December 2004 to measure the causal and dynamic relationships between stock returns, volatility and trading volume.

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[3] SIRCA, the Securities Industry Research Center of Asia Pacific, provides historical market data service, including intraday Time and Sales of global markets, Time and Quotes, Market Depth and Corporate Actions since January 1996. SIRCA has also supplied global news transmitted from the international Reuters newswire from as early as 2003.

Prior research closely related to this study in using trading volume data includes Stephan and Whaley (1990) and Shahzad et al. (2014) who use five-minute data to investigate relations between price changes and trading volume. Trading volume used by Shahzad et al. (2014) is based on bid-ask order level and not based on transaction. They further decompose the trading volume into three different categories: total trade volume, average trade size, and total number of trades. Meanwhile, Stephan and Whaley (1990) measure the trading volume as the proportion of total daily trading volume for each five-minute interval, averaged for each sample and across sample days.

Similar to Stephan and Whaley (1990), we measure trading volume increments for each five-minute over sample period, as follows:

$$\Delta V = V_t - V_{t-1} \tag{1}$$

where $\Delta V(t_i)$ is the increments in trading volume in five-minute intervals and V_t is the total shares traded at time *t*, and V_{t-1} is the total shares traded at time *t* at every five-minute during a trading day over the sample period.

We then estimate the moving-average of the volume increments for a thirty-minute window each transaction day. The thirty-minute volume moving-average ($VMA_{t,h}$) is calculated every five minutes to correspond with realized volatility data and can be explained as follows:

$$VMA_{\mathrm{t,h}} = \frac{1}{n}\sum_{h=1}^{n} \Delta V_{t,h} \tag{2}$$

where $\Delta V_{t,h}$ is the increments in trading volume in five-minute intervals and *n* is the number of intervals which is six, or equal to a thirty-minute window.

3.2 Intraday volatility

We use the realized volatility model due to its simplicity, ease of application in high-dimensional volatility modelling, and freedom from seasonality and heterogeneity issues (Andersen et al. 2001; Andersen et al. 1999; Andersen et al. 2003; Dacorogna et al. 2001; Hansen and Lunde 2006).

We calculate intraday volatility of returns using the five-minute returns data over thirty-minute windows and rolling every five-minute (see figure 1). Muller et al. (1997) and Smales (2013), for example, argue that the thirty-minute window is long enough for asset price to absorb news but at the same time, short enough to complete the price adjustment process. In addition, most information such as macroeconomic announcements usually affect volatility in 20 minutes or more, except for employment news which is still significant after 40-45 minutes (Ederington and Lee 1993). Moreover, Andersen et al. (2003) show that the impact of information arrivals is usually gradual and completed in 12 five-minute periods. Therefore, volatility in this study was estimated by summing the squared 5-minute log returns series over 30-minute windows.

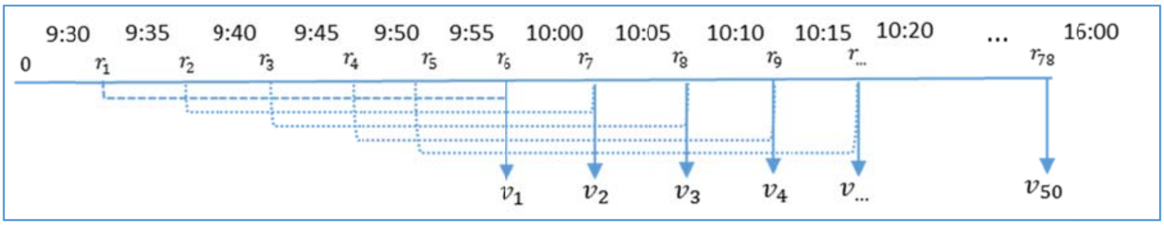

Fig. 1 – Thirty-minute rolling window volatility

The five-minute log returns of the LQ45 index are calculated during trading days as follows:

$$r_t = \ln(\frac{P_t}{P_{t-1}}) \tag{3}$$

where t is the homogeneous sequence of times regularly spaced by Δt five-minute intervals and P_t is the average price of the index at every five-minutes during a trading day over the sample period.

Furthermore, assuming that the mean of high-frequency returns is approximately zero[4], following Andersen et al. (1999), Andersen et al. (2003), Gropp and Kadareja (2012), realized volatility is measured the sum of quadratic returns, as follows:

[4] As returns are computed as log differences of asset prices and interval becomes infinitely small, the quadratic variation of continuous finite-variation process becomes zero. Therefore, the mean component becomes irrelevant for the quadratic variation (Andersen et al. 2003; Gropp & Kadareja 2012).

$$\mathrm{RV}_{t,h} = \sum_{j=1\ldots,h/\Delta} r^2_{t-h+j\Delta,\Delta} \tag{4}$$

where $r^2_{t-h+j\Delta,\Delta}$ is the compounded return over Δ trading interval and h is the observation window.

In this study, volatility is calculated as the sum of squared five-minute returns over thirty-minute windows (see equation (4)). This process is repeated every 5 minutes from 9:30 am to 4:00 pm for each trading day.[5,6] As a result, there are 50 thirty-minute rolling volatility windows from Monday to Thursday and 38 rolling volatility windows for Fridays. The difference in the number of observations is caused by differences in trading hours in the Indonesian Stock Exchange between Friday and other days of the week. Differences in trading hours between Fridays and other days of the week motivate us to, later on, distinguish the analysis based on group of days, (i) Monday-Thursday and (ii) Friday. Previous studies find that patterns of volume and volatility are different during days of the week.

3.3 Trading volume and volatility relations

To investigate the dynamic relationships between trading volume and realized volatility of LQ45 index, we follow Brailsford (1996) and Shahzad et al. (2014) who use similar 5-minute data to estimate the relationships. Furthermore, due to differences in trading hours, we separate the regression process based on groups of days of the week: (i) from Monday to Thursday and (ii) Friday. During Monday-Thursday, the relationships are explained in

[5] The IDX's trading hours consist of two sessions. From Monday to Thursday, the morning session starts from 9:30 am – 12:00 am and the afternoon session starts from 1:30 pm – 4:00 pm. On Friday, the trading hours begins from 9:30 am – 11:30 am and from 2:00 pm to 4:00 pm . Weekends and holidays are excluded from the sample.

[6] Starting from 2 January 2013, the IDX has extended trading hours of regular market both to synchronize global trading hours and accommodate trading hours of investors from central and eastern region of Indonesia. The pre-opening session is divided into two periods; from 8:45:00 – 8:55:00 AM for order submission, and from 8:55:01-8:59:59 pm for order matching based on price and time priority. The IDX has also introduced new closing trading hour; pre-closing and post-closing sessions. The pre-closing session starts from 15:50:00-16:00:00 for order submission and from 16:00:00-16:04:59 for order matching based on price and time priority. The post-closing or market clearing period then begins from 16:05:00-16:15:00 based on time priority.

equation (5). Furthermore, we use the same equation as in equation (5) to run regression for Fridays but without dummies $dday_k$.

$$RV_t = a_o + a_1 RV_{t-1} + a_2 VMA_{\mathrm{t}} + \sum_{i=1}^{2} a_3 dsubs_i + \sum_{j=1}^{11} a_4 dmonth_j + \sum_{k=1}^{3} a_5 dday_k + \varepsilon_t \quad (5)$$

where a_o is positive and significant if the moving average trading volume $VMA_{t,h}$ has a positive relationship with volatility, or negative otherwise. Furthermore, following Pisedtasalasai and Gunasekarage (2007), we use the first lag realized volatility $RV_{i,t-1}$ as an independent variable to take into account the autocorrelation process of this high-frequency data. We also introduce dummies $dsubs_i$ to examine the relationship over different subsample periods, and $dmonth_j$ and $dday_k$ to take account the patterns and relationships between months of the year and days of the week.

4. Results

Descriptive statistics

Table 1 shows the summary statistics of 30-min average trading volume and realized volatility of LQ45 index constituents from 2 January 2006 to 28 December 2012. Panel A of table 1 reports that there are positive relationships between trading volume and volatility based on sub-sample periods.[7]

During the global financial crisis, trading volume increases (27.4 million shares) and the level of volatility of returns is high (0.1320). After the crisis, trading volume decreases slightly to 26.9 million shares which is higher than the period before the crisis. A similar pattern occurs for volatility which decreases significantly to 0.0403, which is lower than that prior to the crisis.

[7] These findings are supported with our findings for 30-min average returns of LQ45 index. We find that GFC is the period when returns decrease to its lowest level (-0.005%). Before the GFC, the 30-min average returns of LQ45 index is -0.001%, and is reported -0.002% after the GFC. The summary statistics of the 30-min average returns of LQ45 index are available upon request.

Table 1 Descriptive statistics of trading volume & realized volatility of LQ45 index

	N	Mean	SD	Min	Max	Skewness	Kurtosis
Panel A: Sub-sample periods							
Period 1 (pre-GFC)	18,518	0.1720	0.1450	0.0047	1.7500	2.3079	11.8027
		0.0529	*0.1462*	*0.0001*	*5.0747*	*16.8456*	*406.8866*
Period 2 (GFC)	27,593	0.2740	0.2850	0	5.1100	4.4052	41.2936
		0.1320	*0.3020*	*0.0000*	*13.0125*	*13.1706*	*337.0011*
Period 3 (post-GFC)	35,129	0.2690	0.2550	0	3.3000	3.0809	19.0561
		0.0403	*0.1243*	*0.0001*	*12.4114*	*50.7920*	*4222.1280*
Panel B: Month of the year							
January	6,819	0.2490	0.2260	0	2.1900	2.3754	12.1682
		0.0866	*0.2186*	*0.0002*	*5.9004*	*12.0135*	*230.3534*
February	6,525	0.1920	0.1610	0	1.3200	1.9321	8.4390
		0.0455	*0.0742*	*0.0001*	*2.9283*	*13.0848*	*391.1767*
March	6,965	0.1880	0.1530	0	1.4300	2.1757	10.5821
		0.0570	*0.1120*	*0.0002*	*1.7780*	*6.4966*	*65.6873*
April	6,734	0.2220	0.1720	0	2.0000	2.4677	15.1443
		0.0643	*0.1358*	*0.0003*	*4.7581*	*12.5862*	*311.2420*
May	6,823	0.2970	0.2760	0	3.2100	3.0542	17.3917
		0.0877	*0.2199*	*0.0006*	*5.0747*	*10.9562*	*182.2752*
June	7,035	0.2010	0.1610	0	1.5100	1.9805	9.5078
		0.0576	*0.0812*	*0.0004*	*1.0786*	*4.1039*	*30.2875*
July	7,174	0.1900	0.1660	0	2.1900	2.7870	17.8367
		0.0490	*0.0822*	*0.0004*	*1.9249*	*6.9571*	*86.2815*
August	6,645	0.3460	0.4250	0	5.1100	4.0781	28.6851
		0.0706	*0.1572*	*0.0005*	*4.7269*	*14.7685*	*364.4597*
September	6,522	0.2810	0.2630	0	3.0600	2.6084	14.2847
		0.0896	*0.3057*	*0.0006*	*12.4114*	*19.5996*	*624.2566*
October	6,691	0.2950	0.2610	0	2.6400	2.2709	11.3665
		0.1140	*0.3722*	*0.0000*	*13.0125*	*13.3095*	*310.2019*
November	7,011	0.3100	0.3180	0	3.3000	3.1571	18.8643
		0.1042	*0.3194*	*0.0001*	*10.7891*	*16.5718*	*439.5159*
December	6,296	0.2160	0.1920	0	1.9100	2.4175	12.9697
		0.0663	*0.1525*	*0.0004*	*2.4776*	*6.7202*	*64.3342*
Panel C: Day of the week							
Monday	17,000	0.2380	0.2190	0	2.8100	2.6730	15.0696
		0.0681	*0.1444*	*0.0004*	*4.3560*	*7.6092*	*105.8084*
Tuesday	17,328	0.2570	0.2610	0	5.1100	5.0120	55.7255
		0.0825	*0.2654*	*0.0005*	*10.7891*	*16.8214*	*455.7715*
Wednesday	17,610	0.2640	0.2630	0	3.2400	3.5965	23.6139
		0.0726	*0.2010*	*0.0000*	*8.0489*	*14.8251*	*372.1041*
Thursday	16,920	0.2520	0.2660	0	4.6700	4.2732	37.8867
		0.0663	*0.1384*	*0.0001*	*4.7581*	*8.9081*	*159.1639*
Friday	12,382	0.2250	0.2250	0	2.7600	2.7441	15.9377
		0.0849	*0.2816*	*0.0002*	*13.0125*	*23.0392*	*847.0816*
Full sample	81,240	0.2490	0.2490	0	5.1100	3.9290	34.5895
		0.0743	*0.2104*	*0.0000*	*13.0125*	*19.5215*	*741.3819*

Note: The table reports the summary statistics of trading volume and realized volatility of LQ45 index constituents from 02/01/2006 to 28/12/2012. Trading volume is measured as 30-min moving average of shares traded. Realized volatility is measured as sum of squared log returns over 30-min window. Panel A shows the statistics by subsample periods. Panel B shows the statistics by month of the year and panel C is by day of the week. Mean, SD, min, and max value of the trading volume are expressed in hundred-million shares. Realized volatility values are shown in italics. Table of Means, SD, Min, Max, Skewness and Kurtosis of realized volatility are 10^4 times actual figures.

Panel B of table 1 shows that August is the month when shares of LQ45 index constituents are heavily traded (34.6 million shares). The high trading volume corresponds with a moderate level of volatility during the month (0.0706). In addition, from August to November the volatility records high (0.0706, 0.0896, 0.1140 & 0.1042 respectively) although it is not followed by high trading volume. Meanwhile, we find that thin trading volume occurs in March and the lowest volatility is recorded in February.

Furthermore, we find negative relationships between trading volume and volatility when the observations are decomposed into days of the week. Panel C of table 1 shows that Friday is the day when trading volume is the lowest (22.5 million shares) but volatility is high (0.00849).

However, a day with low volatility such as Thursday (0.0663) is not necessarily followed by high trading volume. On Wednesday, trading volume is the thickest (26.4 million shares) although the volatility is moderate (0.0726).

We further conduct correlation tests to measure the direction and strength of relationships between trading volume and volatility variables. We also decompose the tests of correlation by categories provided in table 1: subsample periods, months of the year and days of the week. Table 2 shows that there are positive relationships between trading volume and volatility of returns in all categories. The highest positive relation between trading volume and volatility is reported during the pre-GFC period although the correlation between variables is far from significant. Furthermore, March and April are periods when the movements of trading volume and volatility are higher than other months of the year. Moreover, Monday, Tuesday and Thursday are days when the positive relations between trading volume and volatility are high.

Table 2 Correlation matrix trading volume and volatility

		Trading volume	Volatility
Trading volume		1	
Volatility:			
Panel A: Periods	Pre-GFC	0.2148	1
	GFC	0.1127	
	Post-GFC	0.0403	
Panel B: Month	Jan	0.1425	
	Feb	0.0615	
	Mar	0.1720	
	Apr	0.1748	
	May	0.1562	
	Jun	0.0622	
	Jul	0.0186	
	Aug	0.1415	
	Sep	0.0961	
	Oct	0.0541	
	Nov	0.0926	
	Dec	0.1315	
Panel C: Day	Mon	0.1364	
	Tue	0.1328	
	Wed	0.0862	
	Thu	0.1373	
	Fri	0.0986	

Note:The table shows the correlation matrix between trading volume and volatility. We decompose the observation by subsample periods, month of the year and day of the week.

Intraday patterns of trading volume and volatility

Before investigating the dynamic relationships between trading volume and volatility we examine the patterns of trading volume and volatility of returns of the Indonesian equity index during intraday. Furthermore, due to differences in intraday trading hours, we divided the analysis of the patterns of trading volume and volatility according to their trading days over the week which are divided into two groups: (1) Monday-Thursday and (2) Friday.

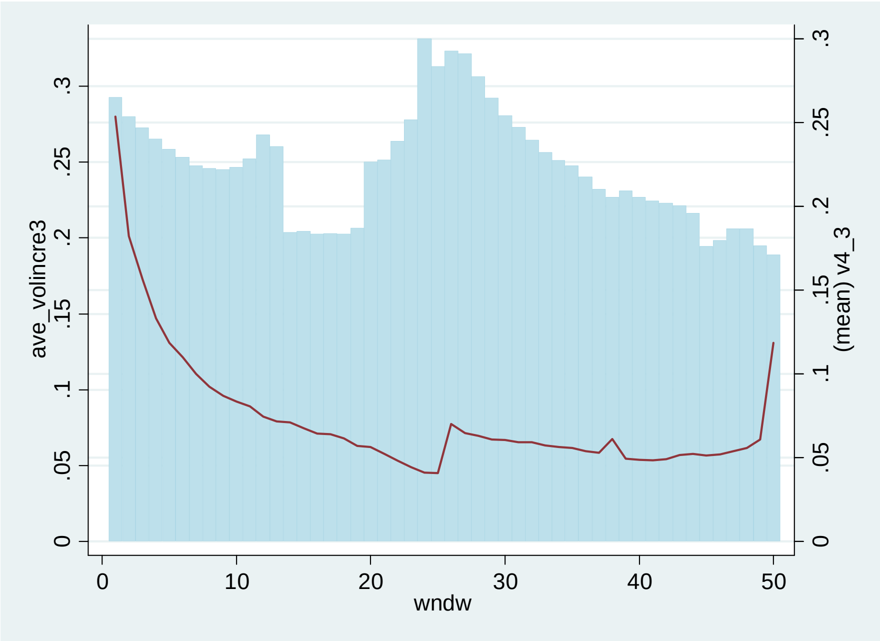

Figure 1 – Intraday patterns of 30-minute window trading volume and volatility

Figure 1 shows the intraday patterns of trading volume and volatility during the sample period. We find the typical U-shaped pattern for volatility during intraday, the pattern is similar to that of trading volume as the two indicators simultaneously decrease from the first hours of market opening to midday. However, there is a different decreasing pattern between trading volume and volatility. Volatility drops drastically during market opening whereas trading volume declines gradually and with lower percentage. Moreover, whilst the volatility still shows a decreasing pattern, trading volume bounces back near the closing of the morning session. In the afternoon session, trading volume shows a similar pattern to that of morning except it keeps declining during closing hours, in contrast with volatility which increases significantly just before and around market closing.

We further investigate the intraday patterns of trading volume-volatility if the observations are decomposed by category: by subsample periods, months of the year and days of the week. Figure 2 shows that the volatility of LQ45 returns shows different intraday patterns between subsample periods. Before and after the GFC, the volatility of LQ45 returns forms a U-shape when the volatility is high around both opening and closing, but low during midday. During

GFC, however, the volatility of LQ45 index returns forms a reverse J-shaped (or L-shaped) pattern during intraday. It means that the volatility is significantly high during opening hours and then declines drastically during midday. Before closing hours, the volatility increases slightly but is lower than in the morning. However, in all periods, the volatility fluctuates during midday adjusting between the morning session closing and the afternoon session re-opening.

Similar to volatility, we find different patterns of trading volume during intraday when we decompose the observations into subsample periods. In pre-GFC period, trading volume shows a U-shaped pattern during intraday. Consistent with Jain and Joh (1988), the pattern indicates thick trading during opening and closing to respond to/or anticipate information that arrives before/or after trading hours. Before the GFC, trading volume moves in the same direction as volatility. During the GFC, trading volume also moves symmetrically with volatility although there are hours when decreases of trading volume in the morning are steeper than that volatility. In addition, instead of bouncing back in volatility pattern around closing hours, trading volume keeps declining until the end of the day. In the contrary to the previous two periods, the intraday pattern of trading volume changes significantly in post-GFC period. Instead of decreasing, trading volume increases and inversely moves with volatility throughout the morning hours. Subsequently, trading volume decreases consistently for the rest of the day whilst volatility jumps just near market closing. This finding is similar to Girard and Biswas (2007) who find a negative relation between volume and volatility which is common in emerging markets due to informational inefficiency of their markets.

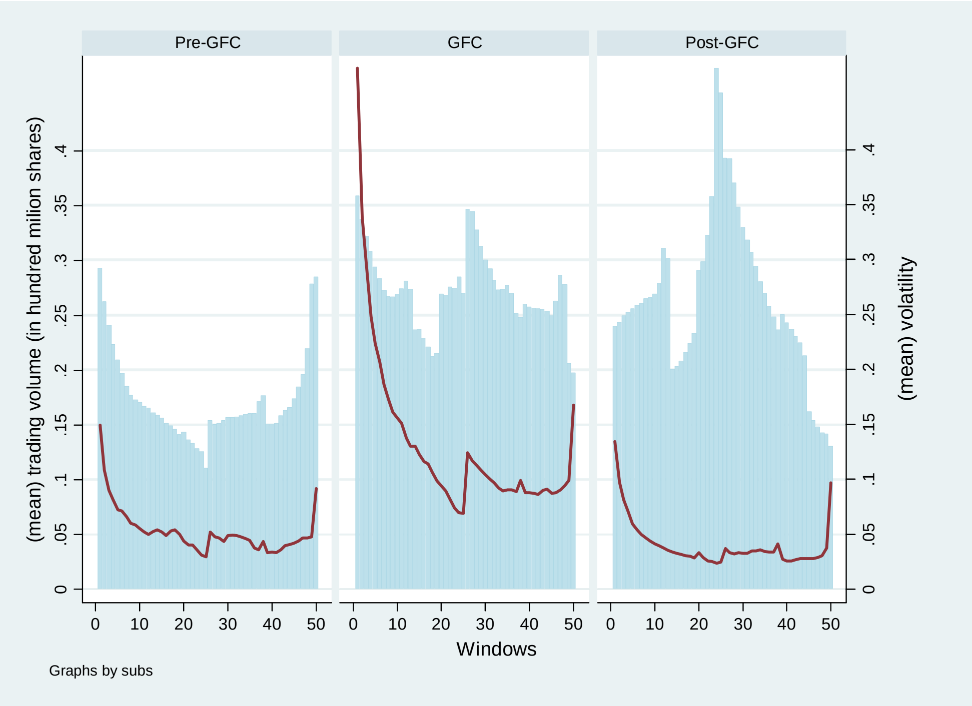

Figure 2 – Intraday patterns of 30-minute window trading volume and volatility – by subsample periods

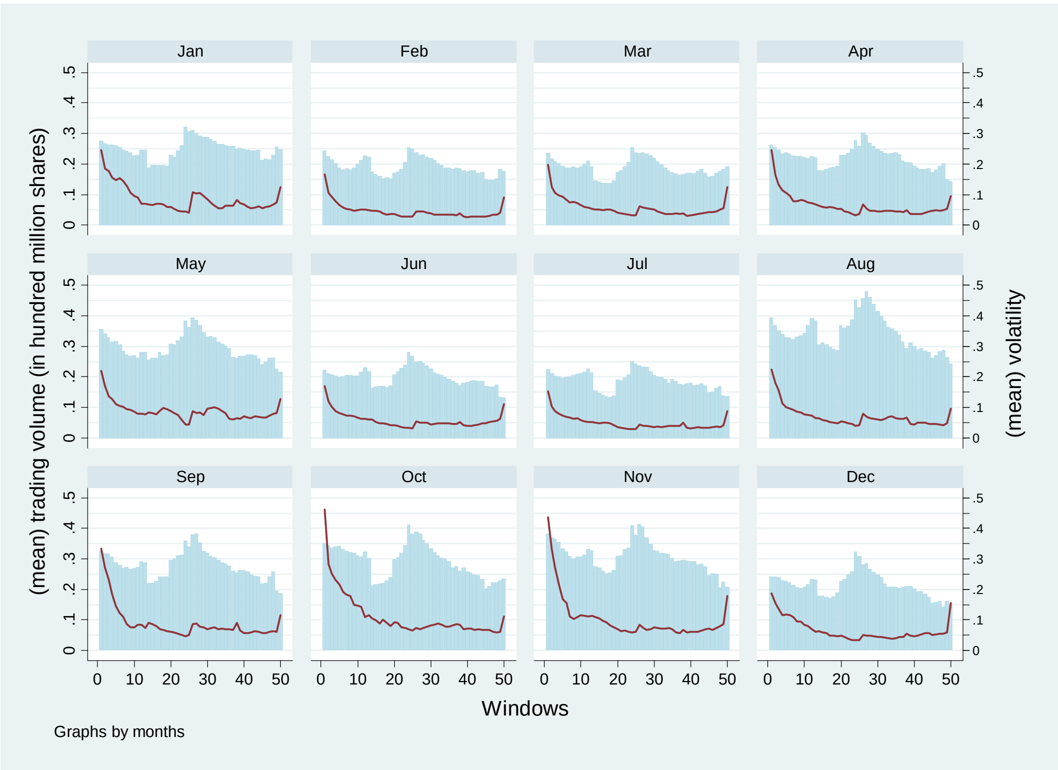

Figure 3 – Intraday patterns of 30-minute window trading volume and volatility – by months

Figure 3 shows the intraday patterns of trading volume and volatility if the observations are decomposed into months of the year. In general, the volatility creates a U-shaped intraday pattern throughout the year, except between September and November. October is the month when the pattern of intraday volatility is an L-shape. This finding is not unusual since the 2008 financial crisis occurred in this period and is consistent with Schwert (1989) who suggests that volatility changes over time and is usually higher during financial crises. However, compared to past financial crises, the impact of the 2008 financial crisis was more short-lived, as was expected by the market (Schwert 2011).

In contrast to volatility, the intraday patterns of trading volume are not significantly different between months of the year. Trading volume is relatively higher during the opening but then decreases near closing hours, both in morning and afternoon sessions. However, trading volume is significantly thicker during intraday windows from August to November, the period when the 2008 global financial crisis came into effect.

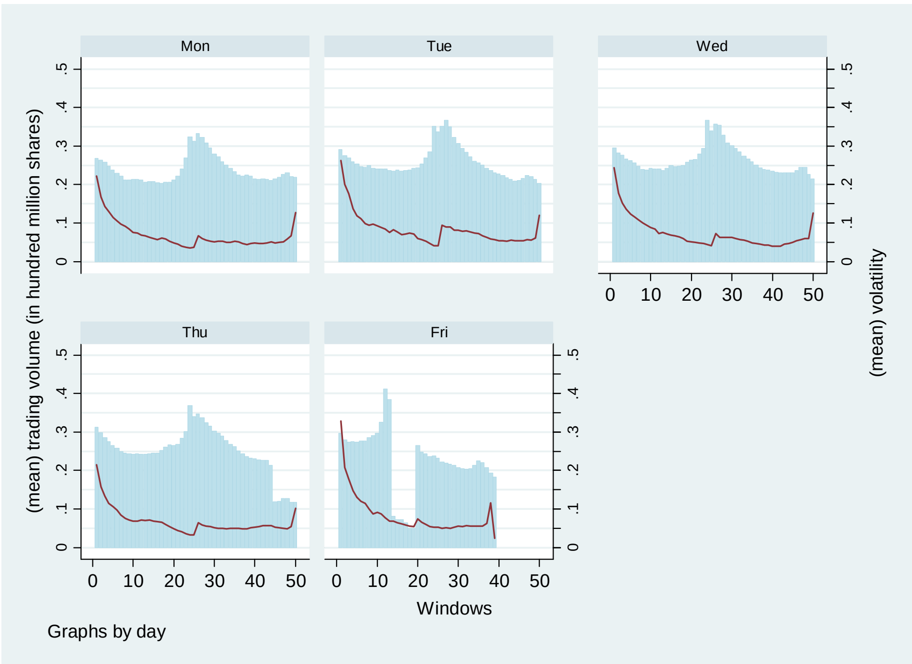

Figure 4 – Intraday patterns of 30-minute window trading volume and volatility – by days

Figure 4 shows the intraday patterns of volatility over days of the week. The figure shows a U-shaped intraday pattern for the whole week except Friday. The volatility during morning opening hours is higher on Fridays than on other days of the week. Thus, the decline of volatility during midday is significantly steeper than on other days. Similarly, there are different patterns of trading volume over the week. From Monday to Wednesday, trading volume shows a W-shaped patter n due to high intensity during opening and closing hours in both trading sessions whereas Thursday and Friday show lower activity during midday compared to that during opening and closing hours. According to the literature, the low trading intensity at midday is because all information has been available in the marketplace.

Contemporaneous relationships between trading volume and volatility

Subsequently, we check the results of correlation matrix shown in table 2 by investigating the relationships between trading volume and volatility during the day using equation (5). In this step, we estimate the relations using OLS regression with robust standard errors. Furthermore, we examine the relations by groups of days and subsample periods.

Table 3 Regression of trading volume moving average on volatility

	Monday – Thursday			Friday		
VARIABLES	(Pre-GFC)	(GFC)	(Post-GFC)	(Pre-GFC)	(GFC)	(Post-GFC)
Lag RV	0.8718***	0.8617***	0.8449***	0.8747***	0.6804***	0.8167***
	(23.2596)	(36.3202)	(30.5463)	(15.6376)	(5.1131)	(11.1071)
VMA	0.0003***	0.0001***	-0.0000***	0.0473***	0.0164*	0.0019
	(5.6923)	(4.4094)	(-2.9140)	(3.9176)	(1.8865)	(0.8396)
Constant	0.0005	0.0096***	0.0054***	-0.0033	0.0423**	0.0072**
	(0.2901)	(3.1429)	(5.8206)	(-1.1556)	(2.0395)	(2.0548)
Observations	15,744	23,381	29,731	2,774	4,211	5,397
R-squared	0.8670	0.8638	0.8123	0.8834	0.7312	0.9342

Note: the table reports the estimation results of equation (5) using OLS with robust t-statistics in parentheses. The table demonstrates regression results of 30-min window volume moving average (VMA) on volatility decomposed by subsample periods and days of the week. For brevity we do not show the result of dummies of sub-sample period and days of the week. ***,**, and * suggest significance at 1%, 5%, and 10%, respectively. The data is from January 2006 to December 2012.

Table 3 shows that there is a positive and statistically significant relationship between volume and volatility throughout the week, both before and during the GFC periods. After the GFC, however, the relationship between volume and volatility is negative and recorded during Monday-Thursday.

The positive relationship between trading volume and volatility is consistent with Pisedtasalasai and Gunasekarage (2007) who find positive and significant correlation between trading volume and market volatility in Indonesia, Malaysia, Singapore and Thailand during 1990-2004 due to increased level of information in the markets. The positive correlation between volume and volatility is also caused by unexpected trading volume made by noise traders and speculative traders (Girard and Biswas, 2007) and increased foreign transactions (Wang, 2007).

Furthermore, Girard and Biswas (2007) suggest that the negative relation between expected volume (EV) and volatility is caused by informed traders who "tend to lead the speculative trading activity and drive bid-ask spread higher, further diminishing the liquidity of the market." The negative relationship between trading volume and volatility is generally reported in studies within the market where information is asymmetrically distributed.

Causal relationships realized volatility and trading volume

Furthermore, we conduct Granger-causality tests between trading volume and volatility as in Pisedtasalasai and Gunasekarage (2007) using the following VAR estimation model:

$$RV_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i RV_{t-i} + \sum_{i=1}^{k} \beta_i VMA_{t-i} + \varepsilon_{1_t} \qquad (6)$$

$$VMA_t = \varphi_0 + \sum_{i=1}^{k} \varphi_i RV_{t-i} + \sum_{i=1}^{k} \gamma_i VMA_{t-i} + \varepsilon_{2_t} \qquad (7)$$

to test either H_0: $\beta_1 = \beta_2 = \ldots = \beta_k = 0$ against the alternative that the trading volume Granger-causes realized volatility, or H_0: $\varphi_1 = \varphi_2 = \ldots = \varphi_k = 0$ against the alternative that realized volatility Granger-causes trading volume. We use a standard t-test to examine Granger-causality between realized volatility and trading volume. Furthermore, in running the tests, we decompose the observations into full and subsample periods, and by groups of days of the week.

To run the Granger causality test, dependent variable has to be stationary. Shahzad et al. (2014) use the 5 lags based on the Schwarz criterion to conduct the test. Pisedtasalasai and Gunasekarage (2007) find that the Indonesian stock returns series are stationary from lag 0 up to lag 13 whilst for trading volume the data series are stationary from lag 9 to lag 25. As in Pisedtasalasai and Gunasekarage (2007), we conduct stationary tests for both realized volatility and trading volume variables using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit-root tests. However in this study, we use 6 lags in the tests because it is within the range suggested by Pisedtasalasai and Gunasekarage (2007). In addition, 6 lags of our data series represent 30-minute observation where, empirically, the impact of information arrivals on prices has been completed (Andersen et al. 2003).

Table 4 reports the statistics of both ADF and PP unit-root tests for both realized volatility RV_t and trading volume VMA_t. Panel A shows the results for full sample period while panel B, C and D report the results for pre-GFC, GFC and post-GFC periods. The ADF statistics suggest reject the null hypothesis meaning that both realized volatility and trading volume series follow a stationary process both at full sample and at every sub-sample period, and all the t-statistics are significant at 1% level. The PP unit-root test results confirm the test results of ADF.[8]

[8] We found similar results when we experiment with different number of lags (e.g. lag 4 & lag 13), both for the ADF and PP-unit root tests. The calculation of ADF and PP-unit root tests are available upon request.

Table 4 Tests for unit-roots

Variables		Lag (n)	ADF	PP
Panel A: Full sample period				
Volatility	RV_t	6	-85.854***	-156.595***
		12	-42.225***	-155.857***
Volume	VMA_t	6	-61.899***	-89.500***
		12	-48.562***	-82.696***
Panel B: Pre-GFC period				
Volatility	RV_t	6	-52.533***	-47.314***
		12	-23.689***	-46.800***
Volume	VMA_t	6	-35.302***	-47.987***
		12	-28.996***	-44.177***
Panel C: GFC period				
Volatility	RV_t	6	-49.213***	-93.404***
		12	-25.843***	-92.822***
Volume	VMA_t	6	-34.116***	-50.166***
		12	-27.032***	-46.226***
Panel D: Post-GFC period				
Volatility	RV_t	6	-41.615***	-130.925***
		12	-16.001***	-129.149***
Volume	VMA_t	6	-44.564***	-62.634***
		12	-35.095***	-57.746***

Note: this table reports the results of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests for unit roots. The RV_t and VMA_t denote realized volatility and volume moving average respectively. Both ADF and PP are computed with trend and divided into full sample and three sub-sample periods. The number of lags is chosen based on Pisedtasalasai and Gunasekarage (2007) and Andersen et al. (2003). The null hypothesis of the tests is that the data contains unit-root. For consistency, we use the same length of lags used in ADF for the PP test. The critical value for both statistics at the 1%, 5% & 10% level is -3.960, -3.410 and -3,210. The ***,**, and * suggest significance at 1%, 5%, and 10% respectively.

Table 5 shows the results of Granger-causality tests using VAR model in equation (6) and (7). Panel A of table 5 reports the results when realized volatility RV_t is the dependent variable. Meanwhile, panel B of table 5 shows the results when trading volume VMA_t is the dependent variable. In both panels, the results are presented by full sample and sub-sample periods, and further decomposed by groups of days of the week.

Panel A of table 5 reveals that, for full-sample period, trading volume Granger-causes volatility only during Monday-Thursday. Trading volume has impact on volatility at the fifth and sixth lag levels when its β_{-5} and β_{-6} coefficients are -0.0126 and 0.0092, with 5% and 1% significance level respectively. In Friday, trading volume does not Granger-cause volatility. Panel A of table 5 also shows that, prior to GFC and during Monday to Thursday, trading volume Granger-causes volatility in the first lag level with positive coefficient (0.0626) and 1% level of significance.

Table 5 Results of the VAR estimation and Granger-causality test

	Monday-Thursday				Friday			
Var.	Full sample	Pre-GFC	GFC	Post-GFC	Full sample	Pre-GFC	GFC	Post-GFC
Panel A: Coefficient Estimates of Eq. (6)								
Lag(k)								
α_0	0.0075***	0.0040***	0.0085***	0.0138***	0.0096***	0.0138***	0.0043***	0.0077***
	(21.5556)	(6.8006)	(5.7869)	(15.5071)	(10.1650)	(5.7128)	(15.0311)	(9.0750)
α_{-1}	1.0575***	1.1565***	0.9798***	1.0115***	1.0372***	1.0119***	1.2848***	1.1437***
	(242.7049)	(122.9432)	(55.2853)	(139.4137)	(98.9545)	(56.3830)	(152.3832)	(59.6936)
α_{-2}	-0.1295***	-0.1774***	-0.3032***	-0.1036***	-0.1834***	-0.1114***	-0.3975***	-0.2935***
	(-20.8271)	(-12.7997)	(-11.8677)	(-10.1818)	(-12.4803)	(-4.5278)	(-30.1206)	(-10.1720)
α_{-3}	-0.0048	-0.0593***	0.1512***	-0.0013	0.0880***	0.0677***	0.1196***	0.0340
	(-0.8128)	(-4.9204)	(5.8050)	(-0.1295)	(6.1374)	(2.8362)	(9.1382)	(1.2056)
α_{-4}	-0.0484***	-0.0983***	0.1550***	-0.0397***	-0.0406***	-0.0774***	-0.0496***	0.0087
	(-9.0908)	(-8.6942)	(6.0731)	(-4.5497)	(-3.0216)	(-3.3787)	(-4.0422)	(0.3773)
α_{-5}	-0.0352***	0.0451***	-0.1839***	-0.0388***	-0.0733***	-0.0360**	-0.1099***	-0.1885***
	(-7.1115)	(4.1780)	(-7.6648)	(-4.7798)	(-8.3463)	(-2.3687)	(-10.2465)	(-9.7697)
α_{-6}	0.0335***	0.0145**	-0.0124	0.0289***	0.0371***	0.0275***	0.0682***	0.1196***
	(11.1909)	(2.2113)	(-0.8136)	(5.8644)	(9.7540)	(4.5641)	(11.3447)	(13.5699)
β_{-1}	0.0039	0.0626***	0.1132***	-0.0042	0.0008	-0.0264**	-0.0032	0.0064*
	(1.2253)	(8.8843)	(6.6524)	(-0.5845)	(0.1518)	(-1.9841)	(-1.3429)	(1.6691)
β_{-2}	0.0059	-0.0572***	-0.1046***	0.0223*	0.0023	0.0306	0.0045	-0.0065
	(1.1402)	(-5.3531)	(-3.9398)	(1.8747)	(0.2957)	(1.5039)	(1.1549)	(-1.1793)
β_{-3}	0.0040	0.0055	-0.0233	0.0193	0.0037	0.0163	-0.0044	0.0012
	(0.7406)	(0.5155)	(-0.8661)	(1.4774)	(0.4700)	(0.7371)	(-1.1253)	(0.2184)
β_{-4}	-0.0087	0.0225**	0.0485*	-0.0306**	0.0006	-0.0166	0.0031	0.0011
	(-1.6174)	(2.1397)	(1.8257)	(-2.3338)	(0.0718)	(-0.7395)	(0.7981)	(0.2003)
β_{-5}	-0.0126**	-0.0398***	-0.0535**	-0.0147	-0.0062	-0.0086	-0.0079**	-0.0008
	(-2.4830)	(-3.8599)	(-2.0184)	(-1.1893)	(-0.7978)	(-0.3916)	(-2.1747)	(-0.1394)
β_{-6}	0.0092***	0.0178***	0.0316*	0.0092	-0.0002	0.0052	0.0065***	-0.0020
	(2.9410)	(2.6377)	(1.8125)	(1.2147)	(-0.0392)	(0.3593)	(2.9698)	(-0.5353)
Panel B: Coefficient Estimates of Eq. (7)								
Lag(k)								
φ_0	0.0165***	0.0181***	0.0210***	0.0149***	0.0276***	0.0206***	0.0199***	0.0324***
	(34.1388)	(23.6407)	(10.6289)	(15.7899)	(14.1637)	(5.9151)	(24.7565)	(9.0392)
φ_{-1}	-0.0003	0.0492***	0.0211	-0.0046	0.0183	0.0100	-0.0183	-0.0128
	(-0.0476)	(4.0613)	(0.8825)	(-0.5911)	(0.8435)	(0.3861)	(-0.7631)	(-0.1583)
φ_{-2}	-0.0086	-0.0439**	-0.0711**	-0.0075	-0.0293	-0.0350	0.0297	0.1212
	(-0.9939)	(-2.4610)	(-2.0602)	(-0.6994)	(-0.9602)	(-0.9863)	(0.7917)	(0.9971)
φ_{-3}	-0.0048	-0.0052	0.0438	-0.0055	0.0258	0.0415	0.0002	-0.0961
	(-0.5877)	(-0.3324)	(1.2446)	(-0.5343)	(0.8662)	(1.2050)	(0.0063)	(-0.8088)
φ_{-4}	-0.0041	-0.0115	0.0036	-0.0017	-0.0280	-0.0265	-0.0379	-0.0267
	(-0.5481)	(-0.7914)	(0.1032)	(-0.1800)	(-1.0039)	(-0.8019)	(-1.0865)	(-0.2742)
φ_{-5}	0.0033	0.0058	-0.0280	-0.0004	0.0121	0.0043	0.0576*	0.0273
	(0.4845)	(0.4142)	(-0.8645)	(-0.0465)	(0.6644)	(0.1980)	(1.8887)	(0.3362)
φ_{-6}	0.0045	0.0102	0.0099	0.0058	0.0064	0.0037	-0.0113	0.0125
	(1.0796)	(1.2109)	(0.4828)	(1.1039)	(0.8149)	(0.4246)	(-0.6614)	(0.3368)
γ_{-1}	1.1642***	1.1250***	1.1528***	1.1533***	1.0292***	1.0466***	1.1744***	1.0008***
	(264.8038)	(124.0624)	(50.1228)	(152.6584)	(94.4988)	(54.5530)	(174.5016)	(61.5173)
γ_{-2}	-0.1367***	-0.1445***	-0.2322***	-0.1365***	-0.2974***	-0.2739***	-0.1331***	-0.3048***
	(-19.0063)	(-10.5004)	(-6.4700)	(-10.8272)	(-18.6828)	(-9.3323)	(-12.1301)	(-13.1916)
γ_{-3}	-0.0525***	-0.0419***	0.0451	-0.0298**	0.1649***	0.1455***	-0.0729***	0.1759***
	(-6.9466)	(-3.0252)	(1.2435)	(-2.1529)	(9.9877)	(4.5703)	(-6.5001)	(7.4771)

	Monday-Thursday				Friday			
Var.	Full sample	Pre-GFC	GFC	Post-GFC	Full sample	Pre-GFC	GFC	Post-GFC
γ_{-4}	-0.0138*	0.0123	0.0072	-0.0348**	-0.0388**	-0.0527	-0.0035	-0.0381
	(-1.8432)	(0.9078)	(0.2021)	(-2.5054)	(-2.3463)	(-1.6252)	(-0.3148)	(-1.6285)
γ_{-5}	-0.0656***	-0.0665***	-0.0941***	-0.0478***	0.0105	0.0224	-0.0792***	0.0163
	(-9.2845)	(-5.0093)	(-2.6247)	(-3.6491)	(0.6508)	(0.7036)	(-7.6712)	(0.7152)
γ_{-6}	0.0376***	0.0087	0.0170	0.0358***	-0.0354***	-0.0153	0.0402***	-0.0541***
	(8.6665)	(1.0075)	(0.7200)	(4.4386)	(-3.2368)	(-0.7368)	(6.4248)	(-3.3877)
Obs.	52,273	11,964	1,898	17,745	8,457	2,878	22,564	3,681

Note: The table reports the results of the VAR estimated by the following models:

$$RV_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i RV_{t-i} + \sum_{i=1}^{k} \beta_i VMA_{t-i} + \varepsilon_{1_t}$$

$$VMA_t = \varphi_0 + \sum_{i=1}^{k} \varphi_i RV_{t-i} + \sum_{i=1}^{k} \gamma_i VMA_{t-i} + \varepsilon_{2_t}$$

where RV_t and VMA_t are realized volatility and volume moving average respectively. The Granger-tests are decomposed by subsample periods to capture the effect of the 2008 global financial crisis, and by day groups of the week to examine the difference in relationships between realized volatility and trading volume. We select the optimal lag length (k) in the VAR model based on Pisedtasalasai and Gunasekarage (2007) and Andersen et al. (2003). Panel A of the table reports the results when realized volatility RV_t is the dependent variable in the regression model. The relevant t-statistics tests are used to test the hypothesis that the trading volume moving average Granger-causes intraday realized volatility. Panel B reports the results when trading volume moving average VMA_t is the dependent variable in the regression model. The relevant t-statistics tests are used to test the hypothesis that the trading volume Granger-causes volatility. An ***, **, * denotes statistical significance at 1%, 5% and 10% respectively.

Similar results are found until the sixth lag level with different impact directions and level of significance. Meanwhile, Friday data shows that a significant relationship between trading volume and volatility occurs only in the first lag level with negative coefficient -0.0264 and significant at 5%.

During the GFC and from Monday to Thursday, the Granger-cause of trading volume on volatility is higher than in other periods. The coefficient is positive (0.1132) with 1% level of significance. In Friday, trading volume is Granger-cause volatility in the fifth (-0.0079) and sixth (0.0065) lag levels, significant at 5% and 1% level respectively. After the GFC and from Monday-Thursday, trading volume Granger-causes volatility in the second (0.0223) and fourth (-0.0306) lag levels with 10% and 5% significance level respectively. However during

Friday, the trading volume Granger-causes volatility in the first lag level (0.0064) with 10% significance level.

Panel B of table 5 shows that, during full sample period, volatility does not Granger-cause trading volume, both for Monday-Thursday and Friday. The volatility Granger-causes trading volume only in the first (0.0492) and second (-0.0439) lag levels with 1% and 5% significance level respectively during pre-GFC and from Monday-Thursday. During GFC, volatility has negative impact on trading volume in the second lag level (-0.0711) with 5% significance level, during Monday-Thursday. However, there is no predictive power of volatility on trading volume for trading in Friday during GFC forward.

5. Conclusion

This paper aims to measure the contemporaneous and causal impact of trading volume and the volatility of Indonesian stock returns from 2006-2012 using five-minute data. Although there are a great number of empirical evidence on relationships between trading volume and volatility, studies on the relationships between the two variables in an emerging market using high-frequency data are rare.

Consistent with literature, we find that trading volume and volatility increase during the GFC. Furthermore, we find different patterns of intraday trading volume and volatility before, during and after the GFC. We also find a positive relationship between trading volume and volatility, particularly before and during the GFC. However after the GFC, the trading volume and volatility are negatively correlated. Moreover, we find mixed results on the degrees and directions of causality between trading volume and volatility when observations are decomposed into subsample periods and days of the week.

This study has both important academic and practical implications. This study should enhance the understanding of Indonesian financial market microstructure by investigating the trading volume-volatility relations before, during and after the global financial crisis. The practical implication of our study will be to provide additional measures in analysing the impact of information arrives in the market using by looking at changes in patterns of its proxies: trading volume and volatility.

We believe further research regarding the impact of public information (e.g. macroeconomic announcements) on the patterns of trading volume and volatility of returns of the Indonesian stock market is warranted. Additionally, investigation on the speed and persistence of the impact on patterns of trading volume and volatility may provide further valuable insight. Another possible direction for future research would be using different stock market index and different asset class to measure the relationships.

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