VOLATILITY OF RETURNS, TRADING VOLUME AND THE IMPACT OF MACROECONOMIC ANNOUNCEMENTS: HIGH-FREQUENCY EVIDENCE FROM THE INDONESIAN STOCK MARKET

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ABSTRACT

A great amount of research has been undertaken into the patterns of, and the contributing factors to, the volatility of emerging equity market returns. One of the most common findings in the research is that the volatility of emerging market returns is high compared to that of developed markets. One factor contributing to the high volatility of returns in emerging markets is a lack of informational efficiency in the markets. The objective of this thesis is to examine the informational efficiency of the Indonesia Stock Exchange (IDX) by looking at the impact of the arrival of public information on the volatility of returns and investigating the relationship between trading volume, which is used as a proxy for the arrival of information, and volatility.

Scheduled U.S. and Indonesian macroeconomic announcements are used as indicators for the arrival of public information. High-frequency data and an autoregressive econometric models are employed to examine the extent to which the volatility is affected by the macroeconomic announcements. Contrary to the literature, this thesis has found that, while most domestic macroeconomic announcements impact significantly on the volatility, there is no evidence that the U.S. Federal Open Market Committee announcements have an impact on volatility. In addition, the 2008 Global Financial Crisis significantly influenced the impact of macroeconomic news on the volatility of Indonesian equity market returns.

This study also examines the relationship between market-wide realized volatility and trading volume of the Indonesian equity market. Trading volume has been used to indicate the arrival of new information, and its use as a proxy for information can improve understanding of the IDX's microstructure. Consistent with the literature, this thesis reports different patterns of trading volume and returns volatility of the IDX during intraday trading. Using the Granger-causality test model, the study finds mixed results on the significance and direction of volume-volatility relationships. There are no Granger-causality relations between trading volume and volatility of returns of the Indonesian equity market during the full sample period. However, there is evidence of bi-directional causality relationships when observations are decomposed into subsample periods and days of the week.

DECLARATION

I, Haryadi, declare that the DBA thesis entitled 'Volatility of Returns, Trading Volume, and the Impact of Macroeconomic Announcements: High-frequency Evidence from the Indonesian Stock Market' is no more than 65,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work.

[redacted]

Haryadi
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ABBREVATIONS

ADF	Augmented Dickey-Fuller
AFC	Asian Financial Crisis
AOI	All Ordinary Index
ARC	Advanced Release Calendar
ARCH	Autoregressive Conditional Heteroscedasticity
ASIC	Australian Securities and Investments Commission
ASX	Australian Securities Exchange
Bapepam	Badan Pengawas Pasar Modal (Indonesian Capital Market Supervisory Agency)
BapepamLK	Badan Pengawas Pasar Modal dan Lembaga Keuangan (Indonesian Capital Market and Financial Institutions Supervisory Agency)
BEI	Bursa Efek Indonesia (Indonesia Stock Exchange)
BI	Bank Indonesia
BI Rate	Bank Indonesia Target Interest Rate
BPS	Badan Pusat Statistik (Statistics Indonesia)
CAR	Capital Adequacy Ratio
CBOE	Chicago Board Options Exchange
CCI	Consumer Confidence Index
CPI	Consumer Price Index
C-BEST	Central Depository & Book Entry Settlement
EMH	Efficient Market Hypothesis
FOMC	The Federal Open Market Committee
FKSSK	Forum Koordinasi Stabilitas Sistem Keuangan (Financial System Stability Coordination Forum)
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GDP	Gross Domestic Product
GFC	Global Financial Crisis

HARCH	Heterogeneous Autoregressive Conditional Heteroscedasticity
IDX	Indonesia Stock Exchange
IMF	International Monetary Fund
IP	Industrial Production
IPO	Initial Public Offering
ITF	Inflation Targeting Framework
JCI	Jakarta Composite Index
JSX	Jakarta Stock Exchange
KOSPI	Korea Composite Stock Price Index
KPEI	Kliring dan Penjaminan Efek Indonesia (Indonesian Clearing and Guarantee Corporation)
MDH	Mixture of Distribution Hypothesis
M2	Money supply
NYSE	New York Stock Exchange
OJK	Otoritas Jasa Keuangan (Financial Services Authority)
OLS	Ordinary Least Square
PAKDES	Paket Desember (December Package)
PAKJUN	Paket Juni (June Package)
PAKTO	Paket Oktober (October Package)
PMI	Purchasing Manager Index
PP	Phillips-Perron
REPELITA	Rencana Pembangunan Lima Tahun (Five Year Development Plans)
RS	Retail Sales
SAI	Sequential Arrival of Information
SBI	Sertifikat Bank Indonesia (Bank Indonesia Certificate)
SIRCA	Securities Industry Research Centre of Asia Pacific
STP	Straight Through Processing
TRTH	Thomson-Reuters Tick History
UE	Unemployment
VAR	Vector Autoregressive
VIX	Volatility Index

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Alhamdullillaahi rabbil 'alamiin
(Praise be to Allah, Lord of the Worlds)
Quran 1:1

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CHAPTER 1
INTRODUCTION

1.1 Background and motivation

A great amount of research has been undertaken into the patterns of, and the contributing factors to, the volatility of emerging equity market returns. One of the most common findings in the research is that the volatility of emerging market returns is high compared to that of developed markets. The research also finds that the high volatility of emerging market returns is caused by global and local factors. In segmented emerging markets, the volatility tends to be influenced by local factors such as social, political and economic events, rather than by global factors (Aggarwal, Inclan & Leal 1999; Bekaert & Harvey 1997).

The volatility of emerging equity market returns has become more important since the inception of financial market liberalization policies in these markets. The policies have contributed to the increased participation of both domestic private and foreign capital in the economy, and improved efficiency and returns. One of the consequences of that liberalization policy is that returns from emerging stock markets are increasingly affected not only by local macroeconomic factors, but also by macroeconomic and monetary policy decisions of developed countries. On the one hand, liberalization policies have caused emerging stock markets to be more attractive because of their high returns but, on the other hand, they have become riskier because returns from these markets are volatile.

A recent example of the high volatility of emerging market returns was in May 2013 when the U.S. Federal Reserve announced the possibility of ending its quantitative easing policy. This announcement triggered massive capital outflows from emerging markets to the U.S. and other developed markets in favour of safer and higher return investments (Adam & Hamlin 2013). As a result, the economies of emerging countries that contributed to world growth, including Brazil, India, Indonesia, Turkey and South Africa, experienced significant pressures as foreign investors took billions of dollars out of these countries. As a consequence, bond yields in emerging economies rose by 2.5

per cent, the equity market fell by nearly 14 per cent, and exchange rates in these economies depreciated, on average, by more than 13 per cent (IMF 2014). In the case of Indonesia, the announcement of the U.S. Federal Reserve created uncertainty among market participants and caused its stock market value to decline by 20 per cent in August 2013 (Cahyafitri 2013) and caused the Indonesia Stock Exchange's annual returns to drop by more than 21 per cent (Indonesian Stock Exchange 2014a).

Macroeconomic announcements are expected and reacted to rapidly by the market as the announcements send signals of future changes of government policy or directions of the economy (Thenmozhi & Nair 2014). Significant improvements in trading mechanisms and technology since the 1980s have increased the speed of market reaction, demonstrated by rapid adjustments of stock prices, in response to the arrival of information and thereby increased the level of informational efficiency of the market. The availability of high-frequency data has allowed researchers and policy makers to examine the impact of macroeconomic announcements on asset prices at announcement times without being contaminated by the impact of other news or events occurring around that time. Although the impact of macroeconomic announcements on the volatility of market returns has been shown in both developed and emerging markets, their impact in emerging markets has been found to be higher than that in developed markets (Aggarwal, Inclan & Leal 1999; Bekaert & Harvey 1997). According to Aggarwal, Inclan and Leal (1999), the high volatility of emerging market returns is caused more by country-specific political, social and economic events than by global events.

Given this background, four motivations underlie this study of informational efficiency of the Indonesia Stock Exchange (IDX) using volatility of returns**.** First, although previous studies show that returns from the Indonesian equity market are very volatile (Bekaert et al. 1998; Bekaert & Harvey 1997; Bekaert & Harvey 2002; De Santis & Imrohoroglu 1997), the performance of the Indonesian stock market consistently showed strong positive growth after the 2008 Global Financial Crisis (GFC). However, when the U.S. Federal Reserve began a phased reduction in its quantitative easing policy in 2013, the Indonesian equity market was one of the emerging markets which suffered as foreign investors continued selling their stocks causing the market index to lost another 1 per cent to close at 4,172. 09 on August 23, 2013 compared to previous day. This condition raises questions about the stability of what appeared to be typical volatility patterns of Indonesian equity market returns. For example, were the patterns consistent over the calendar year and to what extent, if any, was the volatility of market returns affected by the GFC and macroeconomic announcements?

Second, previous studies show that the volatility of equity returns is typically higher during a financial crisis. Study of the effect of a financial crisis on volatility, and the identification of volatility patterns before, during, and after a crisis, will provide regulators and market participants with greater understanding on market dynamics. In the case of Indonesia, the 1997 Asian Financial Crisis (AFC) caused the Jakarta Composite Index (JCI) to decrease by more than 60 per cent and market capitalization to shrink by almost a quarter. In contrast to the impact of the 1998 crisis, the impact of the 2008 GFC on the Indonesian financial markets was minimal. While this has been argued to be a result of the Indonesian government's prudent macroeconomic policy (Sangsubhan & Basri 2012), it will be instructive to examine whether the release of information about other relevant macroeconomic factors continued to influence market behaviour in a consistent manner. This study will therefore examine the impact of macroeconomic announcements on the volatility of returns before, during, and after the GFC.

Third, previous studies have provided mixed conclusions on the degree of informational efficiency of the Indonesian stock market. Although the level of information transparency has improved following the implementation of a new information regime and market liberalization policy in the 1990s (Cajueiro & Tabak 2004; Kung, Carverhill & McLeod 2010), a study by Kim and Shamsuddin (2008) found that the Indonesian stock market showed no sign of being more efficient when a martingale test was conducted on its index value.[1] This thesis will use an alternative approach to provide additional evidence on the informational efficiency of the IDX.

[1] A martingale test can be used to test the weak-form efficient market hypothesis. The random walk model used to test the weak-form efficient market hypothesis requires the returns to be identically and independently distributed. However, the martingale model does not require returns to be identically and independently distributed. A martingale test can be applied to asset prices with conditionally heteroskedastic increments (Campbell, Lo & MacKinlay 1997).

Fourth, previous studies have shown that trading volume increases with the arrival of information and correlates with increases in volatility (Admati & Pfleiderer 1988; Foster & Viswanathan 1994; Karpoff 1987). The availability of high-frequency data for the Indonesian market has made it possible to examine in greater details the intraday patterns of volatility and examine the relationship between volatility and trading volume.

1.2 Research aims and questions

This thesis will use high-frequency data to examine the impact of macroeconomic announcements on the volatility of returns and the relationships between trading volume and volatility, thereby providing a measure of stock market informational efficiency. To achieve this aim, the thesis will answer the following research questions:

1. What is the pattern of intraday volatility of returns of the IDX?
    - 1.1 Is the pattern of intraday volatility in the Indonesian stock market consistent with prior research?
    - 1.2 How do seasonal factors such as month of the year and day of the week influence the pattern of intraday volatility of Indonesian equity returns?
    - 1.3 What was the impact of the 2008 GFC on the volatility patterns? Were there differences in volatility patterns before, during, and after the GFC?
2. How, and to what extent, is intraday volatility of the Indonesian stock market returns influenced by macroeconomic announcements?
    - 2.1 What is the impact of domestic and foreign macroeconomic announcements and news on the intraday volatility of Indonesian equity returns?
    - 2.2 What was the impact of macroeconomic announcements and news on the intraday volatility of Indonesian equity returns during the GFC?
3. How does the trading volume of the Indonesian stock market correlate with its volatility of returns?
    - 3.1 Do patterns of trading volume and volatility of the Indonesian stock market have similar patterns?
    - 3.2 Does trading volume cause volatility or does volatility cause trading volume?

1.3 Conceptual framework

The research questions put forward in Section 1.2 can be positioned in a conceptual framework which is shown diagrammatically in a Figure 1.1 as follows:

Figure 1.1 Conceptual framework

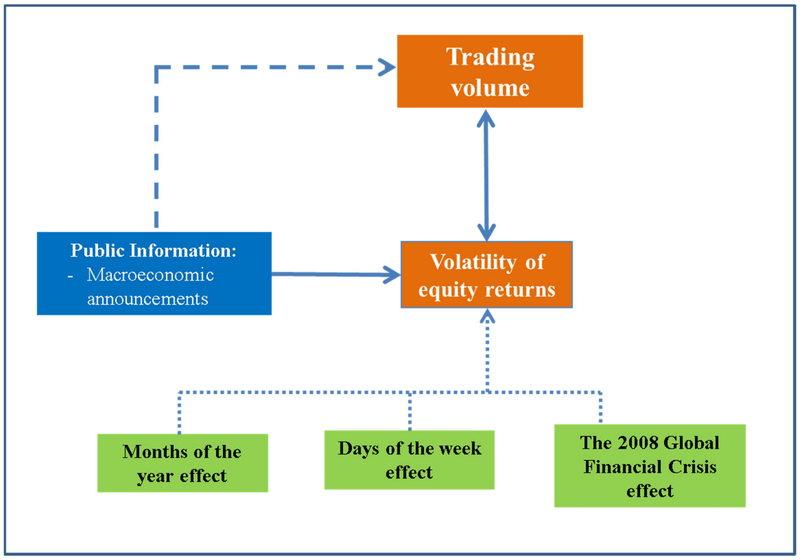


Figure 1.1 depicts the centrality of the volatility of equity returns and shows the relationships between variables investigated in this thesis: the volatility of equity returns, macroeconomic announcements and trading volume. The relationships represent the three main research questions of this study. Research question 1 will be addressed by identifying the pattern of intraday volatility. As the pattern of intraday volatility has been found to correlate with seasonal factors, including the months of the year and the days of week, correlation with these factors will be examined as well as the influence of financial crises on volatility, represented by the 2008 GFC. Research question 2 addresses the impact of the arrival of public information, in this case announcements of relevant macroeconomic information, on the intraday volatility of returns. Seasonal factors will also be incorporated in the test of the macroeconomic announcement impact on volatility for more robust results. Finally, research question 3 will address the relationship between information arrival, proxied by trading volume, and the intraday volatility of returns. These research questions will measure both the direct impact and the causality relations between trading volume and the volatility of returns.

1.4 Contribution to knowledge

This thesis will contribute to the literature in several ways. First, it will further the understanding of IDX efficiency. Unlike previous studies on market efficiency which predominantly use (cumulative) abnormal returns as the metric for gauging efficiency in the market, this study will use volatility (or the second moment of the stock market returns) and macroeconomic information to gauge market efficiency.

The second contribution of this thesis is to the growing literature on high-frequency data analysis (using five minute data) in investigating the patterns in volatility in the context of emerging markets. While high-frequency data analysis is commonly used in the context of more developed markets (Andersen & Bollerslev 1998; Ederington & Lee 1993; Smales 2013), most studies of the impact of macroeconomic news on volatility in emerging countries have only been able to use lower frequency data, typically daily data or weekly data (Bekaert & Harvey 1997; Kim & Singal 2000; Rangel 2011).

The third contribution of this thesis is the application of a rolling volatility model to examine the impact of macroeconomic announcements. Previous studies, for example Gropp and Kadareja (2012) and Smales (2013), use separate window observations in examining the impact of the announcements on the volatility of returns.

Fourth, this thesis contributes to the literature by examining the impact of the 2008 GFC on the pattern of intraday volatility of returns and the informational efficiency of an emerging market.

Last, this study contributes to the literature by enhancing the understanding of trading volume-volatility relations, conditional upon the rate of information flow to the market. Although trading volume-volatility relations have been studied previously, to the author’s knowledge, this study is the first in the context of the IDX using high-frequency data.

1.5 Statement of significance (practical contribution)

The practical contribution of this study is to reveal the intraday patterns of volatility and trading volume across different periods: before, during and after the GFC, which will be of interest of market participants. Another contribution of this study is to propose an alternative measure of the IDX volatility of returns with high-frequency data, which is relevant not only for short-term trading strategy but also for long-term investment decisions. This study shows that readily available trading volume data can be used as a proxy for the arrival of macroeconomic information when examining the impact of macroeconomic information on the volatility of returns.

This study also aims to provide a better understanding of intraday volatility patterns during different periods and during a financial crisis. Furthermore, it examines the degree of informational efficiency of the Indonesian stock market and highlights the importance of trading volume as an indicator of the value of public information arrivals. The outcomes of these aims will be of interest to market regulators and to market participants.

1.6 Structure of the thesis

The thesis comprises seven chapters and is structured as follows:

Chapter 1 discusses the motivations and contribution of this research and presents the research questions.

Chapter 2 begins with the history and development of the IDX as the context of this study. It further discusses the relationships between financial liberalization policies and capital market development in Indonesia, as indicated by financial deregulation, market-oriented macroeconomic policy decisions and monetary policy decisions. This chapter also presents the regulatory framework, market structure and latest developments in the Indonesian capital market. Last, this chapter discusses the background of two financial crises and compares their impacts on the volatility of IDX returns.

Chapter 3 reviews theoretical and empirical studies related to volatility of returns, identifying gaps in the literature. The chapter begins with definitions of volatility, discussion of its different models, and empirical studies of volatility in the emerging markets context. The chapter also discusses the application of high-frequency data in finance studies to explore the typical patterns of volatility. Two major streams in the finance literature are discussed to explain the impact of macroeconomic announcements on volatility: the theory of efficient markets and the theory of market microstructure.

Chapter 4 discusses data and variables required to achieve the research objectives and to answer the research questions. The chapter explains types and sources of market data, sample period and macroeconomic announcements, including methodology to construct datasets of macroeconomic announcements. This chapter also provides details of methods used to calculate the variables including returns, volatility and trading volume. The chapter ends with description of datasets of macroeconomic announcements and news.

Chapter 5 provides the descriptive statistics of the returns volatility of the sample. In this chapter, the results of statistical tests of datasets are presented before conducting data analysis. The chapter shows the movement patterns of price, returns and volatility of returns during intraday trading. This chapter also describes the methodology used to measure the impact of macroeconomic announcements and news on the volatility of returns.

Chapter 6 presents the statistical and graphed results of the analysis of correlations between trading volume and volatility. Two empirical tests of the relationships between trading volume and volatility are discussed in this chapter. The impact of the 2008 GFC on the relationships is also discussed here.

Finally, Chapter 7 concludes the thesis and sets out the limitation of the studies and recommendations for further research.

CHAPTER 2
THE INDONESIAN CAPITAL MARKET: AN OVERVIEW

2.1 Introduction

This chapter describes the historical development and current conditions of the Indonesian capital market.[2] The chapter begins with a brief history of the establishment of a capital market and its development in Indonesia. The chapter subsequently describes macroeconomic policy and macroeconomic indicators relevant to the Indonesian economy. Last, it describes the structure of Indonesian financial markets, securities market microstructure and its key statistical highlights.

2.2 The Indonesian stock market: History and development

The history of the stock market in Indonesia began on 14 December 1912 when the Dutch *Amsterdamse Effectenbuers* (Amsterdam Stock Exchange) established its securities exchange branch in Batavia (now Jakarta). The newly established exchange, which was named *Vereniging voor de Effecttenhandel* (Amsterdam Stock Exchange Association), was the fourth exchange to open in Asia after Bombay, Hong Kong and Tokyo. The exchange was officially opened by starting the trading of 13 stocks of Dutch firms in Batavia (Bapepam 1999).

The securities exchange was used not only as a source of funding for Dutch firms to develop plantation businesses in Indonesia, but also for the colonial government to fund its administration by issuing bonds. The exchange was also engaged in selling certificates of securities of American companies in the Netherlands and securities of Dutch companies. The demand for the exchange as a source of funding in Indonesia was high, indicated by the growing number of issuers and the amount of funds raised. Therefore, to accommodate the high demand for the securities, the government opened two other exchanges in 1925, one in Semarang and one in Surabaya. However, the three

[2] A capital market consists of markets for long-term debt and equity securities. However in this study, the terms of capital market, stock market, securities market and equities market will be used interchangeably, unless mentioned otherwise.

stock exchanges finally consolidated into one exchange in Jakarta before it was then closed down due to World War II (Bapepam 1999; Indonesia Stock Exchange 2013a).

After Indonesia regained its independence in 1945, the Indonesian capital market was still not active due to political upheaval. During the first years after the War of Independence, the government's poor budget management resulted in huge spending on 'ambitious projects of questionable economic benefits' and a tight capital control policy, which had caused the Indonesian economy to become underdeveloped relative to other economies, hyper-inflated, and to suffer a shortage in money supply (Cole & Slade 1996, p. 9; Sabirin 1991).

Cole and Slade (1996) argued that a good financial system can encourage economic development by allowing financial intermediation between savers or investors and borrowers. A newly elected government introduced the Five Year Development Plans (REPELITA) in 1969 to stimulate development by encouraging government-owned banks to channel credit into the economy. Cole and Slade (1996) called the period from 1968 to 1972 the period of 'recuperation' from hardships. As a result, from 1969 to 1971, inflation reduced to one digit and the economy grew 8 per cent on average (Sabirin 1991). Furthermore, after the first five year development plan, Indonesia became one of best emerging economies with average annual Gross Domestic Product (GDP) of more than 6 per cent, single digit inflation and significant poverty alleviation (World Bank 1994).

Despite the significant growth of the Indonesian economy during the 1970s (Booth 1979), the Indonesian capital market was dormant until 1977 when the Jakarta Stock Exchange (JSX) officially reopened with the initial public offering of the PT Semen Cibinong Indonesian cement producer. However, during its first years of operation, trading activities in the JSX were very limited because of tight restrictions imposed by the regulator on price movements (Bapepam 1999). As a result, until the end of the second REPELITA, the capital market remained underdeveloped. Companies were still heavily relying on the banking sector for funding (Hamada 2003).

Although Indonesia has implemented an open capital account policy since the 1970s, which imposed no restrictions on capital outflows, the Indonesian financial system was not well-developed until the late 1980s when the government deregulated the banking and capital market sectors. However this policy, which contributed to the increase of private corporate borrowings in the mid-1990s, eventually failed and led to the 1998 financial crisis that cost the Indonesian economy billions of U.S. dollars for recovery programs (Matsumoto 2007).

2.2.1 Deregulation of Indonesian financial sector

Oil was once Indonesia's main export commodity and contributed significantly to national income during the first few decades after Indonesian independence. The significant drops in the global oil price in the early 1980s, which caused a deficit in the government's budget account, led the government to restructure its fiscal policy and undertake programs to increase economic efficiency. The government passed more than twenty regulation packages during the 1980s to increase efficiency and promote non-oil and gas exports (Soesastro & Basri 2005). Deregulation packages were also introduced in financial sectors to increase domestic private and foreign capital participation in the economy (Matsumoto 2007).

The first deregulation in the financial sector, also known as the June Package — PAKJUN — was introduced in June 1983. The regulation alleviated restrictions on limits of interest rates offered by state-owned banks for term deposits and allowed banks to determine interest rates charged to debtors for loans without central bank intervention. As a result, the number of private bank loans increased significantly since then (Bennett 1995; Cole & Slade 1996).

Deregulation continued when the government passed another deregulation package in October 1988, popularly known as the October Package — PAKTO. Under this new regulation, banks could have an operating license with capital of only 10 billion IDR, open new offices in non-capital cities, and establish joint ventures with foreign counterparts in Indonesia. The policy succeeded in encouraging the opening of new privately-owned banks and collected public money to fund the economy. As a consequence, the number of banks and the amount of money deposited increased (see Table 2.1).

Table 2.1 The growth of demand deposits and the number of bank offices

Year	M1: Demand (deposits, excl. govt. deposits*)	Number of banks			
		Privately owned		State-owned	
		HO	Branches	HO	Branches
1988	8,146	104	876	7	852
1989	12,688	141	1,656	7	922
1990	14,456	164	2,545	7	1,018
1991	16,996	185	3,203	7	1,044
1992	17,301	201	3,341	7	1,066
1993	22,605	213	3,382	7	1,066

* in billions IDR rupiah. Data are available from Bank Indonesia and Asia Development Bank. M1 is a measure of money supply which consists of almost all demand deposits, except government deposit. HO is the number of banks' head offices.

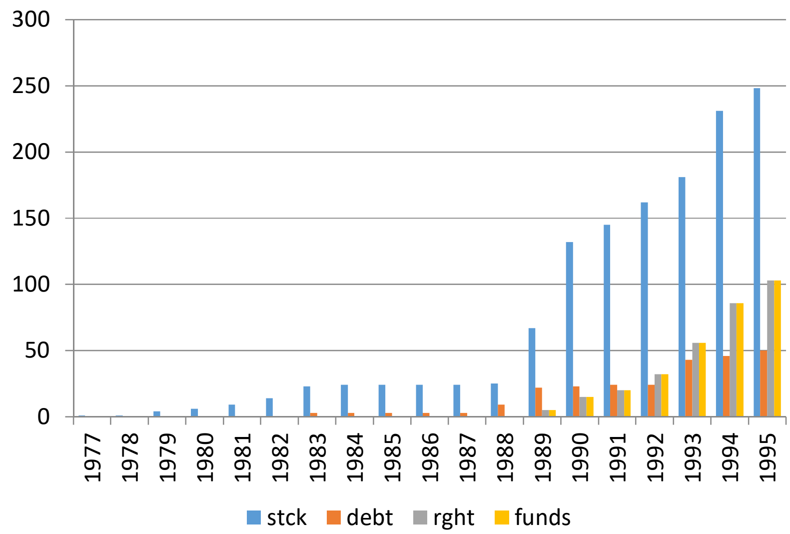
Due to a significant increase in the number of bank loans to the private sector and the increase in risks associated with these loans, the government amended the 1988 PAKTO policy, particularly for provisions related to banks' net foreign borrowing position. In addition, in the 1989 deregulation package, banks were allowed to invest in other financial institutions and create new lending with short-, medium-, and long-term periods. As part of risk management policy, the central bank also required banks to maintain a capital adequacy ratio (CAR) of minimum 8 per cent, which started in 1991 (Matsumoto 2007).

The significant improvement in the banking sector brought about by the regulation overhauls, however, was not followed by the capital market. The public still relied heavily on banks for financing. Until 1987, there were only 24 companies listed on the stock exchange with a total value of about 129 billion rupiah, and only one new listing company on the stock exchange in the following year.

To stimulate the capital market sector, in 1987 the government introduced the December Deregulation Package I, known as PAKDES I, which relaxed procedures for companies issuing new securities and allowed foreign investors to purchase up to 49 per cent of Indonesian listed companies (Matsumoto 2007). The results of the new regulatory package were shown in the following years. Companies issuing stocks on the Jakarta Stock Exchange increased and reached a peak of 65 new issuers in 1990 (Bapepam 1999).

Deregulation in the capital market sector continued in 1988 when the government launched PAKDES II which allowed foreign ownership of Indonesian securities companies, the privatization of the Jakarta Stock Exchange and the reopening of the Surabaya Stock Exchange. During this period, the number of finance companies also increased significantly (Bapepam 1999; Santoso 2000).

Figure 2.1 Total stocks, bonds, rights and investment funds from 1977 to 1995



Source: Bapepam (1999)

In May 1995, the Indonesian stock market introduced a new trading platform to accommodate the financial market boom in Indonesia and to counter increased competition from peer exchanges in the region. Since then, securities transactions in the Jakarta Stock Exchange have been computerized, faster and more accurate.

In the same year, the Indonesian Government and House of Representatives passed Capital Market Law No. 8 of 1995, a supreme regulatory framework of conduct in the capital market (Indonesia Stock Exchange 2013a). The law mandated issuers to be more transparent in their financial and operating conditions in order to achieve an orderly, fair and efficient capital market and to protect the interests of public investors (Republic of Indonesia 1995).

2.2.2 Indonesian stock market and two financial crises

Indonesia has become one of the most studied emerging markets because of its notable economic achievements following the introduction of the liberalization policy in the 1980s. However, although it had been one of fastest growing economies in the region, the Indonesian economy was not sufficiently sound to withhold the adverse effects of the Asian Financial Crisis (AFC) of 1998; a crisis that caused the Indonesian economy to weaken, and then triggered multidimensional crises (Hill 2000; Hill & Shiraishi 2007). Furthermore, although the impact was not as severe from the 1998, the Indonesian financial markets suffered shocks again by the 2008 Global Financial Crisis (GFC).

The 1998 Asian Financial Crisis

In 1998 the Indonesian economy was hit by the 1998 AFC. Originating from Thailand's currency losses in 1997, the crisis quickly spread across other countries in the region including Indonesia. The 1998 crisis swept away the wealth that had been created by the economic growth in the previous two decades. From 1997 to 1998, Indonesian GDP dropped by 13.13 per cent, the rupiah currency rate depreciated more than 80 per cent against the U.S. dollar, and the inflation rate rose to 77.60 per cent.[3] The crisis had caused 'the strange and sudden death of a tiger economy' (Hill 2000, p.117).

In Indonesia, the effect of the AFC was severe as it had escalated to a multi-dimensional crisis which took longer to recover from compared to other countries in the region. The crisis had affected not only the economic structure but also the social and political systems which resulted in high costs for the nation, not only in monetary terms but also in trauma due to civil unrest following the crisis (Basri 2013).

During the crisis, the Jakarta Composite Index (JCI) fell to its lowest level of 256.83 on 21 September 1998, or reduced by 64.90 per cent since July 1997. Trading value also decreased from 489.4 billion IDR rupiah in 1997 to about 403.6 billion IDR rupiah and total market capitalization shrank by about 24 per cent from 226 billion IDR rupiah on 1

[3] Basri (2013) reported slightly different figures regarding the impact of the 1998 crisis on the Indonesian economy where the GDP contracted by 13.7 per cent, rupiah deflated by 79 per cent and inflation jumped to 70 per cent.

July 1997 to 196 billion IDR rupiah a year later. In addition, there were only three companies issuing new stock in 1998, which was notably low compared to the 34 new issues in the previous year. There was also no new debt issuance during the crisis (Bapepam 1999). With the assistance of International Monetary Fund (IMF), the Indonesian economy gradually recovered from the crisis. There were disagreements between the IMF and the incumbent President Soeharto, however, regarding the crisis formulation and recovery procedures. This situation often put key decision-makers in economic ministries in a dilemma facilitating both the demands of the president and those of the IMF (Cole & Slade 1996).

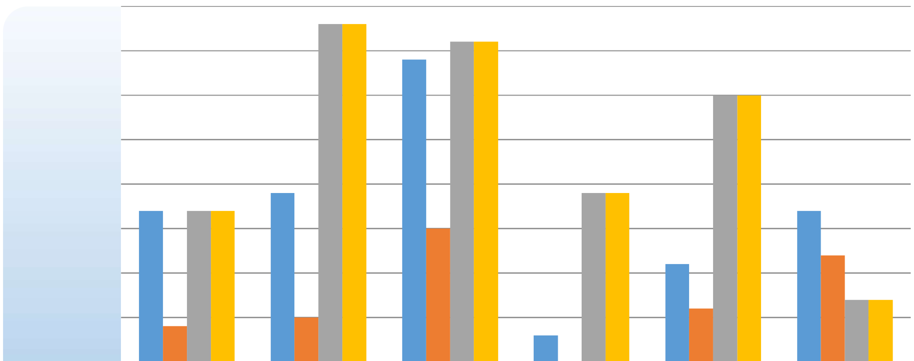
The Indonesian Government introduced various economic policies to cope with the crisis. For example, in monetary policy, the Indonesia Central Bank increased interest rates to manage high inflation and control capital flight during the crisis. However, instead of resolving the crisis, the policy created a negative spread due to lower interest rates for loans than for savings. Consequently, banks were unable to channel credits to real economic sectors to produce goods and services. Furthermore, the crisis created liquidity problems in the banking sector which triggered a bank rush, massive capital flights, and forced liquidation of national banks (Cole & Slade 1998; Hill & Shiraishi 2007). Furthermore, in the banking and corporate sectors, the government took legal action against banks and conglomerates that caused or were involved in the crisis, which caused huge but unnecessary costs to the Indonesian economy. The bank recapitalization and rehabilitation programs cost approximately 643 trillion IDR rupiah (or 91 billion U.S. dollars), which is equivalent to 60 per cent of Indonesian GDP. That cost excluded expenses related to the IBRA's[4] operation, asset disposal, Initial Public Offerings (IPOs) and privatization (Matsumoto 2007).

A relatively peaceful transition of political power through the first direct election in 1999 helped regain foreign investors' confidence in investing in Indonesia. The new government committed to reform all economic, social and political problems. The

[4] Indonesian Bank Restructuring Agency (IBRA) was formed in January 1998 to carry out the restructuring of the banking sectors following the 1998 financial crisis. The agency was responsible to manage the assets, including banks, handled by the Indonesian Debt Restructuring Agency as settlement for the corporate sectors' debt problems that led to the crisis.

reformation helped prevent Indonesia from becoming 'a failed state' (Hill & Shiraishi 2007, p. 139).

Figure 2.2 The number of securities and funds issuance before and after the 1998 crisis



	1995	1996	1997	1998	1999	2000 - Juni
stck	17	19	34	3	11	17
debt	4	5	15	0	6	12
rght	17	38	36	19	30	7
funds	17	38	36	19	30	7

Source: Bapepam

Post-1998 financial crisis recovery

From 1999 to 2000, signs of recovery from the crisis emerged which were marked by increased trading activity and new IPOs in the capital market. The Jakarta Stock Exchange's composite index increased significantly, signalling the return of investors' confidence to trade and invest in Indonesian stocks (Figure 2.2). To accelerate the recovery, capital market regulators restructured the trading and settlement process by upgrading the system and technology for securities transactions. In 2000, the regulator introduced a scriptless trading system, called C-BEST: the Central Depository & Book Entry Settlement, where securities can be rapidly traded and stored with less human interference (Jakarta Stock Exchange 2006).

Following the development of the internet and computer technology, in 2002 the Jakarta Stock Exchange introduced a remote trading system which allows its members access to the stock exchange's trading engine and permits orders to be sent directly from their offices (Indonesia Stock Exchange 2006). Crisis recovery programs continued. One program enacted was the introduction of stock options in October 2004 to diversify products in the capital market. Furthermore, to increase the market liquidity and competitiveness with regional exchanges, on 1 December 2007 the Surabaya Stock Exchange merged with the Jakarta Stock Exchange to become the Indonesia Stock Exchange (IDX) (Indonesia Stock Exchange 2008).

The 2008 Global Financial Crisis

In the beginning of 2008, the Indonesian economy was bullish, despite increasing awareness of the U.S. subprime mortgage lending problems. The JCI recorded its highest level of 2,830.26 on 9 January 2008, an increase of 58.92 per cent, compared to the previous year. In 2007, total trading value in the IDX recorded more than 1,050 trillion IDR rupiah, or more than twice that of 2006 (Indonesia Stock Exchange 2009b). The market was optimistic that the subprime mortgage crisis in the U.S. would be contained and solved immediately, and would create no contagion effects globally.

The 2008 GFC resulted in the global equity market capitalization decreasing by more than 56 per cent at the end of February 2009 compared to the beginning of 2007. The crisis which initially started in the U.S. market also panicked investors in emerging markets. As a result, there were massive capital outflows and asset prices dropped to their lowest level since the 1998 crisis. To avoid further loss in market value, the Indonesian stock market regulators decided to temporarily suspend market-wide transactions in the IDX from the middle of the day of 8 October 2008 until 10 October 2008. Short-selling and margin trading were also prohibited to protect the market from further losses. However, these measures could not prevent the index changing. By the end of 2008, the JCI recorded a 50.64 per cent drop to level at 1,355.408 compared to December 2007, accompanied by a 26.73 per cent increase in trading volume during the same period (Indonesia Stock Exchange 2009a).

The IDX again recorded high returns a few years after the crisis. The JCI increased by 58.03 per cent from 2731.51 on January 2 2008 to 4,316.69 at the end of 2012. The index once slumped to as low as 1,111.39 on 28 October 2008, but then gradually recovered and achieved its peak of 4,375.17 on 26 November 2012 (YahooFinance 2014). For this achievement, the *Alpha South East Asia* Magazine awarded the

Indonesia Stock Exchange as one of the best stock exchanges in Asia Pacific for three consecutive years from 2009 to 2011 (Indonesia Stock Exchange 2011).

2.3 Macroeconomic policy and financial markets stability

The development of a country's capital market relates to the general economic conditions of the country. It is widely known that stock market and individual stock prices are influenced by the aggregate economy of the country in which the stock market operates. Information about the macroeconomic indicator series and monetary policy is expected by investors and market analysts and is an essential input in industry analysis and securities valuation. The stock market is often regarded as a leading indicator of the economy due to its ability to forecast future economic activity (Reilly & Brown 2012).

2.3.1 Indonesian key macroeconomic indicators

A stable macroeconomic policy framework and prudent macroeconomic policy setting after the 1998 financial crisis have contributed significantly to the stability of Indonesian economy and financial system. However, there were challenges to the economy in 2013 when there was speculation that the U.S. Federal Reserve would terminate its quantitative easing policy. Pressures from global financial markets called for further structural reforms in the Indonesian economy and financial markets in areas such as market supervision, free trade and market competition, and the stability of government income (Allford & Soejachmoen 2013).

The macroeconomic policy of an economy is considered sound if it is able to absorb shocks in prices and maintain growth. Table 2.2 shows that the Indonesian economy has been able to maintain growth to approximately 6 per cent per year, although there is a decreasing trend every quarter over the period and recorded 5.8 per cent in June 2013. This decreasing trend of the Indonesian economy is related to slowing economic trends in the countries of Indonesia's trading partners, which started to cut (or withdraw) investment flows in (or from) Indonesia.

Table 2.2 Components of Indonesian GDP Growth 2012–2013

	Jun 2012	Sep 2012	Dec 2012	Mar 2013	Jun 2013
GDP	6.4	6.2	6.1	6.0	5.8
Excluding oil & gas	6.9	6.9	6.7	6.7	6.4
By expenditure					
Private consumption	5.2	5.6	5.4	5.2	5.1
Government consumption	8.6	–2.8	–3.3	0.4	2.1
Investment	12.5	9.8	7.3	5.9	4.7
Construction	7.3	7.6	7.8	7.2	6.9
Machinery & equipment	20.9	11.4	4.3	0.0	–2.6
Transport	52.9	25.9	10.1	4.4	–1.4
Other	–2.0	9.7	18.7	22.3	11.6
Exports	2.6	–2.6	0.5	3.4	4.8
Imports	11.3	–0.2	6.8	–0.4	0.6
By sector					
Tradables	4.6	4.7	4.2	4.2	4.0
Agriculture, livestock, forestry & fisheries	4.0	5.3	2.0	3.7	3.2
Mining & quarrying	3.3	–0.3	0.5	–0.4	–1.2
Manufacturing	5.2	5.9	6.2	5.8	5.8
Excluding oil & gas	10.1	11.3	10.7	9.8	6.4
Non-tradables	7.9	7.4	7.7	7.6	7.4
Electricity, gas & water supply	6.5	6.1	7.3	6.5	6.6
Construction	7.3	7.6	7.8	7.2	6.9
Trade, hotels & restaurants	8.7	7.2	7.8	6.5	6.5
Communications	10.8	10.9	10.0	11.4	13.6
Financial, rental & business services	7.1	7.5	7.7	8.4	8.1
Other services	5.8	4.5	5.3	6.5	4.5

Note: The data use 2000 base prices and are presented in per cent year-on-year. The data are available from CEIC Asia Database (cited in Allford & Soejachmoen 2013).

The decrease in GDP is also due to decreasing government spending and investment, especially for machinery and equipment and transportation. The decrease of investment expenditures in machinery and equipment and transportation is caused mainly by soaring fuel prices after the government's decision to cut fuel subsidies. A similar trend is also found in transport expenditure during the same period.

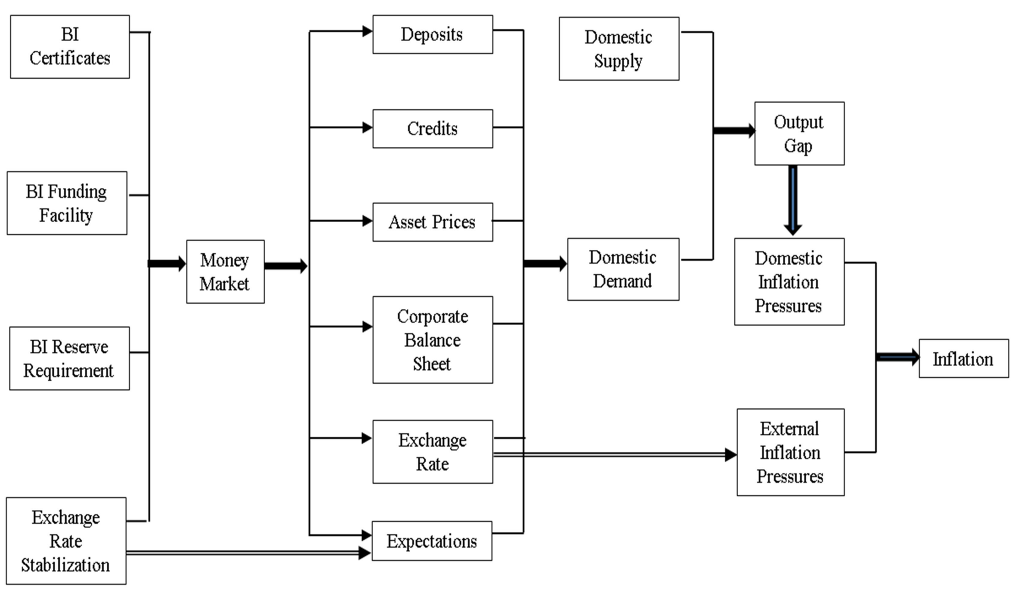
In addition, the manufacturing sector has consistently and significantly contributed to Indonesian economic growth — from 5.2 per cent in June 2012 to 5.8 per cent in June 2013. Table 2.2 shows that the non-tradable sector achieves more than the tradable sector over time. Furthermore, among the non-tradable sector, communication remained the greatest contributor to growth. The communication sector's contribution to Indonesian GDP increased by 25.3 per cent from 10.8 per cent in June 2012 to 13.6 per cent in June 2013.

2.3.2 Indonesian macroeconomic policy

Given the importance of macroeconomic policy to maintain the stability of the financial system, the Central Bank of Indonesia (Bank Indonesia) coordinates with the Ministry of Finance to control inflation, maintain public purchasing power, and build certainty for economic development (Inflation Monitoring and Control Coordination Team 2011).

In 2005, the Central Bank of Indonesia introduced a new monetary policy — the Inflation Targeting Framework (ITF), which aims to achieve the inflation rate targeted by the government. The policy reflects the central bank's stance on future monetary policy, which is indicated by the Bank Indonesia interest rate (BI rate). By communicating the policy to the public, the rate is expected to influence the deposit and lending rates in the banking system, which will finally affect output and prices. In this way, the BI rate announcements influence the inflation rate through movements in domestic demand and supply (Figure 2.3). In its implementation, the Board of Governors of the Bank Indonesia meet regularly, a minimum of once a month, to discuss, determine and announce the stance on monetary policy, and evaluate whether the policy is still viable for achieving the inflation target (Bank Indonesia 2013b).

Figure 2.3 Bank Indonesia's policy transmission mechanism



Source: Adapted from Bank Indonesia (cited in Syurkani 2010, p. 39)

2.4 The structure of Indonesian financial markets

According to the IMF 2010 report on *Financial System Stability Assessment,* Indonesia's financial system was still dominated by banks, which account for more than 75 per cent of total assets in the financial system, or a half of Indonesian GDP. Within the banking system, about two-thirds of the total bank assets and deposit base belongs to the top 15 banks, including state-owned banks. The non-bank financial sector such as insurance companies, pension funds and finance companies account for about 10 per cent of GDP. Until June 2014, the banking sector still played a significant role in the Indonesian financial markets with about 79 per cent of total financial market assets (Bank Indonesia 2014).

Although the IDX was one of the fast growing securities exchanges from 2009 to 2011, its market capitalization remained small compared to Indonesian financial markets as a whole or with its competitors in the region. In 2009, for example, the banking sector accounted for 80 per cent of the Indonesian financial system or 50 per cent of its GDP, while the total market capitalization of the IDX was only 36 per cent of the GDP (International Monetary Fund 2010). According to the World Federation of Exchanges (2011), Indonesia was third after the Philippines and Thailand in terms of growth of market capitalization from 2006 to 2014. Table 2.3 shows that the growth of the IDX capitalization was 203.9 per cent from 2006 to 2014, while those of the Philippines and Thailand rose by 285.9 per cent and 207.1 per cent, respectively, during the same period. Furthermore, the Indonesian stock market's capitalization in 2014 was only 422,127 U.S. dollars or the fifth after Korea, Singapore, Thailand and Malaysia, and was only above the Philippines.

Table 2.3 The market capitalization of the Indonesia Stock Exchange and the stock exchanges of selected Asian countries

Exchanges Name	2006	2007	2008	2009	2010	2011	2012	2013	2014	Growth
Indonesia SE	138,886	211,693	98,761	214,941	360,388	390,107	428,223	346,674	422,127	203.9%
		52.4%	*–53.3%*	*117.6%*	*67.7%*	*8.2%*	*9.8%*	*-19.0%*	*21.8%*	
Bursa Malaysia	235,581	325,290	189,239	289,219	408,689	395,624	466,588	500,387	459,004	94.8%
		38.1%	*–41.8%*	*52.8%*	*41.3%*	*–3.2%*	*17.9%*	*7.2%*	*–8.3%*	
Korea Exchange	834,404	1,122,606	470,798	834,597	1,091,911	996,140	1,179,419	1,234,549	1,212,759	45.3%
		34.5%	*–58.1%*	*77.3%*	*30.8%*	*–8.8%*	*18.4%*	*4.7%*	*–1.8%*	
Philippine SE	67,852	102,853	52,031	86,349	157,321	165,066	229,317	217,320	261,841	285.9%
		51.6%	*–49.4%*	*66.0%*	*82.2%*	*4.9%*	*38.9%*	*–5.2%*	*20.5%*	
The SE of Thailand	140,161	197,129	103,128	176,956	277,732	268,489	389,756	354,367	430,427	207.1%
		40.6%	*–47.7%*	*71.6%*	*56.9%*	*–3.3%*	*45.2%*	*–9.1%*	*21.5%*	
Singapore Exchange	384,286	539,177	264,974	481,247	647,226	598,273	765,078	744,413	752,831	95.9%
		40.3%	*–50.9%*	*81.6%*	*34.5%*	*–7.6%*	*27.9%*	*–2.7%*	*1.1%*	

Note: The table shows the statistics of market capitalization of the Indonesia Stock Exchanges and other stock exchanges from 2006 to 2014. The statistics are in U.S. dollars. The Ho Chi Minh Stock Exchange of Vietnam is deleted from the list due to insufficient data. Data are available from the World Federation of Exchanges. Annual growth of each market capitalization is provided in italics. Growth of market capitalization is calculated as the ratio between market capitalization data from 2006 to 2014.

2.4.1 The Indonesian stock market microstructure

Market microstructure is an area of study in finance focussing on mechanisms through which investors' demand is translated into prices. The literature in this area includes both theoretical and empirical studies related to: (1) price formation process, (2) market structure and design, (3) market transparency and (4) other related areas such as asset pricing and international finance (Madhavan 2000).

Since its activation in 1912, the Indonesian capital market has developed products, transaction and settlement mechanisms, and listing rules to increase the depth of the market and widen its investor base. For example, to increase operational efficiency the IDX upgraded its trading platforms. The new JATS-NextG system can handle all financial products traded in the exchange at the same time including stocks, bonds and derivatives. In the same year, the IDX introduced Straight Through Processing (STP) to increase the efficiency of securities transactions starting from order placements, order execution, to settlement without manual intervention (Indonesia Stock Exchange 2013b).

Stocks traded in the IDX are distributed into three segments: regular, negotiated and cash markets.[5] However, this study focusses only on stock trading in the regular market for two reasons. First, stock prices shown in the regular market are formed by matched buy-sell orders in the exchange's continuous auction system. Second, prices quoted in the regular market are published globally and used as a benchmark for indices measurement (Indonesia Stock Exchange 2013b). Stock prices and trading mentioned in this study are, therefore, referred to those derived from the regular market.

Trading hours

The IDX trades from Monday to Friday except public holidays. IDX's trading hours are divided into two sessions: mornings and afternoons. Table 2.4 shows that, from Monday to Thursday, the morning session starts from 09:30 to 12:00 and the afternoon session starts is 13:30 to 16:00. On Friday, the trading hours are from 09:30 to 11:30 and from 14:00 to 16:00. Before the regular trading starts (closes), there are pre-opening (closing) sessions where orders from members of the exchange are submitted and matched to construct an opening price. Different stock markets have different rules on trading hours during the week.

[5] Further details on the market segmentations, respective trading schedules and settlement mechanisms are available in the IDX *Fact Book*.

In Indonesia, Friday has longer trading break hours to allow the majority Muslim population to attend Friday congregation and prayer (Comerton-Forde 1999). Table 2.4 compares the different trading hours of major stock exchanges in the region.

Table 2.4 Trading hours of the stock exchanges in selected Asian countries

No.	Stock exchanges	Trading days	Trading hours
1.	Indonesia Stock Exchange	Monday to Friday	**Monday to Thursday:** 1st Session: 09:00 to 12:00 2nd Session: 13:30 to 16:00 **Friday:** 1st Session: 09:00 to 11:00 2nd Session: 14:00 to 16:00
2.	Bursa Malaysia	Monday to Friday	1st Session: 09:00 to 13:30 2nd Session: 14:30 to 16:45
3.	Singapore Exchange	Monday to Friday	09:00 to 17:00
4.	The Philippines Stock Exchange	Monday to Friday	1st Session: 09:00 to 13:30 2nd Session: 14:30 to 16:45
5.	Thailand Stock Exchange	Monday to Friday	1st Session: 10:00 to 12:30 2nd Session: 14:30 to 16:30
6.	Vietnam Stock Exchange	Monday to Friday	1st Session: 09:00 to 11:30 2nd Session: 13:00 to 14:45

Source: Indonesia Stock Exchange (2013b), World Federation of Exchanges (2010)

Starting from 2 January 2013, the IDX has extended the trading hours of the regular market both to synchronize global trading hours and to accommodate the trading hours of investors from the central and eastern regions of Indonesia. The pre-opening session is divided into two periods: from 08:45:00 to 08:55:00 for order submission, and from 08:55:01 to 08:59:59 for order matching based on price and time priority. Since extending the trading hours, the IDX has also introduced new closing trading hours which are divided into two: pre-closing and post-closing sessions. The pre-closing session starts from 15:50:00 to 16:00:00 for order submission and from 16:00:00 to 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 to16:15:00 based on time priority. Table 2.5 shows the difference in trading hours of the Indonesia Stock Exchange before and after January 2013.[6]

[6] This study uses market data until December 2012, therefore the new rules on trading hours does not apply.

Table 2.5 Trading schedule of the Indonesia Stock Exchange

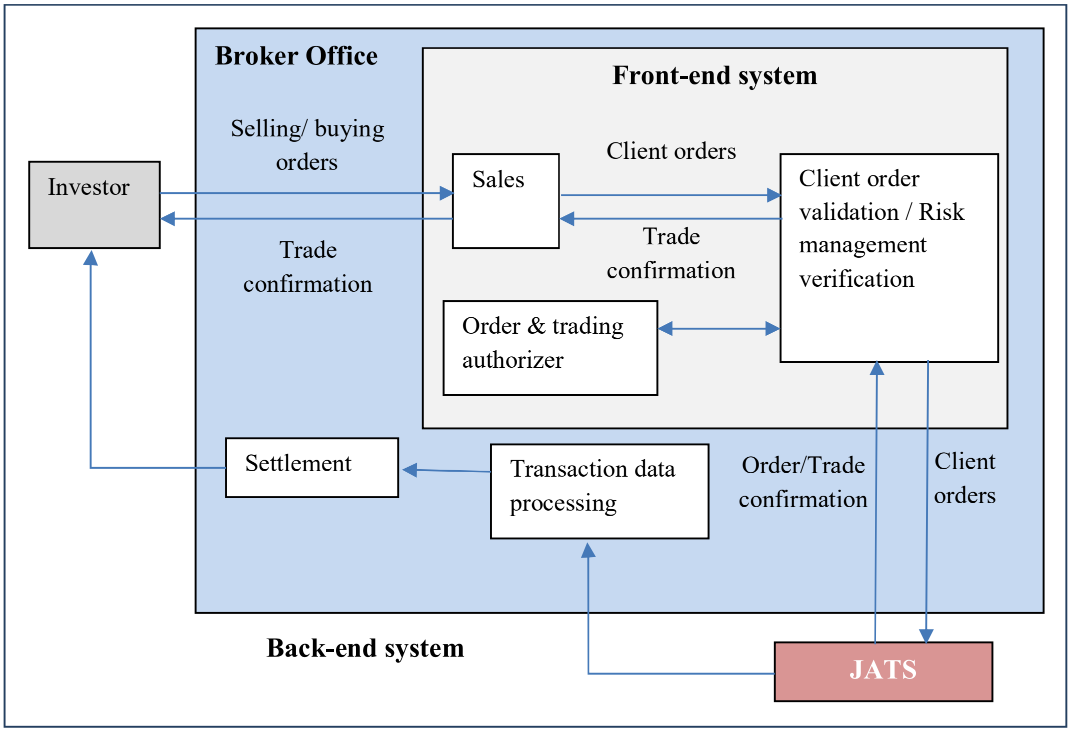
Days	Sessions	Hours
Before 2 Jan 2013		
Monday to Thursday	Session I	09:30 to 12:00
	Session II	13:30 to 16:00
Friday	Session I	09:00 to 11:30
	Session II	14:00 to 16:00
Pre-opening session:		
Monday to Friday	Put orders	09:10:00 to 09:25:00
	Orders allocation	09:25:01 to 09:29:59
After 2 Jan 2013		
Monday to Thursday	Pre-opening	08:45:00 to 08:54:59
	Orders allocation	08:55:00 to 08:59:59
	Session I	09:00:00 to 11:59:59
	Session II	13:30:00 to 15:49:59
	Pre-closing	15:50:00 to 15:59:59
	Put orders	16:00:00 to 16:04:59
	Post-closing	16:05:00 to 16:15:00
Friday	Pre-opening	08:45:00 to 08:54:59
	Orders allocation	08:55:00 to 08:59:59
	Session I	09:00:00 to 11:29:59
	Session II	14:00:00 to 15:49:59
	Pre-closing	15:50:00 to 15:59:59
	Put orders	16:00:00 to 16:04:59
	Post-closing	16:05:00 to 16:15:00

Source: Indonesia Stock Exchange (2013b)

Trading mechanism

Stock trading in the Indonesia Stock Exchange is based on an order-driven system. The validity of transaction orders is limited to within a day or sessions in that day. Furthermore, orders can only be submitted during trading hours via securities companies who have been a member of both the exchange (stockbrokers) and the Indonesian Clearing and Guarantee Corporation (KPEI). Investors can trade and submit orders after becoming a client of a stockbroker. Furthermore, trading systems of the stockbrokers and the stock exchange will validate before accepting and executing the orders (Indonesia Stock Exchange 2013b). The process of submission, validation and execution, as well as settlement of the orders is provided in Figure 2.4.

Figure 2.4 The Indonesia Stock Exchange: Trading mechanism



Source: Indonesia Stock Exchange (2013b)

Lot size, price movements (tick sizes), and auto rejection

Stocks traded in the regular and cash markets of the Indonesia Stock Exchange are processed through a 'continuous-auction' market mechanism. In the continuous-auction market mechanism, transaction orders are executed continuously during trading hours based on time and price priority. Stocks traded in the regular market are quantified in 'round lots' with a minimum quantity of one lot which, before 1 January 2014, was equal to 500 shares. To increase the market liquidity and capitalization of the exchange, on 8 November 2013 the IDX reduced the number of a round lot from 500 shares to 100 shares. The decree applied from 6 January 2014 (Indonesia Stock Exchange 2014b).

The IDX also applies multilevel price increments between orders which are divided based on shares' market prices. The price increment (tick size) rules have been modified several times to accommodate the dynamic changes in the market and to increase liquidity. Following the decree on 8 November 2013, the IDX amended the price increments rule which came into effect from 6 January 2014. Previous changes in price increments also occurred in 2007. Table 2.6 shows differences in stock price tick rules from 2006 to 2014.

Table 2.6 Price increments between orders 2006 – 2014

Before 2006			2007–2013			After 2014		
Price	Step value	Max price step	Price	Step value	Max price step	Price	Step value	Max price step
<500	5	50	<200	1	10	<500	1	20
500 – <2,000	10	100	200 – <500	5	50	500 – <5,000	5	100
2,000 – <5,000	25	250	500 – <2,000	10	1000	>5,000	25	500
>5,000	50	500	2,000 – <5,000	25	250			
			>5,000	50	500			

Note: All the prices are in IDR rupiah. The data are available from the Indonesia Stock Exchange (2014).

Along with price increments rules, starting 19 January 2009, the IDX implemented an auto rejection system which automatically rejects any order if the increase in stock price exceeds its specified price levels. However, while the price increment rules apply for stocks, rights and warrants, the auto rejection system applies only on stocks either in regular or corporate action markets. Table 2.7 shows that the auto rejection system is divided into three price levels of the regular market's previous price, as follows:

Table 2.7 Auto Rejection System Levels

	Auto Rejection Percentage	
Previous price of regular market	Regular condition	Corporate action (4 days)
50 – ≤200	35%	35%
>200 – ≤5,000	25%	25%
>5,000	20%	20%

Note: All the prices are in IDR rupiah. The data are available from the Indonesia Stock Exchange (2014).

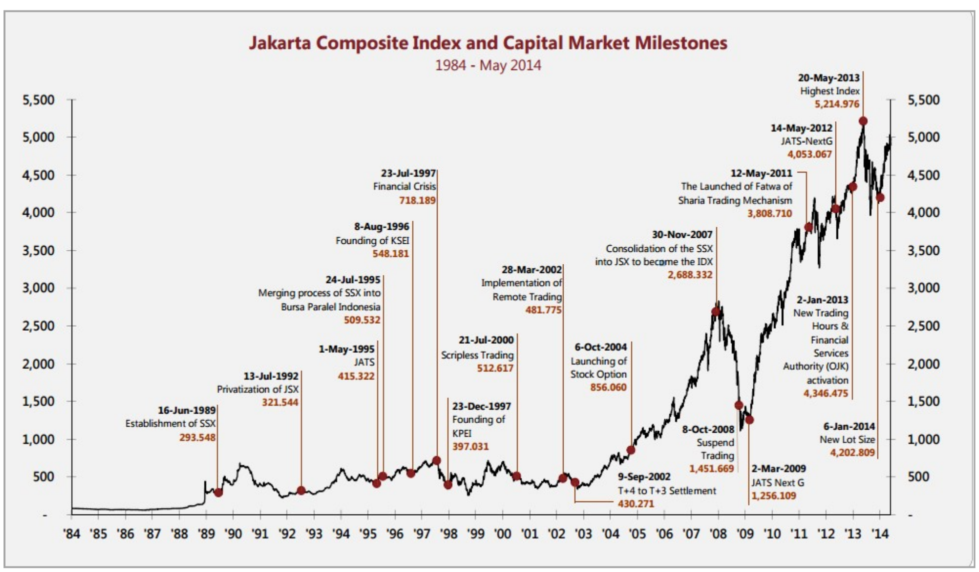
2.4.2 The Indonesian stock market's performance: Key statistics

As mentioned in Section 2.2, although significantly influenced by the 2008 GFC amid the downward trends of major developed economies, the Indonesian capital market continued to show positive growth from 2006 to 2014 (Figure 2.5). It is believed that the experience of managing the impact of the AFC of 1998 and the improvement in macroeconomic indicators enabled the government to minimize the effect of the GFC. There has also been an increase in investors' confidence leading to increased resilience in the Indonesian economy (Ghon Rhee & Wang 2009; Hadad et al. 2011; Mudrajad, Tri & Ross 2009).

The JCI, as a general indicator of returns in Indonesia equity market, increased by 52.08 per cent from 1805.52 in December 2006 to 2745.83 at the end of 2007. However, similarly to world capital markets, the JCI index decreased significantly by 50.64 per cent to 1355.41 at the end of 2008 due to the GFC. As the economy improved, the stock market recovered and the index increased gradually during the post-GFC period until it closed at 4316.69 at the end of 2012. In addition to high volatility of returns resulting from the 2008 crisis, there was a significant drop in market value in 2013 when investors were anxious about the possibility of the U.S. Federal Reserve to taper its quantitative easing policy. However, stable economic growth, high domestic consumption and investors' increased confidence in the Indonesian economy had helped the stock market recover from that possible crisis quickly (Indonesia Stock Exchange 2013a). Subsequently, the JCI Index increased considerably from 4274.18 in 2013 to 5226.95 at the end of 2014 (Figure 2.5).

The performance of the IDX from 2006 to 2014 is also reported based on the market indicators presented in Table 2.8. The table shows that market capitalization more than quadrupled during the period, even though the increase in the number of listed companies less than doubled. Furthermore, there was a significant increase in market liquidity as shown by significant growth in the number and frequency of shares traded during the period. Although the IDX had been used as a major source of company financing until 2010, there has been a decreasing trend in the use of IPOs for fundraising since then.

Figure 2.5 The Indonesian Stock Composite Index and Capital Market Milestones



Source: Indonesia Stock Exchange (2014b)

Table 2.8 Key Market Indicators of the Indonesia Stock Exchange 2006 – 2014

Market indicators	2006	2007	2008	2009	2010	2011	2012	2013	2014
Value of Jakarta Composite Index	1,805.52	2,745.83	1,355.41	2,534.36	3,703.51	3,821.99	4,316.69	4,274.18	5,226.95
Market capitalization	1,249,074	1,988,326	1,076,491	2,019,375	3,247,097	3,537,294	4,126,995	4,219,020	5,228,043
Number of shares traded (total)	436,936	1,039,542	787,846	1,467,660	1,330,870	1,203,550	1,053,760	1,342,660	NA
Trading frequency (total)	4,810.90	11,861.06	13,417.14	20,976.60	25,918.56	28,023.05	29,941.04	37,499.46	NA
Number of shares traded (daily average)	1,805.52	4,225.78	3,282.69	6,089.87	5,432.10	4,872.67	4,283.59	5,502.96	NA
Trading frequency (daily average)	19.88	48.22	55.91	87.04	105.79	113.45	121.71	153.69	NA
Listed companies	344	383	396	398	420	440	459	483	506
New listing	12	22	19	13	23	25	23	31	23
Delistings	4	8	6	11	1	5	4	7	NA
Investment flows — IPOs	3,010	16,870	24,390	3,850	29,678	19,593	10,136	16,747	9,016
Investment flows — Already listed companies	12,580	29,500	56,610	8,560	48,160	42,140	18,190	38,800	34,116
Trading Days	242	246	240	241	245	247	246	244	242

Notes: Market capitalization is in billions IDR rupiah and Investment flows are in millions IDR rupiah. Number of shares traded is in million shares. Trading frequency is in thousand (times). Investment flows are in billion IDR rupiah. Data are available from the Indonesia Stock Exchange Annual Reports and from the World Federation of Exchanges for 2014 data.

2.5 Conclusion

Financial markets, which were originally introduced as an alternative to traditional banking systems, have played an important role in economic development, particularly in an emerging country like Indonesia. Although the banking sector is still dominant in the Indonesian financial system, the contribution of the capital market to the national economy has increased.

For the decade before the 1980s, the Indonesian economy achieved exceptional growth and prosperity due to an economic boom, windfall profit from global commodity price increase and capital inflows. However, similarly to other emerging markets, the Indonesian economy has been heavily exposed to global market conditions as a result of its market liberalization policy. Indonesia has suffered from two financial crises: the 1998 AFC and the 2008 GFC; the former was the worst economic crisis since the 1960s Great Recession. Therefore, the economic development in one country is not only affected by domestic macroeconomic factors but also by those of other countries. Although there are opportunities for portfolio diversification and high returns, the globalization of capital market creates contagion effects.

Having learned from the 1998 financial crisis, the Indonesian economy has been resilient and the government was more effective in managing the crisis in 2008 than before. Appropriate macroeconomic policy, growth stability and market confidence are key factors required to recover from the crisis. In addition, Indonesia's capital market is still an attractive alternative both for financing and investing. This is reflected by the performance of key market indicators such as the stock index, market capitalization and trading volume, which have increased greatly over time. Therefore, it is worthwhile to mention that the next tasks for government and market regulators are to increase the role of the capital market in economic activity, maintain market confidence and increase efficiency.

CHAPTER 3

VOLATILITY OF RETURNS, TRADING VOLUME AND THE IMPACT OF MACROECONOMIC ANNOUNCEMENTS: A REVIEW OF THE LITERATURE

3.1 Introduction

Chapter 2 discussed the importance of having an orderly, fair and efficient capital market to support a country's economic development because it helps allocate capital resources, foster growth and improve productivity (Levine & Zervos 1998b; Wurgler 2000). As mentioned in Chapter 1, this thesis aims to examine the degree of informational efficiency of the Indonesian capital market by measuring the impact of macroeconomic announcements, as proxies for public information, on the volatility of market returns and examines the relationship between volatility and trading volume. The key purpose of this chapter is to review theories and existing empirical work related to the research questions outlined in Chapter 1.

Chapter 3 is structured as follows: Section 3.2 discusses the theoretical background and empirical literature on volatility. Section 3.3 reviews studies of high-frequency data and their application in measuring volatility. Both Section 3.2 and 3.3 aim to answer research question 1: What is the pattern of intraday volatility of returns of the Indonesian stock market? Section 3.4 discusses the theoretical background and empirical studies on the impact of information on volatility and is related to research question 2: How and to what extent is intraday volatility of stock market returns influenced by public information? Section 3.5 reviews literature related to question 3: What is the relationship between trading volume and volatility? Finally, Section 3.5 suggests a gap in the literature and Section 3.6 concludes the chapter.

3.2 The volatility of returns: Theory and evidence

This section begins with the theoretical and practical definition of volatility. Then it discusses theories and empirical studies on types of volatility. It also reviews theories and empirical work related to the importance and factors contributing to the volatility of emerging market returns.

3.2.1 Definition of volatility

Due to its extensive use in finance, the definition of volatility varies depending on the approach and application used in a particular study (Altman & Schwartz 1970; Brailsford 1994). Therefore, a clear understanding of both the concepts and models of volatility is demanded as incorrect interpretation and application of volatility measures can mislead and create adverse effects in financial decision-making, risk management, or in interpreting market conditions (Goldstein & Taleb 2007).

There are many definitions of volatility in the finance literature. In line with this study, the definition used is based on investment theory and observed from the perspective of financial market participants and regulators. First, from the perspective of market participants, volatility is defined as the risk of an asset due to the uncertainty of its future returns. Here, volatility is measured by the variance or standard deviation of expected returns of an asset during certain time periods (Bodie, Kane & Marcus 2008; Reilly & Brown 2012). From this definition one can assume that the higher the variance or standard deviation of returns, the higher the risk or volatility in asset returns.

The second way to define volatility is from the perspective of market regulators who look at the volatility in individual stock or market-wide levels. After the 1929–1939 Great Depression, U.S. stock market regulators paid more attention to volatility because volatility during that time increased rapidly and was significantly higher when compared to other periods (Schwert 1989, 2011). Having had that experience, the U.S. Securities and Exchanges Commission describes the market as volatile when there are extraordinary and sudden changes of prices either in individual stocks or in the market in general (SEC 2012). Similarly, the Australian Stock Exchange (2014) defines volatility as ‘a measure of how wild or quiet a market is relative to its history’ whilst the Australian Securities and Investments Commission (ASIC) (2014) describes volatility as ‘the rate when the price of a security moves up and down’.

A variation of the investment theory definition of volatility is one that develops in parallel with the development of financial markets and products. As a result, volatility is not only measured by variance or standard deviation of returns but also, as Reilly and Brown (2012) propose, can include three additional measures of risk: range of returns, semivariance and below zero returns. Using the range of returns means that the wider the range of assets returns, the higher the risk of the assets and vice versa. The semivariance and the below-zero risk types apply only when the returns of the assets are under their mean or recording negative values, respectively.

A significant development in financial markets has been the availability of high-frequency 'tick-by-tick' data and the consequent ability to calculate intraday volatility using the data. A further discussion of high-frequency data and their application to the measurement of volatility will be provided in Section 3.3.

The next section discusses the importance of volatility and major factors contributing to high volatility of emerging market returns.

3.2.2 The importance of volatility

There is a large volume of studies in the finance literature describing the significant role of volatility in finance research. For brevity, and consistent with the definition of volatility in Section 3.2.1, the important role of volatility will also be described from the perspective of market participants and regulators.

Andersen, Bollerslev and Das (2001), and Andersen, Bollerslev, Diebold and Labys (2003) note that volatility measures help market participants quantify risks to be used in asset pricing models, portfolio selection and risk management.

Studies in international investment find that volatility helps investors indicate which markets are riskier than others. This claim is supported by Schwert (1989), who argues that volatility is important for financial resources reallocation as volatility reflects the underlying condition in the market. Although there is evidence that volatility fluctuates and that the volatility of returns of a developed market can be significantly higher during particular periods (Schwert 1989), the volatility of emerging markets returns is consistently higher than the volatility in developed markets (Aggarwal, Inclan & Leal 1999; Bekaert & Harvey 1995). Based on data from the ten largest emerging stock markets in Asia and Latin America from 1985 to 1995, Aggarwal, Inclan and Leal (1999) found that the returns of emerging equity markets are highly volatile due to sudden changes in returns. Lee and Suh (2005) support this finding based on a study of the return volatilities of the New York Stock Exchange (NYSE) index and Korea Composite Stock Price Index (KOSPI) composite index over the sample period of 1980 to 2001.

Understanding the typical behaviour or patterns of volatility can help identify changes in market efficiency or indicate the vulnerability of a financial market (Kalev et al. 2004; Poon & Granger 2003). Volatility can be a signal of potential financial crises and/or instability. Consequently, volatility has long been used as an important indicator in monetary policy decisions. The CBOE Volatility Index (VIX) which was introduced in 1993 has become one of the main measures of U.S. stock market volatility.[7]

Volatility is also used by market regulators to detect price manipulation activities in financial markets. Admati and Pfleiderer (1988) found that the high volatility of emerging market returns correlates with price manipulative. This finding is supported by Bekaert and Harvey (2000), Aggarwal and Wu (2006) and Öğüt, Mete Doğanay and Aktaş (2009) who found that liquidity, returns and volatility are positively correlated during periods of market manipulation. This correlation occurs due to the nature of information asymmetry, market structure and the institutions involved in the emerging markets.

3.2.3 The volatility of emerging stock market returns

Previous studies found that returns from emerging markets are more volatile than those from developed markets (Bekaert & Harvey 1997; Bekaert et al. 1998). Returns from emerging equity markets are usually not normally distributed, typically being negatively skewed and leptokurtic. In addition, the volatility of returns differs among emerging markets, depending on their macroeconomic characteristics and market microstructure, asset concentration and level of economic and financial integration. The differences play a major role in the determination of the level of risk premiums and the cost of capital of each emerging market (Bekaert & Harvey 1997; Bekaert et al. 1998).

In Indonesia, early studies by Chang, Ghon Rhee and Soedigno, (1995), Bekaert and Harvey (1997), De Santis and Imrohoroglu (1997), and Bekaert et al. (1998) are among the first to study volatility. Indonesia has become one of most studied emerging economies due to its experience of boom and bust cycles in its economy, particularly since the liberalization of its financial markets.

[7] The Chicago Board Options Exchange (CBOE) firstly introduced the CBOE Volatility Index (VIX) in 1993. The index aims to measure the market's expectation of 30-day volatility implied by at-the-money S&P 100 Index option prices. In 2003, the benchmark for the index was updated to the S&P500 index so that it can be widely used by market participants, and academics. In its development, VIX is not only used as a benchmark for implied volatility, but can also be traded.

Several studies have investigated the causal factors underlying emerging market volatility. These can be grouped under three headings: financial market liberalization (Bekaert et al. 1998; Bekaert & Harvey 1995; Bekaert, Harvey & Lundblad 2003), macroeconomic factors (Aggarwal, R, Inclan & Leal 1999), and political and social instability (Arin, Molchanov & Reich 2013; Białkowski, Gottschalk & Wisniewski 2008; Erb & Harvey 1996; Herron 2000). In the case of financial market liberalization, the volatility of emerging markets can be due to a volatility spillover effect from developed or other developing countries (Korkmaz, Cevik & Atukeren 2012; Mulyadi 2009).

3.2.3.1 Financial market liberalization

Financial liberalization policies in emerging markets were characterized by the lifting of government restrictions on foreign and private participation in domestic financial markets. The implementation of financial market liberalization policies by most emerging economies in the early 1980s transformed the countries from being isolated, into being more globally integrated. This affected returns and the volatility of returns enormously (Bekaert & Harvey 1995; Cole & Slade 1996, p. 162). The new policy has allowed a large amount of foreign capital to enter the emerging markets rapidly. However, it has also allowed rapid capital outflows from the markets when there has been an indication of crisis.

In the context of Indonesia, the liberalization of its financial markets was marked by deregulation in the banking sector with its PAKJUN (June Package) in 1983, which alleviated restrictions on interest rates both for time-deposits and loans, and the PAKTO (October Package) in 1988, which enabled banks to establish joint ventures with foreign partners in Indonesia. In the capital market sector, the Indonesian Government passed the 1987 PAKDES (December Package) which allowed foreign investors to purchase up to 50 per cent of Indonesian stocks. The 1987 December Package also aimed to foster greater activity on the Jakarta Stock Exchange by relaxing requirements for securities underwriting, equity public offerings and company reporting. In addition, the Indonesian stock market was initially developed due to the excessive reliance on bank funding in the 1980s which, at the same time, motivated the Indonesian government to increase the private sector's participation in the national economy. The substantial increase in foreign and private investors' participation in the economy following the deregulation has significantly contributed to the development of the Indonesian financial market (Cole & Slade 1996).

Despite evidence that the Indonesian capital market's activities and performance increased after the implementation of the financial sector deregulation packages, previous studies show mixed results on the impact of financial liberalization policies on the volatility of Indonesian stock market returns. For example, using data from 1976 to 1992, Bekaert and Harvey (1997) found that capital market liberalization decreased the volatility of Indonesian stock market returns as soon as the liberalization policy was imposed. Later studies, such as those by Bekaert et al. (1998), Kim and Singal (2000), and James and Karoglou (2010), support this finding and suggest that the negative correlation between liberalization and volatility of emerging market returns is due to the increased number of rational traders, foreign capital inflows and risk-sharing practices in the market. However, other studies have found that, instead of leading to a decrease in volatility, financial liberalization policy increases volatility. Wang (2007a; 2007b), for example, claims that the 1989 financial liberalization policy increased the volatility of Indonesian stock market returns. Wang found a strong positive correlation between foreign transactions and increased volatility due to leverage effects and declines in the investor base. Wang also argues that stocks with higher foreign holdings are likely to be exposed to greater volatility. These findings are consistent with other studies by Bekaert and Harvey (2000) who showed that the level of volatility in emerging markets increases before and after the inception of a market liberalization policy and also Kim and Singal (2000) and Bae, Chan and Ng (2004) who found that financial liberalization significantly increases the domestic market's exposure to world market risk, and by Stiglitz (2004) who argued that market liberalization increases market instability because it channels more short-term capital into the market, therefore causing the market to be more vulnerable. The sudden changes in volatility around the time of the policy implementation were considered to be due to speculative activities, given that information in these markets is asymmetrically distributed.

3.2.3.2 Macroeconomic factors

In addition to the market liberalization factors, country-specific factors can contribute to the high volatility of returns in emerging markets. Aggarwal, Inclan and Leal (1999) argue that the volatility of emerging markets returns is caused more by individual domestic factors, such as political, social and macroeconomics, than by global factors. In a study from the ten largest emerging stock markets in Asia and Latin America from 1985 to 1995, Aggarwal, Inclan and Leal (1999) found that emerging markets experienced high volatility during major adverse economic events such as hyperinflation, balance of payment crises and economic scandals. This finding is consistent with De Santis and Imrohoroglu (1997), Schwert (1989; 2011) and Baur (2012), among others, in that the volatility of equity returns increases significantly during economic crises.

There is evidence that stock markets move in conjunction with macroeconomic variables over time and are affected by the boom and bust cycle of the economy of a country (Chaudhuri & Koo 2001; Engle, Ghysels & Sohn 2013; Errunza & Hogan 1998). Those factors explain why market participants react rapidly to macroeconomic announcements as they are either signalling future changes of government policy or indicating the directions of the economy (Thenmozhi & Nair 2014). Furthermore, numerous studies have found that, as emerging financial markets become globalized, the volatility of emerging market returns is not only influenced by domestic macroeconomic announcements, but also affected by the macroeconomic announcements of developed countries (Fedorova, Wallenius & Collan 2014; Hanousek, Kočenda & Kutan 2009; Nguyen & Ngo 2014; Nikkinen et al. 2006, 2008; Nikkinen & Sahlström 2004).

In Indonesia, there is limited research on the impact on volatility of macroeconomic announcements, both globally and domestically. Furthermore, evidence of the impact of foreign macroeconomic announcements on the IDX is mixed. For example, using macroeconomic announcements of Eurozone countries from 2007 to 2012, Fedorova, Wallenius and Collan (2014) suggest that macroeconomic announcements involving factors such as consumer price index (CPI), industrial production (IP), gross domestic product (GDP), retail sales (RS), unemployment (UE), liquidity by M3 (M3), purchasing manager index (PMI), and consumer confidence (CC), to some extent, have a great impact on the volatility of market returns of most CIVETS (Colombia, Indonesia, Vietnam, Egypt, Turkey, and South Africa) countries. However, since the IDX is separate from the Eurozone market, those macroeconomic announcements do not significantly affect it. This finding is in contrast to previous studies, such as those by Nikkinen et al. (2008) and Nguyen and Ngo (2014), which find that the IDX is significantly affected by the U.S. macroeconomic announcements. The differences of the impact of foreign macroeconomic announcements on the volatility may be explained by the country's dependence on international trade, market size, foreign ownership, and the industrial and economic structure.

3.3 High-frequency data and intraday volatility of returns

Since the late 1980s, the development of information and computer technology has contributed to the increased availability of high-frequency market data. Researchers have used high-frequency data over the last three decades to explain the economic aspects, market impacts and the microstructure characteristics of asset price movements (Smales 2013). Wood, McInish and Ord (1985), French and Roll (1986) and Harris (1986), are among the first scholars who studied the behaviour of asset prices during trading hours using high-frequency data. In this section, the theoretical issues and empirical studies supporting the application of high-frequency data to measure volatility and its reaction to macroeconomic announcement are discussed.

3.3.1 High-frequency data in finance studies

The availability of high-frequency data has had a beneficial effect on financial market research in three areas. First, high-frequency data allows the measurement and estimation of asset returns and volatility at very small time intervals, such as every hour or minute. As a result, high-frequency data analysis benefits research in finance as it improves the size of the sample and the significance of the research (Dacorogna et al. 2001; Muller et al. 1997).

Second, high-frequency data analysis is able to capture the short-term behaviour of asset prices and, therefore, gives added insight when dealing with seasonality issues found in studies using long-term time-series. The high-frequency data analysis also enables the identification of short-lived ‘jumps’ in asset prices during trading hours (Biais, Glosten & Spatt 2005). Therefore, high-frequency data analysis helps enhance the understanding of asset prices and behaviour of financial markets, particularly at times around information arrival during trading hours. It also better examines the impact of a particular information announcement to be isolated from the impact of other factors which might otherwise contaminate the analysis (Dacorogna et al. 2001).

The third reason for using high-frequency data in finance research is because financial data are originally recorded in the ‘tick-by-tick’ format as transaction prices occur randomly and in a heterogeneous time-series (Dacorogna et al. 2001, p. 1). Therefore, the high-frequency data will be able to capture the rapid movements of the prices during the day (Andersen, Bollerslev & Das 2001; Brownlees & Gallo 2006; O'Hara 1996). For institutional investors, for example, knowing the rapid movement of prices during the day is important for making quick investment decisions. Knowing the rapid movements of prices is also important for market regulators to detect irregularities or manipulative behaviours in the market (Aggarwal and Wu 2006; Öğüt, Doğanay and Aktaş 2009; among others).

Dacorogna et al. (2001) and Gropp and Kadareja (2012) argued that high-frequency data analysis is able to look at the impact of particular public information immediately around the announcement times. However, careful attention should be given when determining the interval of the returns observation, as intraday volatility can be a biased volatility estimator if it is measured at very high-frequency intervals (Andersen, Bollerslev, Diebold & Labys 2003).

Another important motivation for using high-frequency data in this study is because previous research in the Indonesian stock market context was dominated with low-frequency data series such as Leeves (2007), and James and Karoglou (2010), among others. One of few studies that uses high-frequency data in the Indonesian market context is Henker and Husodo (2010) that used variance ratio analysis to separate microstructure noise from the variance estimator using 30 minute observation windows. By using the variance signature plot, they find that the optimum sampling frequency for volatility estimation in the Indonesian Stock Exchange is nine minutes. They claim that the optimum frequency interval will be narrower as the efficiency of the market improves.

Empirical studies using high-frequency data find that public information significantly affects volatility of returns in foreign exchange markets (Andersen & Bollerslev 1998; Andersen, Bollerslev, Diebold & Vega 2003), stock markets (Andersen, Bollerslev & Cai 2000; Gropp & Kadareja 2012), bonds markets (Andritzky, Bannister & Tamirisa 2007; Bollerslev, Tim, Cai & Song 2000; Nowak et al. 2011) and futures market (Ederington & Lee 19 93), among others.

3.3.2 Types of volatility estimation

Using high-frequency data, there are three types of volatility that have been frequently studied in finance literature: implied volatility, model volatility and realized volatility (Dacorogna et al. 2001, p. 43). These will be briefly described in the following sections.

(1) Implied volatility

Implied volatility is a volatility forecast and is derived from the market prices of underlying securities. This type of volatility is usually used for evaluating or pricing derivatives such as option contracts (Dacorogna et al. 2001, p. 43). Although in the option pricing model volatility is assumed to be constant during the life of the options contract and is known by all market participants (Black & Scholes 1972), implied volatility tends to increase rapidly during a financial crisis. Implied volatility is, therefore, widely used and also known as an 'investors' fear gauge' (Bodie, Kane & Marcus 2008, p. 757). However, it should be noted that Wang, Yourougou and Wang (2012) found that the implied volatility of the same underlying asset may differ depending on the strike prices and 'moneyness' of the options.

(2) Model volatility

An alternative to implied volatility is model volatility which is the estimated volatility, conditional on its recent volatility. According to Engle and Patton (2001) there are two types of model volatility that have been popularly used in the literature: the ARCH-type and stochastic.

ARCH-type volatility

The ARCH-type (or Autoregressive Conditional Heteroskedasticity) volatility (Engle 1982) assumes the stochastic (random) processes of a time-series value of a variable have zero mean (uncorrelated), non-constant variances conditional on the past values, and constant unconditional variances. In other words, the recent past variance gives information about the one-period forecasted variance. Therefore, Dacorogna et al. (2001) describe the ARCH-type volatility as the function of past returns.

The use of Engle's original ARCH-type volatility in empirical work has led to the development of various new models, for example, the generalisation of the ARCH model – GARCH (Bollerslev 1986), and the ARCH-type volatility with heterogeneous price change intervals — HARCH (Muller et al. 1997).

Stochastic volatility

Instead of using past returns data in calculating volatility, as in the ARCH-type model, the stochastic volatility model estimates volatility of a variable based on past volatility values.

The model assumes that historical volatility variables are latent; therefore it is impossible to calculate volatility directly from returns data. By using a log-normal distribution series, stochastic volatility produces better empirical properties than the ARCH models although there are difficulties in evaluating the exact likelihood and estimating the maximum likelihood of the parameters (Broto & Ruiz 2004; Jacquier, Polson & Rossi 1994).

(3) Realized Volatility

The third type of volatility estimation is a realized volatility model which is measured based on historical asset returns at homogeneous time intervals. Using high-frequency data, realized volatility has become more popular recently due to its superior estimate of volatility compared to the previous volatility models. Under the theory of quadratic variation, realized volatility is free from measurement error and from specific distributional assumptions used in ARCH-type and stochastic volatility models. Furthermore, realized volatility is able to incorporate information in intraday data without explicitly formulating a new specific model and can also be used to forecast volatility (Andersen, Bollerslev, Diebold & Labys 2003).

Realized volatility has been increasingly used in finance research due to its simplicity, ease of application in high-dimensional volatility modelling, and ability to accommodate seasonality and heterogeneity problems (Andersen et al. 2001; Andersen, Bollerslev, Diebold & Labys 2003; Dacorogna et al. 2001; Hansen & Lunde 2006). Nevertheless, realized volatility tends to be biased and cannot be a good predictor of volatility if measured at very high frequency (Dacorogna et al. 2001; Hansen & Lunde 2006).

3.3.3 Patterns of intraday volatility of returns

Admati and Pfleiderer (1988) suggest that asset prices, as well as returns and volatility, move and create particular patterns during a day. Previous studies using high-frequency data reveal that the volatility of returns creates a U-shape pattern during intraday trading. The U-shaped pattern is due to high trading activities surrounding the opening and closing of the market but low trading activities during the middle of the day. This pattern is found in stock markets (Andersen, Bollerslev & Cai 2000; Ozenbas, Pagano & Scwartz 2010; Wood, McInish & Ord 1985), foreign exchange markets (Andersen & Bollerslev 1998) and equity warrants markets (Segara & Sagara 2007).

Admati and Pfleiderer (1988) argue that the U-shaped pattern of intraday volatility is due to the concentration of trading by liquidity traders and informed traders. The rate of information arrival in the stock market is usually high just after the opening and before the closing of the market. As a result, the number of informed traders increases during these periods. Furthermore, as competition amongst informed traders increases, the more private information prevails in the market. This then attracts liquidity traders to enter the market and trade. As a result, trading cost reduces and trading activities intensify during that period, which result in high trading volume and increased liquidity. In a market with asymmetric information, the trading volume is high during this period, although the market is less liquid (Foster & Viswanathan 1994).

Based on a study on the Tokyo Stock Exchange and using the data of Nikkei 225 index returns at the five minute intervals, Andersen, Bollerslev and Cai (2000) suggest that the U-shape pattern of intraday volatility is due to strategic interaction of informed traders during opening hours as a result of information accumulated overnight, including information that arrived just before market closing. The trading activities diminish during the middle of the day when all information has been fully captured in prices. Furthermore, traders tend to increase trading before market closing to avoid the risks that arise from new information which arrives after the market closes. Therefore, the level of trading volume and frequency is usually different across trading hours. The U-shaped pattern of volatility has also been found in markets which are structurally different from the Tokyo Stock Exchange such as in the New York Stock Exchange (Wood, McInish & Ord 1985) and the London Stock Exchange (Ozenbas, Pagano & Scwartz 2010).

Other studies find that volatility of returns follows a reverse-J shaped pattern. Based on the amount of information arrival, the reverse J-shaped pattern is caused by high trading activity during the opening but considerably lower trading during the middle of the day and near market closing (Chan, Chung & Johnson 1995; McInish & Wood 1992). During the market opening, trading activity, transaction costs and risks are usually high due to scant information. In addition, the bid-ask spreads are usually wide during this period, which is inversely related to competition and the amount of information arriving into the market. Therefore, the amount of bid-ask spread decreases when the number of informed traders increases (McInish & Wood 1992). However, the reverse J-shaped pattern of volatility is rare in studies using stock market returns.

Another important element is whether the pattern of intraday volatility is consistent over the year; or whether there are different patterns of intraday volatility during days of the week because, for example, Monday returns are usually higher than Fridays.

Similar to returns, previous studies such as Ederington and Lee (2001), Aragó-Manzana and Fernández-Izquierdo (2003), and Martens, van Dijk and de Pooter (2009), among others, found that the volatility of returns exhibits different patterns in line with seasonal factors.

3.3.4 Intraday volatility and market microstructure noise

As previously mentioned in section 3.3.2, volatility can be free from error when estimated using high frequency data and when using the quadratic variation model. However, a problem arises when the observations of a price discovery process in a finite time scale are conducted at a too high frequency, which can lead to the higher divergence of the observed prices from true prices, and thus makes the variance estimator unreliable. This divergence occurs due to microstructure effects caused by changes in transaction price, the difference in price for the buyer (bid price) and the seller (ask price), and liquidity and information reasons. The divergence then creates a bouncing effect and negative autocorrelation of the returns in a very short time scale (Bandi & Russell 2008; Dacorogna et al. 2001; Hansen & Lunde 2006). Therefore, when applying the realized volatility model, the determination of an effective sampling frequency for the process is important to optimally balance the bias and the variance of the realized volatility model (Bandi & Russell 2006).

The issue of an optimal sampling frequency was addressed by Andersen et al. (1999) which resulted in a ‘volatility signature plot’ formula. Since then, methods to mitigate the effect of microstructure noise on the realized variance estimator have been proposed. For example, Dacorogna et al. (2001) propose the application of larger return intervals and a bias correction factor model to solve the bias problem. Furthermore, Hansen and Lunde (2006b) propose cointegration analysis to distinguish the impact of transaction prices and bid-ask quotes into the estimate of efficient price. Finally, Bandi and Russell (2008) consider microstructure noise a complicating factor and suggest a standardized version of realized volatility in order to separate the noise component out of the realized variance estimator.

3.4 Macroeconomic announcements, volatility of returns, and trading volume

Hanousek, Kočenda and Kutan (2009) and Gaoxiang and Lim (2010) found that periodical announcements of macroeconomic factors, such as unemployment, inflation rate and economic growth, affect stock returns.

Most studies in the literature suggest that the high volatility of emerging stock market returns depends on the degree of informational efficiency in the market. This section discusses how the efficiency of public information arrivals affects stock price, returns and volatility from the perspective of two finance theories: the theory of efficient markets and the theory of market microstructure.

3.4.1 Theory of efficient markets

A capital market is considered efficient if current asset prices fully reflect all information available in the market, meaning that no investors can consistently earn abnormal (that is, greater than normal or risk-adjusted) returns. An efficient capital market is also defined as one in which prices reflect market fundamentals (Fama 1970, 1991; Malkiel 2003; Mishkin & Eakins 2012).

There are several advantages of having an efficient market. In the efficient capital market, securities prices would indicate companies' production-investment activities on which investors could rely in decision-making. Therefore, an efficient capital market may provide accurate signals for a country of its economic capital allocations (Fama 1970). In an efficient market, investors are also able to judge whether asset prices have covered all information available in the market before making economic decisions. The recurring and rapid price adjustments toward information arrivals result in low bid-ask spreads, high trading activity and low transaction costs. These effects help increase the confidence of investors (companies) in trading (raising) funds in the market as the price they paid (raised) have reflected its risk (Reilly & Brown 2012).

Three test forms of efficient market hypothesis: theories and evidence

Fama (1970) originally developed three sub-forms of the efficient markets hypothesis, based on the type of information used to test the hypothesis: (1) weak-form efficiency, (2) semi-strong form-efficiency, and (3) strong form-efficiency. The weak-form Efficient Market

Hypothesis (EMH) asserts that current asset prices fully reflected all historical price-related information. Consequently, past returns and historical prices are independent and cannot be used to predict future prices or returns. The semi-strong EMH asserts that current asset prices fully reflect all publically available information, and adjust immediately to the releases of new public information. This version of the hypothesis expands the information set used in weak-form tests of market efficiency by including not only market information relating to asset prices, trading volume and rate of returns, but also information about fundamentals such as price-to-earnings ratios and economic indicators. Finally, the strong-form EMH asserts that current market prices fully reflect all public and private information. The hypothesis implies that no one can consistently generate above-normal returns from trading. This hypothesis also extends assumptions in the semi-strong EMH that asset prices change immediately to the announcements of public information by assuming that all information is freely available to everyone at the same time (Reilly & Brown 2012).

Furthermore, previous studies by Levine (1997), Levine and Zervos (1998b), and Arestis, Demetriades and Luintel (2001) find that there are positive relationships between efficient capital markets and a country's macroeconomic factors. Levine (1997), for example, suggests that financial (capital) markets perform several functions such as mobilizing savings, allocating resources and facilitating risk management, and eventually channel resources to growth via capital accumulation and technological innovation. However, these functions may not be achieved if the capital markets are not efficient, as indicated by high information and transaction costs.

In Indonesia, studies on EMH have yielded mixed conclusions. Kim and Shamsuddin (2008) and Nelmida, Nassir and Hassan (2009) argue that the Indonesian stock market (IDX) has shown no sign of being efficient. However, a more recent study shows that the level of information efficiency in the IDX has improved over time, particularly since the implementation of a new information regime and a market liberalization policy (Kung, Carverhill & McLeod 2010).

Criticisms of tests of EMH

Although popular in finance studies, there are critics on tests of EMH both in theory and its applications. Grossman and Stiglitz (1980), for example, argue that the market cannot be perfectly efficient in order to compensate arbitrageurs who have spent resources to obtain information. This claim is supported by LeRoy and Porter (1981), and Bapepam (1999) — that there is excess volatility in the aggregate stock market as changes in prices are much greater than would be implied by changes in stocks' fundamentals and dividends. Therefore, stock prices are too volatile to be applied in simple efficient market models. Furthermore, Engle (2002) and Tsay (2006) suggest that the availability of high-frequency market data has helped extend the tests of market efficiency by using volatility measures which focus on their direct response upon macroeconomic announcements during a trading day. Studies such as Shiller (1987; 2003), Hameed and Ashraf (2009) and Chiang, Chung and Huang (2012) have used the second moment, or variance, of returns as an alternative to the use of price and returns in testing market efficiency.

3.4.2 Theory of market microstructure

The increasing availability of high-frequency data during the late 1980s has encouraged the development of a theory to explain how asset prices are continously formed in the market, which is called the theory of market microstructure. This theory emphasizes the mechanisms of how market-related factors, such as information, market structure and design, and traders' ability to observe information which influence the price formation process interact (Madhavan 2000; O'Hara 1996). Early studies in this field include Glosten and Milgrom (1985), Kyle (1985), French and Roll (1986) and Admati and Pfleiderer (1988).

Studies of market microstructure show that the availability of an electronic-based news database has enabled studies to investigate the impact of public information, in addition to private information, on stock price dynamics. French and Roll (1986), for example, suggest that the intraday price volatility during trading periods is considerably larger than during non-trading periods as public information mostly arrives during this period. However, the volatility decreases later in the day as information becomes more widely available in the market before it goes up again near the market closing hours, and therefore, forms a U-shape pattern.

3.4.2.1 Information asymmetry theory

Studies on the impact of asymmetric information on the behaviour of risky asset transactions, such as Admati and Pfleiderer (1988), suggest that the typical U-shaped pattern of volatility reflects the strategic behaviour of informed traders and liquidity traders. The concentration of informed traders in the market has attracted more discretionary liquidity traders to join the trade because there are more informed traders competing in the market. If this is the case, liquidity traders can improve their welfare as the market becomes more liquid, transaction costs decrease, and trading has little effect on prices.

Admati and Pfleiderer (1988) and Muller et al. (1997) further argue that it is noteworthy that transactions in financial markets are motivated primarily by information regarding the future economic value of an asset. Therefore, heterogeneous market participants, with various time horizons, will behave differently to the arrival of information which will be reflected in different patterns of price movements over time.

There are two types of information that have been examined in the market microstructure literature: private and public information. Private information is information that suggests the future economic value of a stock but has not yet been published, while public information is that which has been published in the market. Some investors may trade with private information, hence they are called informed traders, in order to get extra profits (or avoid loss) by purchasing (or selling) stocks. Furthermore, although the impact of information on stock prices is indirect, previous studies found that private information can be detected by abnormality in returns and their volatility. Moreover, the effect of information can also be observed through changes in trading activities, such as trading volume or bid-ask spreads, before and after the time that information becomes public (Darrat, Zhong & Cheng 2007; Glosten & Milgrom 1985; Kyle 1985).

According to Admati and Pfleiderer (1988), the intraday behaviour of stock prices is due to strategic trading behaviour of liquidity traders and informed traders. Liquidity traders, particularly the non-discretionary liquidity traders, possess flexibility as when to trade. Therefore, they usually trade when the market is liquid, that is, when there are informed traders in the market. In addition, the price set by uninformed traders may not reflect inventory or transaction costs, but rather the costs of adverse selection for having transactions with informed traders. Those findings are consistent with previous studies, such as Glosten and Milgrom (1985) and Kyle (1985), that stock price is a result of interactions among liquidity traders, uninformed traders and informed traders. Nevertheless, private information models may only partly explain the intraday behaviour of stock price and volatility. This is because, even with the same amount of private information, informed traders may apply trading strategies heterogeneously due to differences in the confidence levels and processing time of that information.

The impact of macroeconomic announcements and surprises

The theory of market microstructure used in this study helps explain how macroeconomic announcements impact on equity prices and volatility during intraday trading. Another outcome from using the theory is to measure market efficiency by showing the degree and direction of the impact, as well as the speed and persistence of the changes, on volatility due to macroeconomic announcements. In market microstructure studies, macroeconomic fundamentals are treated as important news as they carry expectations of future economic activity in the economy.

In addition to looking at the impact of scheduled macroeconomic announcements, some studies in this field discuss the impact of 'news', or unexpected (surprise) components of the announcements. The studies have benefited from the increasing availability of high-frequency data in the last three decades, which allows the impact of the announcements and news to be observed in shorter time intervals. These studies include Andersen et al. (2001), Andersen, Bollerslev, Diebold and Vega (2003), Hanousek, Kočenda and Kutan (2009), and Gropp and Kadareja (2012), among others.

3.4.2.2 Volatility and trading volume relations

Although there are studies showing the significant impact of public information on volatility, research investigating the relationships between volatility and trading volume is scarce, particularly during the period when the volatility is unusually high. However, due to the availability of high-frequency market data, studies investigating the relationship between trading volume and price variability, by showing the role of informed traders and liquidity traders, and concentration of trading, have increased considerably. Admati and Pfleiderer (1988), Foster and Viswanathan (1994), Andersen (1996), and O'Hara (1996), among others, are among the first suggesting the strong relationships between trading volume and volatility.

An early study by Karpoff (1987) claims that the price-volume relationship is important as it helps (1) identify a financial market's structure, (2) increase the quality of event studies and the power of their tests beyond that available using a single, price indicator, (3) determine the empirical distribution of price changes, and (4) explain implications of transactions in futures markets. Furthermore, Karpoff (1987, p.112) contends that 'it takes volume to make price moves' which means that price changes can only be observed when there are positive changes in demand.

Karpoff (1987) further suggests two models in explaining the relationships between asset price changes and trading volume: sequential arrivals of information (Copeland 1976) and the mixture of distribution hypothesis (Epps 1976; Epps & Epps 1976). According to Karpoff (1987), in the Sequential Arrival of Information (SAI) model, information is assumed to arrive asymmetrically as it is only disseminated to only one trader at a given time and that trades occur immediately after the trader receives the information. If the trader is an optimist, the information causes an upward price movement of a fixed amount, but it will cause a negative shift in the curve if the trader is a pessimist. The information arrival allows for several temporary equilibrium prices before reaching a final equilibrium price. Accordingly, in the SAI model, the price-volume relationship when information arrives is influenced by both the previous pattern of information arrival and whether the next trader is an optimist or pessimist. Meanwhile, as proposed by Epps and Epps (1976), the Mixture of Distribution Hypothesis (MDH) assumes that the changes in log price of one transaction are conditioned on transaction volume over an interval time. In this model, trading volume is considered as a mixing variable and serves as a proxy for asset returns. Trading volume is able to measure the degree of disagreement between traders due to differences in reacting to new information as it arrives in the market. As the disagreement widens trading volume increases, suggesting a positive relationship between volume and variance of returns. In addition, using a modified MDH hypothesis and daily price data on five common stocks from 1973 to 1991, a more recent study by Andersen (1996) suggests that periodic information arrivals, such as scheduled macroeconomic announcements, have only a little and short-lived effect on the persistence of volatility, but have a relatively larger impact on trading volume. This means that changes in trading volume may indicate the presence of new information.

Empirical studies 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 the concentration of trading. Moreover, Admati and Pfleiderer (1988) argue that the significant increase of trading volume can be explained by the extent of public information available in the market and the presence of non-discretionary liquidity traders. It means that trading volume increases when information is no longer asymmetric.

During the concentration of trading, total volume usually increases and the market becomes more liquid. Nevertheless, Foster and Viswanathan (1994) suggest that the high trading volume can occur in a less liquid market since the better-informed traders tend to trade more intensively on the information that is similar with lesser-informed traders but less intensity of trading on their additional information to disguise their strategy from other traders.

Using daily data from the Australian stock market, Brailsford (1996) finds a positive and significant relationship between price changes and trading volume. He further suggests that the price changes are due to either irrational behaviour of traders or the varying rates of private information arrivals. Brailsford's finding is consistent with Karpoff (1987), who proposes an asymmetric volume-price changes hypotheses. The hypothesis suggests a positive correlation between volume and positive price changes, but a negative correlation between volume and negative price changes. Furthermore, tests on volume and either absolute price changes or price changes *per se* result in positive correlation. However, other studies argue that shocks in trading volume are not necessarily caused by information asymmetry but can be due to pressures from liquidity traders (Darrat, Zhong & Cheng 2007; Gropp & Kadareja 2012; Kalev et al. 2004).

Kim and Verrecchia (1991) suggest that the impact of public information on the changes in both asset price and trading volume is dissimilar due to different traders' reactions. The newly arrived public information is much more important for less informed traders; as it increases their belief substantially more than it does the belief of better informed traders. All traders' different reactions to the new information are reflected in trading volume, which has a greater impact than the average changes in traders' belief as shown in price changes. Therefore, careful judgement needs to be taken in using the trading volume indicator as it can be noisier than the price changes when assessing new information.

Despite evidence of public information impacts on asset returns and trading activity, Mitchell and Mulherin (1994) suggest that the number of macroeconomic announcements available in the market positively correlate with market activity. Moreover, important news has greater impact on the changes of asset returns than it does on trading volume. This finding is supported by Kalev et al. (2004), Darrat, Zhong and Cheng (2007), and Storkenmaier, Wagener and Weinhardt (2012).

Kalev et al. (2004), for example, find a positive and significant correlation between public information and volatility of stock returns, even after filtering the effects of trading volume and high opening volatility. Furthermore, Darrat, Zhong and Cheng (2007) suggest that, after decomposing the sample into periods with and without public news, bi-directional Granger-causality exists between volume and volatility during the period with public information. Volatility of returns is also significantly higher in a period with public news, whilst trading volume is significantly higher in a period without public news. Moreover, Storkenmaier, Wagener and Weinhardt (2012) find that there are strong correlations between trading activity of European stocks and public information which is proxied by announcements available from Thomson-Reuters newswire database.

The intraday pattern of trading volume

Similar to patterns of volatility, a U-shaped pattern of trading volume can also be found during intraday trading. Using the New York Stock Exchange (NYSE) hourly data, Jain and Joh (1988) claim that trading volume follows a U-shaped intraday pattern due to the heavy volume of transactions at the beginning and end of trading day, but only light volume during the middle of the day. Furthermore, Jain and Joh find that the average volume of shares traded is significantly different across trading hours of the day and across days of the week. They also 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.

Other 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 as price, returns and volatility do.

3.5 The Global Financial Crisis and macroeconomic policy initiatives

The increased volatility caused by the 2008 Global Financial Crisis (GFC) pushed the governments and market regulators of the U.S. and affected economies to respond to the crisis by introducing policy initiatives and stimulus packages. The initiatives were aimed to address the fragility of, and to restore investors' confidence in, the financial markets (Aït-Sahalia et al. 2012; Baur 2012).

According to Aït-Sahalia et al. (2012), there were five categories of policy initiatives announced by market authorities in the U.S., the U.K, the European Union and Japan in response to the impact of the 2008 GFC, namely (1) fiscal policy, (2) monetary policy, (3) liquidity support, (4) financial sector policy and (5) bank bailouts and failures. In operationalization, the policy initiatives not only demanded coordination between local authorities in the economy but also with those of other jurisdictions as the crisis spread across the world and the financial markets become more globally integrated. During the period from 1 June 2007 to 31 March 2009, there were a total of 234 policy initiatives that were announced by the authorities where the largest share of the announcements were related to financial sector initiatives (37 per cent) and mostly conducted in the U.S. market (46 per cent). However, there was no single particular policy initiative which was able to contain the crisis. The effect of the policy announcements varied across types of policies. For example, the announcements of target interest rate cuts triggered an immediate response from the markets as indicated by the reduction of interbank interest rates, but the announcement of new fiscal policy was less attractive for the market and therefore negligible. Similar findings were found in studies within the Australian market (Kim & Nguyen 2008; McCredie et al. 2014; Smales 2012) and in emerging markets (Nanto 2009).

In the Indonesian market, the impact of the monetary policy initiatives during a volatile market can be examined directly from the reactions of the stock market index returns following the policy announcements. In this context, the BI interest rate announcements were used for the following reasons: First, under the Inflation Targeting Framework, the BI interest rate policy aims to achieve the target inflation rate through BI's influence on credit and lending interest rates which affect domestic demand and supply (Bank Indonesia 2013b). Second, the decision to change the monetary policy tool from using the money base to the BI interest rates was because 'signalling through base money was considered difficult to interpret and lack of clarity to direct market expectations' (Bank Indonesia, cited in Syurkani 2010, p. 44). Third, BI rates have been used to indicate the current conditions and future expectation of the economy; whether in recession, by lowering the interest rates to promote economic activity; or in expansion, by increasing the interest rates to ease inflationary pressures (Bank Indonesia 2013b). Last, but still as important, during the period of crisis, the BI rate was often decided and used by the Financial System Stability Coordination for safeguarding financial market stability in Indonesia. The FKSSK is a high-level coordination venue which was established on 30 December 2005 under a Joint Decree of the Ministry of Finance, the Governor of the Bank Indonesia and the Chair of the Board of Commissioners of the Deposit Insurance Corporation (Bank Indonesia 2013c; FSSK 2015).

3.6 The gap in the literature

A review of the literature shows that there is evidence that information arriving in an efficient market will be immediately reflected in stock prices. However, most studies examine the impact of information arrivals on the first moment of asset returns and with separate observation windows. There are relatively few empirical studies that have investigated the impact of macroeconomic announcements on intraday volatility of returns using rolling windows of observations to examine the informational efficiency of the Indonesian stock market. This study, therefore, fills this gap in several ways. By using high-frequency data, this study will investigate the direct impact of macroeconomic announcements, as proxies for public information, on the second moment of returns (volatility) of Indonesian equities. The effect of surprises due to unexpected information contained in scheduled announcements will also be observed. Last, this study will examine the relationships between trading volume, as an alternative proxy for information, and the volatility of returns.

3.7 Conclusion

This chapter discussed the theoretical background and the existing literature on the relationships between volatility of returns, trading volume and macroeconomic announcements. The literature was reviewed and provided before answering the questions detailed in Chapter 1.

A study on the volatility of returns in an emerging market such as Indonesia is of importance not only from the perspective of market participants, for asset pricing, portfolio selection and risk management, but also for market regulators to help determine whether the market is in or heading towards a crisis or whether there is price manipulative conduct in the market.

The application of high-frequency data in finance studies has helped increase understanding of volatility behaviour during intraday trading. High-frequency data have been used to identify patterns of volatility during trading hours, and to test the level of market efficiency by showing the direct impact and the persistence of the impact of information arrivals on returns and volatility. In addition, high-frequency data has been able to illuminate the price discovery process by showing the patterns of price movements and trading activities. Furthermore, previous studies in the market microstructure literature show that asset prices move with the arrival of new information and there is a joint dependence of asset returns and trading volume on information. The studies have also documented sizeable evidence on both the contemporaneous and causal relationships between trading volume and volatility.

In the next chapter, the data and variable sets used to test and answer the research questions are provided. Moreover, the empirical results of the tests will be given in the following chapters.

CHAPTER 4
DATA AND VARIABLES

4.1 Introduction

This chapter discusses the data and the variables required to address the research questions outlined in Chapter 1. It is structured as follows: Section 4.2 describes the data and samples. Section 4.3 provides the definition and measurement of market variables such as returns, volatility and trading volume. Section 4.4 details the data sets of scheduled macroeconomic announcements and news. Section 4.5 concludes the chapter.

4.2 Data and sample

The discussion about the data and the sample used in this thesis will be divided into two sections: (1) types and sources of data and (2) sample period, asset prices and data intervals.

4.2.1 Types and sources of data

There are two types of data collected in this study: market data and scheduled macroeconomic announcements. Market data are the historical data of asset prices and trading volume during the sample period. These data were collected from the Thomson-Reuters Tick History (TRTH) database, provided by the Securities Industry Research Centre of Asia Pacific (SIRCA).[8]

The second type of data used in this study is the scheduled announcements of key macroeconomic indicators which will be used as proxies for the arrival of public information in the market. In addition to macroeconomic data, data relating to market surveys of forthcoming macroeconomic announcements were collected to enable the measurement of the surprise effects of particular macroeconomic announcements. The data of macroeconomic announcements and market surveys were obtained from the offices and websites of Indonesian government agencies and from the Bloomberg database.

[8] SIRCA, the Securities Industry Research Centre of Asia Pacific, provides historical market data, including intraday Time and Sales of global markets, Time and Quotes, Market Depth and Corporate Actions since January 1996. SIRCA also supplies global news transmitted from of the international Reuters newswire from as early as 2003. The SIRCA data base can be accessed using Victoria University library account.

All numerical and statistical works in this study were conducted using MS-Excel and STATA Statistical/Data Analysis Ver. 12, unless mentioned otherwise.

4.2.2 Sample period, asset prices and sampling frequency

The sample period of this study is from 2 January 2006 to 28 December 2012, or equals to 1,707 trading days. January 2006 is taken as the starting date of the sample period because January 2006 is the first date when the median economic forecasting data from economists surveyed by Bloomberg is available. Furthermore, 28 December 2012 is selected as the last observation day in order to limit the analysis only until after the GFC and avoid inconsistency in the data used for the analysis.[9] There are days excluded from data sampling as there were days when no trading occurred, such as weekends, exchange holidays, and days from 8 to 10 October 2008 when market-wide transactions on the Indonesia Stock Exchange were suspended to avoid further drops in market values due to the GFC.

The sample period of this study covers the period of the 2008 GFC. However, there are debates in the literature as to when the exact dates are when the GFC started and finished.[10] For example, Samarakoon (2011) argues that the crisis period was from late 2007 to early March 2009 whilst Calomiris, Love and Peria (2012) suggest that the period of the GFC was between August 2007 and December 2008. Nevertheless, most studies in the literature suggest that the GFC started in July 2007, when the U.S. securities firm Bear Stearns failed and created contagion effects in the global financial market, and lasted until the end of

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[9] Although adding post-2012 data is possible, this study uses dataset only until the end of 2012 because of three reasons. First, as stated in section 1.2, one aim of this study is to investigate, and limit the investigation on, the different patterns of volatility and impacts of macroeconomic announcements on volatility before, during and after the GFC.

Second, December 2012 was chosen as the last observation date to ensure that the data analysed is only from the post-GFC period, when the market started to recover from the crisis. In 2013, there were massive capital outflows from emerging markets, including Indonesia, to advanced countries as reaction to the US Federal Reserve's talk in May 2013 about the possibility to begin ending its quantitative easing policy as the US economy improved. The talk to possibly end the policy, known as the Taper Tantrum, caused exchange rates weakened dramatically and financial markets plummeted, and put the "Fragile Five" countries consisting of Brazil, India, Indonesia, South Africa and Turkey in a risk of another crisis (Basri 2016).

Third, this study is only until the end of 2012 to avoid data inconsistency due to changes in trading hours in the Indonesia Stock Exchange following the decision of Board of Directors of the Indonesian Stock Exchange No. Kep-00399/BEI/11-2012, Decree No. II-A Kep-00071/BEI/11-2013. Starting from January 2013, the IDX starts trading at 9.00 AM, or 30 minutes earlier than it does before. The IDX has also introduced new pre-opening hours (order submission and order matching sessions) and new closing hours (pre-closing and post-closing sessions) to increase the liquidity and efficiency of the market.

[10] Further discussion on factors caused the 2008 subprime mortgage lending crisis and its policy implications is available from (Aït-Sahalia et al. 2012; Gorton 2009, 2010).

March 2009 when the U.S. and many developed economies released their economic stimulus packages as part of commitments to alleviate the crisis (Aït-Sahalia et al. 2012; Baur 2012; Nanto 2009; Smales 2013). Therefore, to address the impact of the GFC, the sampling period in this study is divided into three subsamples: (1) pre-GFC (January 2006 to July 2007), (2) during GFC (August 2007 to March 2009), and (3) post-GFC (April 2009 to December 2012).

In addition, market price data used in this study are data generated during the exchange's regular trading hours or between 09:30 and 16:00.

Market price data

Following Andersen, Bollerslev and Cai (2000), and Hanousek, Kočenda and Kutan (2009), this study uses stock market price index data to construct the dataset of returns and volatility. The stock market price index is preferred to a stock price or a portfolio of stock prices because the market index can sufficiently replicate price movements of the whole market without the need to construct portfolios of many stocks of different industries and sizes, or as proxies for particular criteria or industries. Moreover, Sadka and Sadka (2009) believe that information about earnings from equities at aggregate market-level will have more predictive power about future returns than information at firm level.

There are sixteen equity indices, including one composite index and one government bond index, available from the Indonesia Stock Exchange (IDX). All the indices are calculated using the same calculation method. The differences are only on the number of stocks (bond for the bond index) taken as the index's constituents in the calculation and the base date of the index.[11]

This study uses the historical price data of the IDX's LQ45 stock index for two reasons. First, the LQ45 index, which was firstly set up in 1994, consists of the 45 most liquid stocks and represents more than 70 per cent of IDX's total market capitalization. Therefore, the movements of the index price are considered to sufficiently replicate the true condition of the market. Second, constituents of the LQ45 index are adjusted every six months (every February and August) based on technical and fundamental valuation by the stock exchange

[11] Full explanation of the calculation method and most recent names of the indices are available from the IDX *Fact Book* (Indonesia Stock Exchange 2014b).

(Indonesia Stock Exchange 2012), and therefore ensure the availability and consistency of the price data.

The IDX calculates the LQ45 index as the ratio of aggregate market value of the LQ45 index's constituents and its base value. The base-date for LQ45 index is 13 July 1994 which equals to 100.

According to the Indonesia Stock Exchange, there are prerequisites for stocks included in the LQ45 index:

(1) The stocks should have been listed at the IDX for at least 3 months;
(2) The performance of the stock in the regular market, which includes its trading value, volume and frequency of transactions;
(3) The number of trading days in the regular market;
(4) The stock's market capitalization at a certain time period;
(5) Besides the liquidity and market capitalization factors, the stocks selection for LQ45 Index is also based on the financial condition and the prospect of growth of the companies (Indonesia Stock Exchange 2013b, p. 85).

Sampling frequency

Following Andersen, Bollerslev and Cai (2000), and Andersen, Bollerslev, Diebold and Vega (2003), this study utilizes the data of five minute LQ45 index price to calculate asset returns. As explained in Section 3.3, five minute price data are applied for several reasons. First, studies using high-frequency data have been able to identify the U-shaped pattern typically observed in the stock market during intraday trading. Second, studies using five minute data have been able to capture the immediate effect of public information arrivals on volatility during the trading day. Third, the use of high-frequency data can significantly reduce statistical error in volatility estimation.

Careful consideration should be given in determining the sampling frequency of the volatility observation. This is because a very small interval between two observations can lead to biased results (Andersen, Bollerslev, Diebold & Labys 2003; Dacorogna et al. 2001; Hansen & Lunde 2006). When applying the quadratic variation theory of volatility estimation, the higher frequency observation of the price process in a finite time scale leads to higher deviation of the observed value from its true value, and thus makes the variance estimator unreliable. The deviation is due to microstructure effects caused by changes in transaction price, different prices for buyer (bid price) and seller (ask price), and liquidity and information reasons. As noted earlier, as a result the noise creates a bouncing effect and negative autocorrelation of the returns in a very short time scale (Bandi & Russell 2006; Dacorogna et al. 2001; Hansen & Lunde 2006).

In the realized volatility model, the determination of an effective sampling frequency of the price process is important to gain the optimum balance between the bias and the variance of the realized volatility (Bandi & Russell 2006). Bandi and Russell (2006) suggested that the five minute price interval is sufficient to reduce error in calculating realized volatility but long enough to reduce bias due to microstructure noise.

4.3 Definition and measurement of variables

In this section major market variables, that is, the LQ45 index returns, volatility of returns and trading volume are defined and measured. Table 4.1 provides the description of the market variables to be used in this study.

Table 4.1 Description of market variables

No.	Variables	Symbol	Description
1.	LQ45 index price	P	Historical price of the LQ45 index from 2 January 2008 to 28 December 2012.
2.	Returns	R	Log LQ45 returns measured at five minute intervals
3.	Volatility	RV	Intraday volatility of returns measured at 30-minute window using realized volatility model
4.	Trading volume	AV	Average trading volume at 30 minute window

4.3.1 Intraday returns of LQ 45 index

The first variable to be measured in this study is the returns of the Indonesian LQ45 index. There are several factors to consider before calculating the returns. First, the study uses the historical data of LQ45 index during trading hours because the impact of public information arrivals on asset prices can only be observed during trading periods (French & Roll 1986).

Second, the price data used in this study are from Monday to Friday, except exchange holidays. However, there are differences in the IDX's trading hours between Friday and other days of the week. From Monday to Thursday, the morning session starts from 09:30 to 12:00 and the afternoon session is from 13:30 to 16:00. On Fridays, the morning session commences trading from 09:30 to 11:00 and resumes at 14:00 and continues to 16:00. Consequently, the number of window observations between those day groups vary when calculating returns, volatility and trading volume.

Third, to calculate returns, this study uses the index average price at five minute intervals over the sample period. Following Ederington and Lee (1993), the five minute returns of the LQ45 index are calculated as the log difference of prices, as follows:

$$r(t_i) = r(\Delta t, t_i) = \ln(\frac{P_t}{P_{t-1}}) \qquad (4.1)$$

where t_i is the homogeneous sequence of times regularly spaced by Δt five minute intervals, whereas *Pt* is the average price of the index at every five minutes during a trading day over the sample period. The five minute log returns dataset starts from 09:35 and ends at 16:00 local time. Having mentioned the differences in trading hours between Friday and other days of the week, there are 50 five minute log returns observations daily for Mondays, Tuesdays, Wednesdays and Thursdays, and 48 observations for Fridays.

4.3.2 Volatility of LQ45 index returns

The process of estimating volatility consists of three steps: determine which model of volatility estimation is to be used in the study, set the observation window, then calculate the volatility. The procedure to estimate the volatility is further explained as follows.

As mentioned in Chapter 3, there are three models of volatility: implied volatility, model volatility and realized volatility. This study uses the realized volatility model because of its simple application in modelling and due to its ability to cope with seasonality and heterogeneity issues (Andersen et al. 2001; Andersen, Bollerslev, Diebold & Labys 2003; Dacorogna et al. 2001; Hansen & Lunde 2006).

In the literature, there are two approaches to calculate realized volatility. The first and most common approach to calculate volatility is by estimating the standard deviation of the asset returns over a time window, and is calculated as follows (Dacorogna et al. 2001, p. 43):

$$RV(t_i) = \left\{ \frac{1}{n-1} \sum_{j=1}^{n} \left| r(\Delta t;\ t_{i-n+j}) - \frac{1}{n} \left[\sum_{k=1}^{n} r(\Delta t;\ t_{i-n+k}) \right] \right|^p \right\}^{1/p} \tag{4.2}$$

where $r(t_i)$ is the regularly spaced log returns, n is the number of observations over Δt time interval, and the value of p is usually 2.

The second approach to volatility calculation is using the theory of quadratic variation where realized volatility is calculated as the sum of the squared log returns over a time window. Since the returns are computed as the log differences of asset prices and the returns interval becomes infinitely small, the quadratic variation of a continuous finite-variation process becomes zero. Therefore, the mean component becomes irrelevant for the quadratic variation (Andersen, Bollerslev, Diebold & Labys 2003; Gropp & Kadareja 2012).

As mentioned in Section 3.3, the squared returns model of realized volatility can be free from measurement error if measured at high frequency (Andersen et al. 1999; Andersen, Bollerslev, Diebold & Labys 2003; Barndorff-Nielsen & Shephard 2002; among others), but can lead to biased results if it is estimated at too narrow intervals due to market microstructure noise (Dacorogna et al. 2001; Gropp & Kadareja 2012).

There are several approaches proposed to handle the microstructure noise or bias problem. One of the approaches is to determine the optimum sampling frequency of data observations using the volatility signature plot (Andersen et al. 1999). The other approach is to use larger return intervals Δt or bias correction factor (Dacorogna et al. 2001), or to conduct cointegration analysis to distinguish transaction prices and bid-ask quotes into the estimate of efficient price and microstructure noise (Hansen & Lunde 2006). Another approach is to use the modified realized volatility measurement, called the microstructure realized volatility model (Du Toit & Conradie 2006). Last, Bandi and Russell (2008) propose a standardized version of realized volatility in order to separate the noise component out of the realized variance estimator.

Under the theory of quadratic variation, the historical realized volatility $\mathrm{v}(ti)$ is measured as follows (Dacorogna et al. 2001, p. 41):

$$RV(ti) = v(\Delta t, n, p; ti) = \left[\tfrac{1}{n} \textstyle\sum_{j=1}^{n} \left| r(\Delta t;\ t_{i-n+j}) \right|^p \right]^{1/p} \tag{4.3}$$

where $r(t_i)$ is the regularly spaced log returns as mentioned in equation (4.1), n is the number of observations over Δt time interval, and the value of p is usually 2.

Furthermore, assuming that the mean of the log returns is approximately zero as data intervals become narrower, Andersen et al. (1999), Andersen, Bollerslev, Diebold and Labys (2003) and Gropp and Kadareja (2012) calculate realized volatility as the sum of squared log returns over observation windows with the equation as follows:

$$RV_{t,h} = \sum_{j=1,\ldots,h/\Delta} r^2_{t-h+j\Delta,\Delta} \tag{4.4}$$

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

Although there is a belief that stock prices follow random walk patterns, Altman and Schwartz (1970) suggest that it is possible, in short time periods, to determine the movements of volatility based on its past values if the statistics of historical volatility is stationary or only shows small changes. Furthermore, Altman and Schwartz (1970) believe that price volatility is not simply measured by the standard deviation of stock price during a period of time. This is because the standard deviation measure of volatility creates higher impacts on stocks with a higher price. Also, standard deviation does not indicate the directions of stock price movements whether the same as or against that of the market, thus, it is usually applied in short-term period studies to avoid long-term cyclical patterns.

However, both standard deviation and the sum of quadratic deviation models provide similar results when the returns have an expectation around zero, which is one of typical properties when using high-frequency data (Dacorogna et al. 2001). Following Andersen, Bollerslev, Diebold and Labys (2003) and Gropp and Kadareja (2012), realized volatility in this study is calculated as the sum of squared 5 minute log returns.

Selection of observation windows and volatility estimation processes

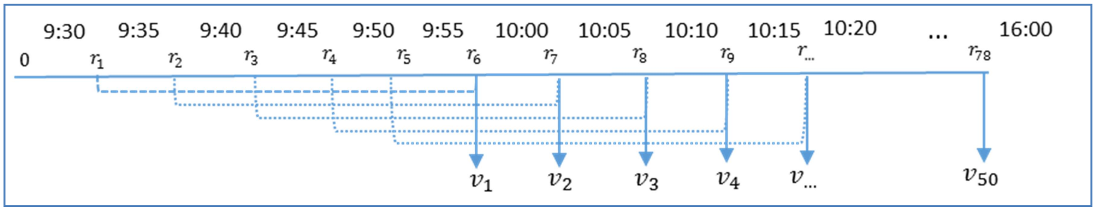
Based on equation (4.4), intraday volatility is estimated using a series of five minute log returns data over a window interval. Therefore, the second procedure in volatility estimation is to determine observation windows.

This study uses a thirty minute observation window to measure volatility for the following reasons: Previous studies such as Ederington and Lee (1993) find that most macroeconomic announcements affect the volatility coefficients only within 20 minutes, except for employment news which is still significant after 40 to 45 minutes. Furthermore, Muller et al. (1997) and Smales (2013) find that the thirty minute window is long enough for the asset price to gradually absorb news and, at the same time, short enough to complete the price adjustment process. Moreover, Andersen, Bollerslev, Diebold and Labys (2003) show that the impact of news arrival is gradual and completed in twelve five minute periods, that is, an hour.

After determining the observation windows for volatility estimation, the next and more challenging task is to determine the frequency of window observations. In high-frequency finance literature, there are two approaches in measuring the frequency of observations: non-rolling windows and rolling windows. In the first approach, non-rolling window observations during the day are divided into specified equally-spaced windows. For example, Gropp and Kadareja (2012) divide a trading day observation into ten equally-spaced, non-overlapped 46 minute windows.

The second approach to calculate volatility is using a rolling window model which is similar to the model used to calculate overlapping returns (Dacorogna et al. 2001). In this study, rolling volatility is estimated using the sum of squared five minute log returns over thirty minute windows and the estimation process repeats every five minutes during the trading day. For example, using six five minute intervals, the first volatility window (*v*1) starts from the 09:30 to 09:35 return (*r1*) to the 09:55 to 10:00 return (*r6*). The second volatility window starts from the 09:35 to 09:40 return (*r2*) to the 10:00 to 10:05 return (*r7*), and so on. The last volatility window (*v*50*)* during the day starts from the 15:30 to 15:35 return (*r72*) to the 15:55 to 16:00 return (*r78*). Those rolling volatility estimations are conducted only during trading hours and do not include the lunch break. As a result, there are fifty rolling volatility observations from Monday to Thursday, and 38 equally spaced windows for Fridays. The process of the thirty minute rolling volatility estimation is illustrated in Figure 4.1.

Figure 4.1 Thirty minute rolling window volatility



The overlapping observation technique has been used in most empirical studies, such as Bartram and Bodnar (2009) and Ciupac-Ulici (2012), because it increases the number of observations which results in increasing the precision of the results. Although it does not necessarily improve the accuracy of mean returns, overlapping can increase the statistical significance of the data series because using shorter intervals has the effect of minimizing error as data are more frequently available (Dacorogna et al. 2001; Muller 1993).

The patterns of intraday volatility and seasonality

In time-series studies, it is well known that volatility changes over time and creates particular patterns due to political, social and economic events (Aggarwal, Inclan & Leal 1999; Schwert 1989). Therefore, it is worthwhile to describe the patterns of volatility over time and identify which events have created shocks in volatility. Therefore, the patterns of volatility will be decomposed into subsample periods and months of the year.

This study also examines the different patterns of intraday volatility during days of the week. Study of the patterns of intraday volatility can be insightful if one day of the week exhibits more volatility than other days, and whether the difference is due to differences in trading hours or correlates with seasonality. This exercise is consistent with early research such as Cross (1973) who, using 844 sets of Fridays and following Mondays from 2 January 1953 through to 21 December 1970, suggest that the index increased by more than 60 per cent on Friday and only about 40 per cent on Monday. In addition, the increase of returns on Fridays is 1.57 times than that on Monday. These findings are supported by French (1980) and Gibbons and Hess (1981), and Ederington & Lee (1993) who reported similar findings using high-frequency data.

4.3.3 Trading volume

There are five of the most important proxies to measure trading volume which have been widely used in empirical finance studies as follows:

(1) The proportion of the hourly number of shares traded in relation to the number of shares outstanding (Jain & Joh 1988). For comparison purposes, trading volume in Jain and Joh (1988) is defined as the ratio between the number of shares traded and total outstanding shares. The comparative figures are required due to the steady increase in the number of shares traded and shares outstanding on the NYSE over its five year period of study,

(2) The proportion of total daily trading volume for each five minute interval, averaged for each sample and across sample days (Stephan & Whaley 1990). The proportion of active CBOE call options and their underlying stocks was accounted and then averaged across 364 firm days for the stocks and 726 contract days for the options.

(3) As the daily number of transactions, the daily number of shares traded, or the daily total dollar value of shares traded (Brailsford 1996). The data of daily All Ordinary Index (AOI) index volume statistics from 24 April 1989 to 31 December 1994 were collected by Brailsford from the Australian Stock Exchange (ASX).

(4) As de-trended daily trading volume (Pisedtasalasai & Gunasekarage 2007). The dataset used in this study is the daily equity indices and the corresponding trading volume series for the stock markets in Indonesia, Malaysia, the Philippines, Singapore and Thailand. Due to evidence of linear and non-linear trends in the time-series of the trading volume dataset, Pisedtasalasai and Gunasekarage (2007) use a de-trended trading volume series, which is the trading volume adjusted for those linear and non-linear trends. The de-trended daily trading volume series is also used in Andersen (1996) for the sample of IBM stocks over the period from 1973 to 1991.

(5) Total trade volume, number of trades and average trade size. The average trade size is the total trade volume divided by number of trades (Shahzad et al. 2014). Shahzad et al. (2014) further decompose the trading volume into institutional versus individual trading volume. However, trading volume used by Shahzad et al. (2014) is based on bid-ask orders and not based on transactions.

Similarly to Stephan and Whaley (1990), trading volume in this study is calculated as the average number of shares traded during an observation window. The calculation of trading volume is a two-step process: measure the number of shares traded at five minute intervals and average the number of shares traded within an observation window:

The number of shares traded for each five minute interval is described as the following equation:

$$\Delta V(t_i) = V_t - V_{t-1} \tag{4.5}$$

where $\Delta V(t_i)$ is the changes of volume in five minute 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.

After calculating the number of shares traded, the next step is to average the volume increments over thirty minute windows during the day. The thirty minute average trading volume ($AV_{\mathrm{t,h}}$) is then repeated every five minutes until the end of the trading day in order to match the rolling estimation of intraday volatility. The trading volume averaging process can be explained as follows:

$$AV_{t,h} = \frac{1}{n}\sum_{h=1}^{n} \Delta V_{t,h} \tag{4.6}$$

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

Similar to the period of the LQ45 index data, the period of trading volume data sampled for this study is from 2 January 2006 to 28 December 2012, or a total of 1,707 trading days. The data of trading volume are available from TRTH of SIRCA.

Table 4.2 shows the summary of market variables to be used in this study: log returns, realized volatility and average trading volume at five minute intervals. The sample period is from 2 January 2006 to 28 December 2012 which consists of 1707 trading days and 81,240 observations for each market variable.

Table 4.2 Number of observations of market variables

No.	Variable	Variable names	No. of observations	Freq.	Sample period
1.	Five minute log returns	r	81,240	five minute	2 January 2006 to 28 December 2012 (1707 days)
2.	Realized volatility	RV	81,240		
3.	Trading volume	AV	81,240		

The next section discusses the dataset of macroeconomic announcements required in this study.

4.4 Data of scheduled macroeconomic announcements

The following section describes steps that were taken to prepare the second dataset — macroeconomic announcements. The steps begin with a discussion about the sample period, sources and types of macroeconomic announcements used in this study. This section limits the discussion only to the macroeconomic announcement variables used and does not present models to measure the impact of macroeconomic announcements on the volatility of returns.

The second dataset of this study shows the data of macroeconomic announcements, times of the announcements and market expectation or survey data on forthcoming macroeconomic releases from 2 January 2006 to 28 December 2012. The sample period of the macroeconomic announcements is the same as the sample period of the LQ45 index data.

Macroeconomic announcements in this study are divided according to their sources and types. Following Nikkinen et al. (2008) and Hanousek, Kočenda and Kutan (2009), and Nguyen and Ngo (2014), this study divides the macroeconomic announcements into announcements that come from a developed country and from the home country. A brief description about each type of macroeconomic announcements used in this study is also provided in this section.

4.4.1 The U.S. macroeconomic announcements

This study uses the U.S. economy as a proxy for macroeconomic policy announcements from a developed country due to the following reasons: First, the U.S. economy has the largest GDP in the world although there is a threat that China will be the biggest economy in the near future (Giles 2014). The World Development Indicators of World Bank reported that, as of 2012, the U.S. GDP was recorded at USD16,245 billion or equal to 22.7 per cent of world GDP (World Bank 2014). With around USD4,854 billion worth of direct investments offshore in 31 December 2013, this is equal to 19.2 per cent of world foreign direct investments (Central Intelligence Agency 2014), the presence of U.S. investment in other countries, particularly in emerging markets, is nearly ubiquitous. Therefore, macroeconomic news in the U.S. economy should affect the economies of other countries.

The scale of the macroeconomic announcement's effect on the volatility of other countries depends on their dependence on international trade, market size, foreign ownership and the structure of their economies (Nikkinen et al. 2008).

Second, Indonesia has maintained a relationship with the U.S. since the mid-1960s, not only in politics but also in trade and investment. From 2009 to 2013, Indonesia's trading account balance showed positive trends due to increasing exports of non-oil products to the U.S and, at the same time, decreasing non-oil imports. The Indonesian Ministry of Trade (2014) reported that, in 2013, the value of non-oil exports to the U.S. was 10 per cent of Indonesian total exports; this resulted in the U.S. being Indonesia's third biggest trading partner after China and Japan. During the same year, the value of non-oil imports from the U.S. to Indonesia was around 6.28 per cent of its total import, or the fifth biggest importing country after China, Japan, Thailand and Singapore.

In terms of foreign direct investment (FDI), the number of investment flows from the U.S. to Indonesia reached a peak in 2005 of 3,441 million US dollars. However, the numbers of U.S. FDIs in Indonesia fluctuated and levelled off in 2009 due to the Global Financial Crisis (GFC) (Ministry of Finance of the Republic of Indonesia & University of Indonesia 2012). In 2012, the U.S. recorded USD830 million in investments in Indonesia, which makes it the fourth biggest source of FDI after Singapore, Japan and the U.K. (Bank Indonesia 2013a).

The third reason for including U.S macroeconomic announcements in this study is because it is well known in the volatility spillover literature that U.S. macroeconomic announcements significantly affect emerging markets, including Indonesia (Nguyen & Ngo 2014). A recent example of the impact of U.S. macroeconomic announcements on developing markets was when the U.S. Federal Reserve announced that it would gradually end its quantitative easing policy on May 2013. The announcement signalled the coming end of expansive monetary policy and triggered massive capital outflows from emerging markets to the U.S. and other developed markets. In the case of Indonesia, the announcements caused the market value of Indonesian stocks to drop by 20 per cent (Adam & Hamlin 2013).

As discussed in Chapter 3, there are some U.S. macroeconomic announcements expected by market participants. The types of announcements can be grouped into those related to economic growth, real activity, consumption, investment, government spending, trade balance, prices, the U.S. Federal Reserve's target fund rate and money supply (Ederington & Lee 1993; Andersen, Bollerslev, Diebold & Vega 2003; Nikkinen et al. 2008; Hanousek, Kočenda & Kutan 2009).

Andersen, Bollerslev, Diebold and Vega (2003) show that most U.S. macroeconomic announcements are released between 08:30 and 10:00 Eastern Standard Time. Another announcement is published at 16:30 local time. From this macroeconomic announcements schedule, it is likely that the impact of U.S. macroeconomic announcements on the volatility of Indonesian equity returns can only be examined on the first trading day after the announcement days due to the different time zones between the U.S. and Indonesia. As a result, all information contained in the announcements should have been fully absorbed by market participants before the next trading day starts (Nikkinen et al. 2008; Hanousek, Kočenda & Kutan 2009).

Nevertheless, not all U.S. macroeconomic announcements are taken into account in this study — only those from the U.S. Federal Reserve's Open Market Committee (FOMC) for the following reasons: (1) the U.S. Federal Reserve's announcements of the target interest rate significantly impacts the economy as a whole as it sets a benchmark for lending and borrowing rates, and as a result, prices and inflation rates, (2) through its quantitative easing policy, the U.S. Federal Reserves increased liquidity in financial markets in order to stimulate the U.S. and the global economy after the GFC. The quantitative easing, however, caused excess liquidity and pushed money out from the U.S. markets to emerging markets in the search for higher returns. Both the U.S. and emerging markets have responded rapidly to information, indicating changes in the stance of monetary policy as shown by changes in target interest rates, (3) although most macroeconomic announcements are available on a monthly basis, the FOMC's stance on monetary policy is frequently announced (every six weeks) and, therefore, has become one of the most watched announcements.

4.4.2 Indonesian macroeconomic announcements

Badan Pusat Statistik (Statistics Indonesia) regularly publishes Advanced Release Calendar (ARC) to indicate the dates of releases of macroeconomic indicators and its other official publications throughout the year.[12] Data on inflation, export-import volumes, the consumer

[12] As Article 4 of the Law of the Republic of Indonesia No. 16 of 1997 states, Statistics Indonesia is responsible for complete, accurate and current data to support national development.

confidence index, foreign reserves, money supply, motorcycle sales and the wholesale price index are available monthly, whereas the GDP announcement is released quarterly. These macroeconomic data can be accessed through Statistics Indonesia.

Data of Indonesian inflation are based on the consumer price index and are released regularly by Statistics Indonesia on the first working day of every month. The data cover inflation figures during the month prior to the announcement month. The inflation figures can be different from the rate targeted by the government. The inflation target, based on a recommendation from Bank Indonesia, is announced by government and officially published with a decree from the Ministry of Finance every three years. Furthermore, the GDP data used in this study serve as indicators for the economic growth and size of a country. As well as inflation data, figures on GDP, which reported quarterly, represent actual value of output that have been produced during previous quarter (Statistics Indonesia 2013).

Furthermore, this study examines the impact of monetary policy announcements by the Central Bank of Indonesia (Bank Indonesia). Following Gropp and Kadareja (2012), monetary policy decisions are included in the macroeconomic announcements due to their direct influence on inflation. In the context of Indonesia, the central bank periodically publishes an advance release calendar of its board of governors' monthly meetings to indicate its stance on future monetary policy. Despite disagreements on its effectiveness to support monetary policy, Bank Indonesia's monetary policy announcement has been considered as a transparent tool to communicate its assessments on current and future economic forecast, and its consequences on future monetary policy (Sahminan 2008). This study uses data of Bank Indonesia (BI) target interest rates announcements from January 2006 to December 2012 as a proxy for monetary policy decision. These data are available from Bank Indonesia.

Although both Bank Indonesia and Statistics Indonesia have stored their macroeconomic figures, the time-stamp of each announcement is not available from both institutions. A specific time announcement is needed to measure the significance of the announcements on volatility. To manage this issue, the Bloomberg News database was accessed to collect the announcement times data.

Nevertheless, a problem arises when using different database providers to measure one variable because Statistics Indonesia and Bloomberg use a different title to identify particular announcements. Therefore, to gain consistency in applying announcement times, this study uses those provided by the latter. Table 4.3 shows the differences in titles of macroeconomic announcements used by Bloomberg, Bank Indonesia and Statistics Indonesia.

Table 4.3 Scheduled macroeconomic announcements

No.	Macroeconomic indicators	Bloomberg	Statistics Indonesia	Bank Indonesia
1.	U.S. monetary policy	The U.S. Federal Reserve	-	-
2.	Financial indicators	BI rate	-	BI rate
3.	Prices	Consumer price index	Inflation/ consumer price index	-
4.	Economic growth	GDP	GDP	-
5.	International trade	Export, import, trade balance	Exports and imports	-
6.	Survey & cyclical indicators	Consumer confidence index	Business tendency index	-
7.	Monetary sector	Foreign reserves	-	-
8.	Monetary sector	Money supply	-	-
9.	Retail & wholesales	Motorcycle sales	-	-
10.	Retail & wholesales	Wholesale price index	The wholesale trade price index	-

Note: The list of macroeconomic indicators is based on the Statistics Indonesia's Advance Release Calendar. Data are available from Bloomberg, Statistics Indonesia and Bank Indonesia.

4.4.3 The surprise component of scheduled macroeconomic announcements

Besides the macroeconomic announcements data, this study also collects data which contains the surprise components of scheduled macroeconomic announcements from January 2006 to December 2012. Following Ederington and Lee (1993), Andersen, Bollerslev, Diebold and Vega (2003), Gropp and Kadareja (2012), Smales (2013) and Nguyen and Ngo (2014), the surprise or unexpected component of the announcement is defined as 'news', and is calculated as the difference between the market expectation of the figure to be contained in the forthcoming announcement and the actual figure announced. Market expectations are proxied by the median of the forecasts provided by the economists surveyed by Bloomberg.

Following Nguyen and Ngo (2014), the news or the surprise component of scheduled macroeconomic announcements is defined as follow:

$$News_{k,i} = \left(A_{k,i} - M_{k,i}\right)/\sigma_k \qquad (4.7)$$

where A_k is the actual figures of macroeconomic announcements k, M_k is the median of the Bloomberg surveys, and σ_k is the standard deviation of macroeconomic announcements k.

Table 4.4 shows the summary statistics of the U.S. and Indonesian macroeconomic announcements that will be used in the study. There is a total of 705 observations of macroeconomic announcements and 114 observations of announcement surprises. Macroeconomic announcements with monthly releases such as BI rate, inflation and export-import, have more observation data than those released six weekly or quarterly. The least number of observations of a macroeconomic release is that of GDP since it is announced quarterly. However, not all macroeconomic announcements have an unexpected (surprise) component. Types of macroeconomic announcements associated with market survey data are: the U.S. Federal Reserve's target funds rate (3 observations), BI interest rate (12 observations), inflation (37 observations), GDP (17 observations), and export-import (45 observations).

4.4.4 The time stamps of Indonesian macroeconomic announcements

Most of the Indonesian macroeconomic announcements are released during the IDX's trading hours, and therefore match with the timing of volatility observations. Since the volatility is calculated on a rolling thirty minute basis, the impact of one macroeconomic announcement will be observed over six five minute intervals. For example, on Thursday, 2 February 2012 there is a GDP announcement on Bloomberg News at 11:05. Figure 4.1 indicates that the '11:05' announcement sits exactly on the 14th window during the day. Therefore, the impact of the announcement will be observed from window '14' to window '19' of the day.

However, there are macroeconomic announcements which are released during non-trading hours. In order to measure the impact of those announcements on volatility, the analysis will be conducted in two steps. First, identifying whether the announcements were made during three time periods: (1) before market opening (before 09:30), (2) during the lunch break, and (3) after the market closing (16:00 onward). Second, measuring the impact of macroeconomic announcements released during those non-trading hours by looking at the volatility of the next window.

Table 4.4 Summary of the U.S. and Indonesian macroeconomic announcements & news

No.	Announcements [a]	No. of observations [b]		Frequency [c]	Dates [d]	Announcement time[e]	Symbol
		Announcements	News				
	The U.S. Macroeconomic announcements						
1.	The U.S. Federal Reserve's target funds rate	58	3	Six weekly	31 Jan 06 to 12 Dec 12	Varies	FED
	The Indonesian Macroeconomic announcements						
2.	BI interest rate	83	12	Monthly	9 Jan 06 to 11 Dec 12	Varies	BIRATE
3.	Inflation	83	37	Monthly	2 Jan 06 to 3 Dec 12	Varies	CPI
4.	Gross Domestic Product	28	17	Quarterly	15 Feb 06 to 5 Nov 12	Varies	GDP
5.	Export-Import	84	45	Monthly	2 May 08 to 3 Dec 12	Varies	EXIM
6.	Consumer confidence index	80	n.a.	Monthly	9 May 06 to 5 Dec 12	Varies	CCI
7.	Foreign reserve	84	n.a.	Monthly	3 Jan 06 to 6 Dec 12	Varies	FORES
8.	Money supply	84	n.a.	Monthly	17 Jan 06 to 28 Dec 12	Varies	M2
9.	Motorcycle sales	83	n.a.	Monthly	24 Jan 06 to 12 Dec 12	Varies	MOTO
10.	Wholesale Price Index	38	n.a.	Monthly	4 Jan 06 to 9 Feb 09	11:00	WPI
	Total	705	114				

[a] The types of the macroeconomic announcements, adapted from Ederington and Lee (1993), Andersen, Bollerslev, Diebold and Vega (2003), Nikkinen et al. (2006) and Nguyen and Ngo (2013), [b] The number of observations of macroeconomic announcements and news, [c] Frequency of each announcement release, [d] Starting and ending dates of the announcements' sample period. [e] The U.S. macroeconomic announcement time is in Eastern Standard Time whereas Indonesian macroeconomic announcements are in Indonesian Western Time. The announcement time is considered varies if there are more than two different announcement times during the whole sample period.

Definitions:

1. The Fed: The U.S. Federal Reserve target interest rate (per cent)
2. BIR: Bank Indonesia reference interest rate (per cent)
3. CPI: yearly percentage change of CPI data for the current month over the same month of the preceding year (per cent)
4. GDP: the percentage change of the current quarter over the previous quarter (per cent)
5. EXI: yearly percentage change of export data for the current month over the same month of the preceding year (per cent)
6. CCI: above 100 points indices optimism (positive response) and vice versa
7. FRS: data quoted in billion/USD
8. MOS: yearly percentage change of M2 data for the current month over the same month of the preceding year (per cent)
9. MOT: number of motorcycle sold
10. WPI: yearly percentage change of WPI data for the current month over the same month of the preceding year (per cent)

n.a. not available

The benefit of using high-frequency data is that they can measure the impact of the announcements on volatility, and the persistence of the impact, immediately after the release of the information. However, as the announcements times vary (Table 4.4), consideration should be taken before examining the persistence of the impact during intraday. The magnitude of the impact of macroeconomic announcements, and its persistence, during the day can be significantly different.

4.5 Conclusion

There were two datasets prepared for this study: (1) the dataset of market variables and (2) the dataset of macroeconomic announcements. The dataset of market variables consists of log returns, volatility and trading volume. The dataset of macroeconomic announcements is constructed from two sources: foreign macroeconomic announcements and domestic macroeconomic announcements. Foreign macroeconomic announcements are proxied by the U.S. Federal Reserve's announcements on the target fund rate. The Indonesian macroeconomic announcements consist of nine indicators. Each macroeconomic variable was announced with a different frequency, and therefore has a different number of observations.

CHAPTER 5
VOLATILITY OF RETURNS AND THE IMPACT OF MACROECONOMIC ANNOUNCEMENTS

5.1 Introduction

This chapter presents and discusses the empirical results for research question 1: What is the pattern of intraday volatility of returns of Indonesian equity market? and research question 2: How and to what extent is the intraday volatility of equity returns influenced by the arrival of information? To address these research questions, this chapter is structured as follows: Section 5.2 presents the descriptive statistics and patterns of the volatility of returns. Discussion of the effects of seasonality and the 2008 Global Financial Crisis (GFC) are also included in this section. Section 5.3 discusses the impact of public information arrivals, proxied by macroeconomic announcements, on the volatility of returns. The model and method used to measure the impact of macroeconomic announcements on volatility are provided in Section 5.3.1 and results are discussed in Section 5.3.2. Section 5.4 concludes the chapter.

5.2 The volatility of returns

As discussed in Chapter 4, this study employs the model of realized volatility to estimate the intraday volatility of the LQ45 index returns during the sample period. Using the theory of quadratic variation and assuming the mean of the log returns is approximately zero as data intervals diminish, volatility is calculated as the sum of squared five minute log returns over 30 minute windows and is repeated every five minutes (see equation 4.4 and Figure 4.1). The descriptive statistics and the graphical patterns of the volatility of LQ45 index returns during intraday are provided in the following sections.

5.2.1 Descriptive statistics

This section presents and discusses the summary statistics of the volatility of the LQ45 index returns over the sample period of 2 January 2006 to 28 December 2012. Table 5.1 shows the summary statistics of the volatility of returns during the sample period which is decomposed into subsample periods, month of the year and days of the week.

Table 5.1 Descriptive statistics of 30 minute realized volatility of the LQ45 index

	N	Mean	SD	Min	Max	Skewness	Kurtosis
Panel A: Subsample periods							
Period 1 (pre-GFC)	18,518	0.0529	0.1462	0.0001	5.0747	16.85	406.89
Period 2 (GFC)	18,968	0.1539	0.3525	0.0000	13.0125	11.80	260.96
Period 3 (post-GFC)	43,754	0.0489	0.1252	0.0001	12.4114	40.70	3,285.42
Panel B: Month of the year							
January	6,819	0.0866	0.2186	0.0002	5.9004	12.01	230.35
February	6,525	0.0455	0.0742	0.0001	2.9283	13.08	391.18
March	6,965	0.0570	0.1120	0.0002	1.7780	6.50	65.69
April	6,734	0.0643	0.1358	0.0003	4.7581	12.59	311.24
May	6,823	0.0877	0.2199	0.0006	5.0747	10.96	182.28
June	7,035	0.0576	0.0812	0.0004	1.0786	4.10	30.29
July	7,174	0.0490	0.0822	0.0004	1.9249	6.96	86.28
August	6,645	0.0706	0.1572	0.0005	4.7269	14.77	364.46
September	6,522	0.0896	0.3057	0.0006	12.4114	19.60	624.26
October	6,691	0.1140	0.3722	0.0000	13.0125	13.31	310.20
November	7,011	0.1042	0.3194	0.0001	10.7891	16.57	439.52
December	6,296	0.0663	0.1525	0.0004	2.4776	6.72	64.33
Panel C: Days of the week							
Monday	17,000	0.0681	0.1444	0.0004	4.3560	7.61	105.81
Tuesday	17,328	0.0825	0.2654	0.0005	10.7891	16.82	455.77
Wednesday	17,610	0.0726	0.2010	0.0000	8.0489	14.83	372.10
Thursday	16,920	0.0663	0.1384	0.0001	4.7581	8.91	159.16
Friday	12,382	0.0849	0.2816	0.0002	13.0125	23.04	847.08
Full sample	81,240	0.0743	0.2104	0.0000	13.0125	19.52	741.38

Note: The table reports descriptive statistics for the volatility of the LQ45 index returns. Volatility is measured as the sum of squared log returns over 30 minute window. Panel A shows the descriptive statistics of volatility during full- and three subsample periods: Period 1 is pre-GFC (2 January 2006 to 31 July 2007), Period 2 is during GFC (1 August 2007 to 31 March 2009), and Period 3 is post-GFC (1 April 2009 to 28 December 2012). Panel B of the table provides the descriptive statistics of volatility for each month of the year, whereas Panel C shows volatility for days of the week. Table of Means, SD, Min, Max, Skewness and Kurtosis are 10^4 times actual figures.

There are 81,240 volatility observations during the sample period. Overall, the mean volatility of market returns is 0.0743 with a standard deviation of 0.2104. The distribution of the realized volatility of returns is not normally distributed as it is heavily and positively skewed, and highly leptokurtic.[13] These results confirm previous findings examining the patterns of returns and volatility using high-frequency market data such as Andersen, Bollerslev, Diebold and Labys (2003), and Gropp and Kadareja (2012). Although a normally-distributed data series is preferred in a linear estimation model, a non-normally distributed

[13] A histogram showing the non-normal distribution of the LQ45 index volatility of returns series is provided in Appendix 1.

data may be used in the least-square fitting of the regression model, particularly when dealing with a relatively large set of data (Kleinbaum et al., cited in Lumley et al. 2002).

To reduce bias over the observations due to anomalous data during the GFC and to take account of its impact, the sample period is divided into three subsample periods: pre-GFC, GFC and post-GFC. Panel A of Table 5.1 shows that the mean volatility of the LQ45 returns reaches its highest level during the period of crisis (0.1539), which is around 190 per cent higher than that of the preceding period. This finding is consistent with Schwert (1989; 2011) who found that volatility increases substantially during an economic crisis. After the crisis, the volatility of returns drops by more than two third (0.0489), even to the level that is lower than that before the crisis (0.0529).

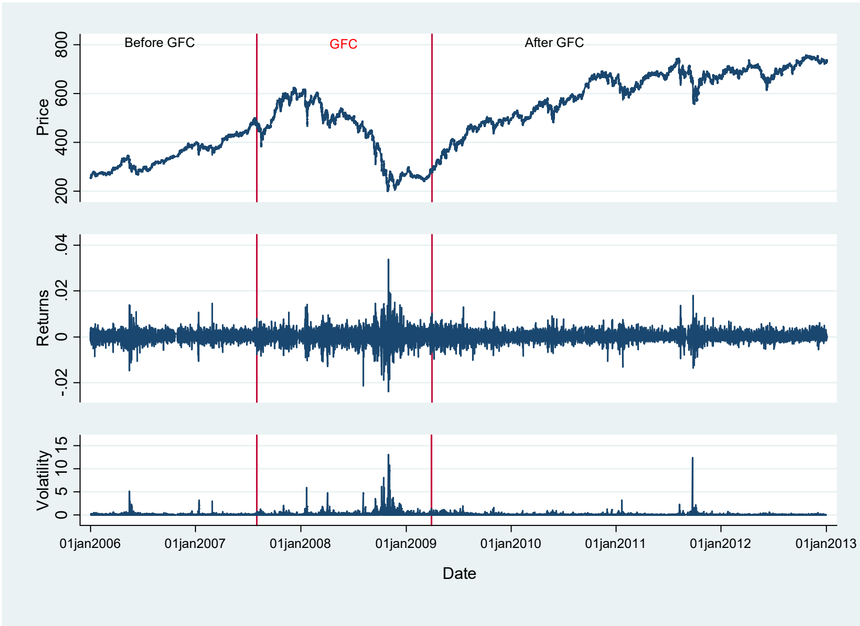
Panel B of Table 5.1 shows the statistics if volatility observations are decomposed into months of the year. The table indicates that the highest average volatility occurs during October (0.1140) which coincided the period when the GFC occurred. October 2008 was, in fact, the period when the returns of the Indonesian equity market dropped substantially and rapidly by more than 8.88 per cent which forced market regulators to suspend all transactions in the Indonesia Stock Exchange for three days (Indonesia Stock Exchange 2009a).

Panel C of Table 5.1 shows the statistics of volatility when the observations are decomposed by days of the week. The table shows that the highest mean volatility is reported on Fridays (0.0849) and the lowest is on Thursdays (0.0663). This finding is consistent with previous studies which found seasonality in the volatility of returns for each day of the week such as Foster and Viswanathan (1990) and Ederington and Lee (1993).

5.2.2 The time-series patterns of LQ45 price, returns and volatility

This section discusses the time-series movements of the LQ45 index price, returns and volatility from 2006 to 2012. Figure 5.1 shows that the LQ45 index price increased from 255.1 in January 2006 to 594.91 in January 2008. During the pre-GFC period, the mean volatility of returns was low (0.0529). However, the trend was not sustained in the next period when, on 28 October 2008, the index fell to the lowest level of 201.31 due to the contagious effect of the GFC. The figure shows that the market returns were below their pre-GFC average and the volatility of returns jumped in this period.

Figure 5.1 Time-series of the LQ45 price, returns and volatility, 2006 to 2012



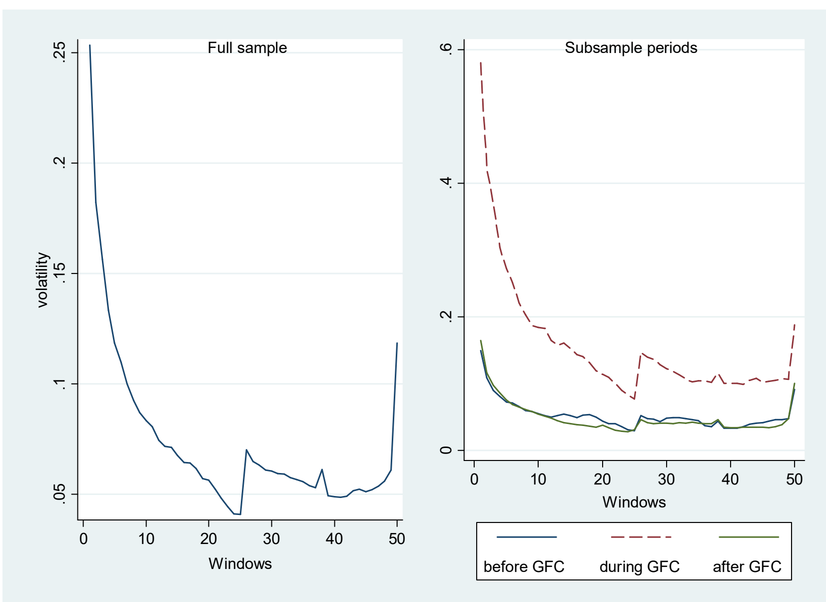
During the GFC, the IDX returns were highly volatile. This finding is consistent with previous studies that shows volatility moves over time and increases considerably during a crisis. However, the impact of the 2008 GFC on the Indonesian economy and stock market was not as severe as that experienced when the Asian Financial Crisis (AFC) hit the economy in 1998. There are at least two reasons for this. First, the 2008 crisis did not originate in Indonesia or other emerging economy but was due to the contagion effect of the subprime mortgage crisis in the U.S. market. Second, the Indonesian macroeconomic policy framework and financial fundamentals have improved substantially since the 1998 financial crisis. The combined effect of improvements in those factors, coupled with the rapid and vigorous fiscal policy responses, meant the impact of the GFC on the Indonesian economy was relatively limited (Basri 2013). The market index increased gradually in the following years after the crisis (Hossain 2013; Sangsubhan & Basri 2012).

5.2.3 The intraday patterns of volatility of returns

Figure 5.2 shows that, in general, the volatility of LQ45 returns forms a reverse J-shaped pattern during intraday over the full sample period. Although the pattern is surprisingly different with that which is typically found in the literature, a similar pattern is found in previous studies such as McInish and Wood (1992) and Chan, Chung and Johnson (1995), among others. The reverse J-shaped pattern of volatility is due to high trading activities during the opening hour and low trading activities during the rest of the day.

To gain greater insight into the behaviour of volatility on the sample period, the intraday pattern of volatility is examined at separate subsample periods. Two distinct patterns of intraday volatility emerged. First, as presented in Figure 5.2, the volatility creates a reverse J-shaped pattern during the period of the 2008 GFC. In addition, Figure 5.2 shows that the mean value of intraday volatility during the crisis is more than tripled than that during non-crisis periods. This finding is consistent with Schwert (1989; 2011) who found that the volatility of stock market returns was substantially higher during a financial crisis. Second, the volatility of the Indonesian stock market returns creates the typical U-shaped intraday pattern both before and after the crisis. That U-shaped pattern reflects the high volatility during the period after market opening and the period prior to closing but low during the day. This U-shaped pattern of volatility is found in previous studies such as Admati and Pfleiderer (1988), Andersen, Bollerslev and Cai (2000), and Ozenbas, Pagano and Scwartz (2010), among others.

Figure 5.2 The patterns of Intraday volatility full sample and subsample periods



Seasonalities

Stock prices and returns fluctuate over time, and the fluctuations can be associated with seasons, months of the year or days of the week. As the patterns of returns and volatility are influenced by the degree of market information and liquidity, this study also finds different patterns of intraday volatility if the observation is decomposed by months of the year and days of the week.

Figure 5.3 shows that before the 2008 crisis, the intraday volatility of returns shows a relatively consistent pattern, which is higher at both the opening and closing hours and low during the middle of the day, over months of the year. However, that pattern of intraday volatility changes dramatically, particularly in October and November, during the period of GFC.

Figure 5.3 The patterns of intraday volatility by months of the year: Before, during, and after the GFC

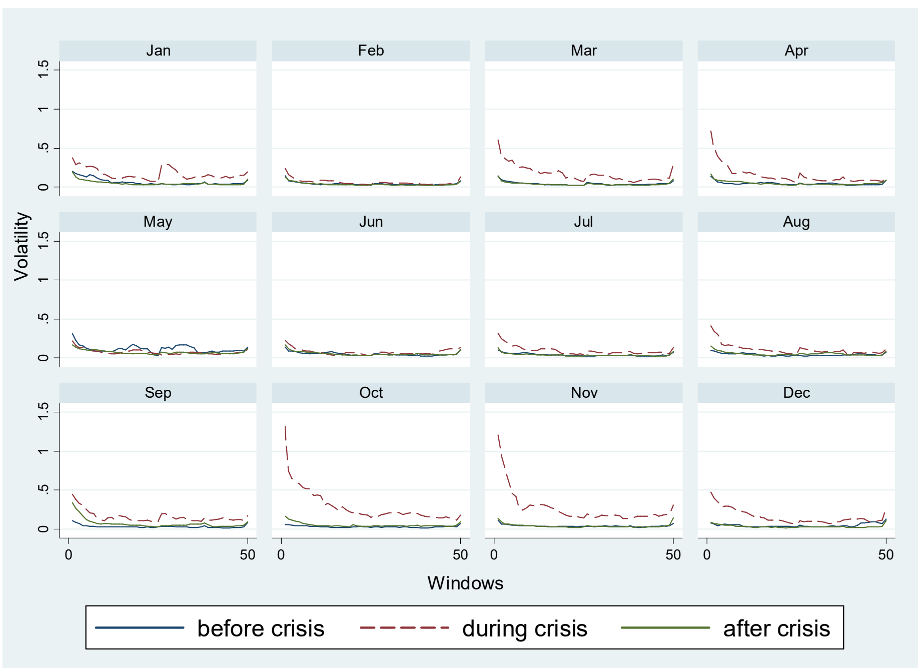


Figure 5.4 The patterns of intraday volatility by days of the week: Before, during, and after the GFC

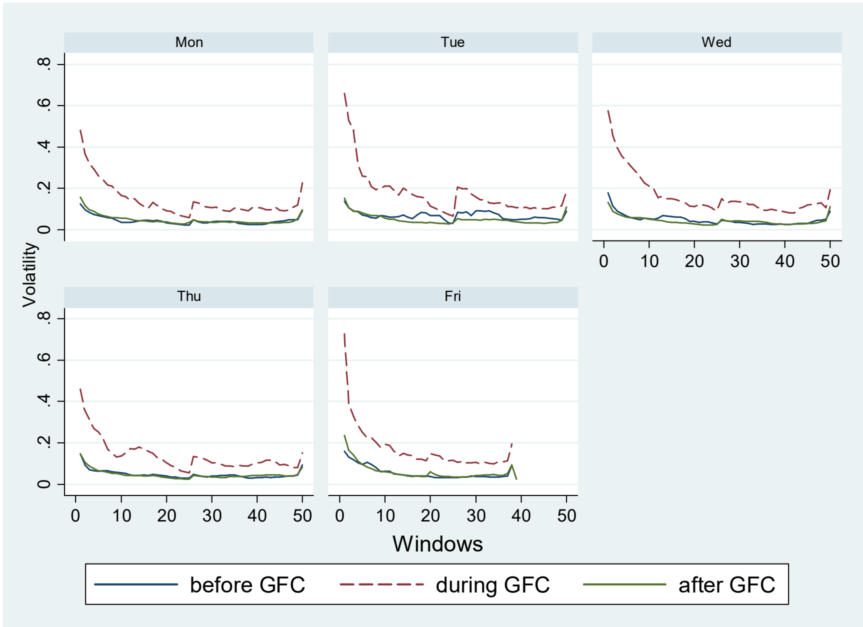


Figure 5.4 shows the patterns of intraday volatility over days of the week. Generally, the pattern of intraday volatility creates a U-shaped pattern over days of the week except on Fridays when the pattern of volatility during opening hours is steeper than on other days. Figure 5.4 also shows that during the crisis the daily intraday volatility is higher than during non-crisis periods.

5.3 The impact of macroeconomic announcements on volatility

Having discussed the summary statistics and patterns of intraday volatility of the IDX returns, the following section presents the methodology to answer the research question: How and to what extent that intraday volatility of equity returns is affected by information arrivals? and discusses the results.

5.3.1 Methodology

To examine the impact of macroeconomic announcements on volatility, this study uses the coefficients that resulted from Ordinary Least Square (OLS) regression with robust standard errors during the sample period. In this section, the impact of each macroeconomic announcement and its surprise components is measured using three models: (1) announcements only (equation 5.1), (2) announcement surprises only (equation 5.2), and (3) announcements and surprises (equation 5.3). This estimation process is conducted for both U.S. and Indonesian macroeconomic announcements.

To measure the impact of macroeconomic announcements on volatility, this study uses an autoregressive AR(1) model as follows:

$$RV_{j,t} = a_{oj} + a_1 RV_{j,t-1} + \sum_{i=1}^{k} a_2 dmacro_k + \sum_{i=1}^{2} a_3 dsubs_i + \sum_{i=1}^{11} a_4 dmonth_i + \sum_{i=1}^{4} a_5 dday_i + \varepsilon_{jt} \tag{5.1}$$

where the dependent variable $RV_{j,\mathrm{t}}$ is the intraday volatility in thirty minute window (j) surrounding the announcements on day t, a_{oj} is positive and significant if announcement type k has a significant impact on volatility, and approximately negative or zero if the announcement has little impact. The study also uses lagged realized volatility $RV_{j,t-1}$ as an independent variable to sufficiently capture the persistence effect of volatility (Andersen, Bollerslev, Diebold & Vega 2003; Gropp & Kadareja 2012). The $dmacr_{\mathrm{k}}$ is a dummy variable for each type of macroeconomic announcements (Table 4.4) which equals 1 if the announcement is made on time t, and 0 otherwise. Subsequently, the model introduces dummies $dsubs_{\mathrm{i}}$ to accommodate the effect of the announcements and news during each subsample period, and $dmonth_i$ to take account of the possible impacts in volatility over months of the year. Furthermore, it has been well documented that there are different patterns of intraday volatility between days of the week. Therefore, the study also uses dummies $dday_i$ to take these into account.

Furthermore, the variable $News_i$ is introduced to take account the effect of macroeconomic surprises.[14] This impact is explained in the following model:

$$RV_{j,t} = a_{oj} + a_1 RV_{j,t-1} + \sum_{i=1}^{k} News_i + \sum_{i=1}^{2} a_3 dsubs_i + \sum_{i=1}^{11} a_4 dmonth_i + \sum_{i=1}^{4} a_5 dday_i + \varepsilon_{jt} \tag{5.2}$$

Finally, the study investigates the interaction effect of macroeconomic announcements and their surprise components on the volatility of returns. This relationship is shown as follows:

[14] News is defined as the unexpected (surprise) component of a scheduled announcement and calculated with equation (4.7).

$$RV_{j,t} = a_{oj} + a_1 RV_{j,t-1} + \sum_{i=1}^{k} a_2 dmacro_k News_i + \sum_{i=1}^{2} a_3 dsubs_i + \sum_{i=1}^{11} a_4 dmonth_i + \sum_{i=1}^{4} a_5 dday_i + \varepsilon_{jt}$$

(5.3)

Moreover, as outlined in section 4.4, this study uses two different sources of macroeconomic announcements: the U.S. and Indonesian macroeconomic announcements. The study measures those impacts and provides the results separately. Furthermore, as previously explained in Section 4.3.1, the results of the estimation are provided for each model based on groups of days of the week: (1) Mondays to Thursdays and (2) Fridays.

5.3.2 Empirical findings

Discussion of empirical findings is divided into three sections: The stationarity and autocorrelation tests of the volatility series, the impact of macroeconomic announcements and news, and the impact of the 2008 GFC on the announcement impacts.

5.3.2.1 The stationarity and autocorrelation tests of the volatility series

Before examining the impact of macroeconomic announcement and news, several tests are conducted to identify the time-series properties in the volatility series: stationarity and autocorrelation tests. The test of stationarity is important to measure whether shocks in the time-series model are only temporary, or whether the impact, if any, will be eliminated after a certain period of time. Using the Dicky-Fuller test of stationarity, the test finds that the absolute value of the test statistic is greater than its absolute critical value.[15] Therefore, the results of the test show the rejection of the null hypothesis of the presence of a unit root in the time-series data and indicate that the dependent variable series follows a stationary process.

The second test is to examine whether the series of realized volatility is from random data or from serially correlated relationships. Using the Breusch-Godfrey LM test for autocorrelation, the results show rejection of the null hypothesis and indicate that there is serial or autocorrelation in the volatility series.[16] Therefore, this study includes the lag-1 dependant variable to better capture the autoregressive function in the model (equation 5.1 and 5.2).

[15] The results of the Dicky-Fuller test for unit-roots of the realized volatility are provided in Appendix 2.
[16] The results of the Breusch-Godfrey LM test for autocorrelation are provided in Appendix 3.

5.3.2.2 The impact of macroeconomic announcements and news

Before explaining the impact of the macroeconomic announcements on volatility, it is worth noting the expected direction of volatility for every macroeconomic announcement released. Following Hanousek, Kočenda and Kutan (2009), this study distinguishes the impact of a macroeconomic announcement on the volatility of returns, in terms of market expectation, into positive and negative. In general, macroeconomic announcements have a positive impact if it is above market expectation, vice versa. For example, higher than expected interest rate has a positive impact as it increases cost of funds and uncertainty of future returns. On the other hand, higher than expected GDP has a negative impact as it shows growth of the economy. Table 5.2 shows types of macroeconomic announcements, expected directions of volatility and their justifications.

Table 5.2 Macroeconomic announcements and expected direction

No.	Macroeconomic announcements	What is measuring	Expected direction of volatility[a]	Why to affect volatility
1.	BI interest rate	BI rate	Positive	Cost of funds
2.	Inflation	Inflation	Positive	Prices
3.	Gross Domestic Product	GDP	Negative	Economic growth
4.	Export-Import	Export-import	Negative	Trading surplus
5.	Consumer confidence index	Consumer confidence index	Negative	Market confidence
6.	Foreign reserve	Foreign reserve	Negative	Net foreign reserve
7.	Money supply	Money supply	Negative	Liquidity
8.	Motorcycle sales	Motorcycle sales	Negative	Retail sales
9.	Wholesale Price Index	Wholesale Price Index	Negative	Wholesale sales
10.	The U.S. Federal Reserve's target funds rate	FOMC target rate	Positive	Global cost of funds

[a] Hanousek, Kočenda and Kutan (2009) differentiated the impact of macroeconomic announcements, in terms of its relation to market expectations into positive (+) and negative (-). In most cases, the macroeconomic announcements has a positive impact if it is above market expectations, vice versa.

The impact of macroeconomic announcements on the volatility of stock market returns has been shown in both developed markets and emerging markets, but there is scant research using high-frequency data in the Indonesian market. An OLS regression with robust t-statistics is used to measure the impact of the announcements on the volatility using the models shown in equation (5.1), (5.2) and (5.3).

Table 5.3 Regression results of the impact of macroeconomic announcements and news during the full sample period

VARIABLES	Model 1	Model 2	Model 3
Constant	0.0051***	0.0051***	0.0051***
	(3.7971)	(3.8086)	(3.7959)
Lag volatility	0.8244***	0.8244***	0.8244***
	(25.5959)	(25.5962)	(25.5956)
BI rate	0.0070*		0.0070*
	(1.8361)		(1.8364)
BI rate — news		–0.1118**	–0.1121**
		(–2.3132)	(–2.3175)
Inflation	0.0024		0.0024
	(0.8853)		(0.8859)
Inflation — news		-0.0238	–0.0238
		(–1.1621)	(–1.1624)
GDP	–0.0001		–0.0001
	(–0.0343)		(–0.0344)
GDP — news		–0.0011	–0.0011
		(–0.3533)	(–0.3533)
Export-import	0.0014		0.0014
	(0.5488)		(0.5484)
Export-import — news		–0.0354**	–0.0354**
		(–2.3133)	(–2.3129)
Consumer Confidence index	–0.0054*		
	(–1.6708)		
Foreign Reserve	–0.0031		
	(–1.4875)		
Money supply	–0.0025		
	(–0.6442)		
Motorcycle sales	0.0378***		
	(4.3052)		
Wholesale price index	0.0150		
	(1.5538)		
FOMC target rate	–0.0037		–0.0037
	(–0.7270)		(–0.7267)
FOMC target rate — news		0.4492	0.4491
		(0.9088)	(0.9089)
Dummy subsample period	yes	yes	yes
Dummy month	yes	yes	yes
Dummy day	yes	yes	yes
Observations	81,238	81,238	81,238
R-squared	0.8493	0.8493	0.8493

Note: The table reports the estimation results of equation (5.1), (5.2) & (5.3) using OLS with robust t-statistics in parentheses. The table demonstrates the impact of macroeconomic announcements and news on volatility of LQ45 returns. Dummies for subsample periods, month of the year and days of the week are also included in the model. ***,**, and * suggest significance at 1%, 5%, and 10%, respectively. The data are from January 2006 to December 2012 and represented 10^4 times actual figures.

Table 5.3 shows the results of the macroeconomic announcements impact on the volatility during the full sample period. The results from the regression estimation are presented based on subsample periods and days group. Table 5.3 demonstrates that the scheduled macroeconomic announcements, in general, do not significantly affect the volatility of equity returns, except for the announcements of the Bank Indonesia (BI) interest rate (positive and significant at ten per cent level), the consumer confidence index (negative and significant at ten per cent level) and the motorcycle sales (positive and significant at one per cent level). Other announcements such of inflation and export-import, although have positive effect, do not significantly impact on volatility. Furthermore, the unexpected announcements of BI interest rate and export-import impact negatively on the volatility of returns (at five per cent level of significance). Similar findings are reported when interaction effect is included in the model as described in equation (5.3).

To gain a greater insight into the impact of macroeconomic announcements and news on the volatility, the results of the regression are decomposed into two groups of days of the week: Monday to Thursday and Friday. Table 5.4 shows that the impact of macroeconomic announcements on the volatility varies depending on the types and the days of the announcements.

Table 5.4 shows that the Bank Indonesia's interest rate (BI rate) announcements positively and significantly impact on volatility from Monday to Thursday. Similar results are reported for the impact of news or surprise components of the announcements from Monday to Thursday which are significant at five per cent level but with a negative relationship. The negative coefficient suggests that the market has over-estimated the BI rate announcements and, as a result, the volatility reduces when the actual interest rates announced are lower than the market's expectation. This finding is consistent with previous studies such as by Andritzky, Bannister and Tamirisa (2007) in an emerging bond market and by Smales (2013) in the context of a developed futures market. However, this finding contrasts with Gropp and Kadareja's (2012) view that unanticipated shocks in monetary policy significantly increase the volatility of banking stocks just before the policy announcement if information is stale: when the unanticipated information from a monetary policy announcement is not covered sufficiently in banks' annual reports.

Table 5.4 Regression results of the impact of macroeconomic announcements and news during the full sample period by days of the week

	Monday to Thursday			Friday		
VARIABLES	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
Constant	0.0042***	0.0043***	0.0042***	0.0128**	0.0129**	0.0128**
	(4.0751)	(4.1313)	(4.0718)	(2.5400)	(2.5499)	(2.5400)
Lag volatility	0.8640***	0.8640***	0.8640***	0.7436***	0.7436***	0.7436***
	(44.0986)	(44.0996)	(44.0978)	(8.7229)	(8.7233)	(8.7229)
BI interest rate	0.0066*		0.0066*	0.0053		0.0053
	(1.6559)		(1.6562)	(0.9744)		(0.9744)
BI interest rate – news		–0.0930**	–0.0933**			
		(–2.4577)	(–2.4614)			
Inflation	0.0023		0.0023	–0.0057**		–0.0057**
	(0.7995)		(0.8001)	(–2.1669)		(–2.1666)
Inflation – news		–0.0250	–0.0250		0.0064	0.0064
		(–1.1412)	(–1.1414)		(0.8690)	(0.8713)
GDP	0.0006		0.0006	–0.0101		–0.0101
	–0.2471		–0.2472	(–1.5443)		(–1.5418)
GDP – news		0.001	0.001		–0.0400**	–0.0398**
		–0.2846	–0.2854		(–2.4934)	(–2.4582)
Export-import	0.0013		0.0013	–0.0085**		–0.0085**
	(0.4609)		(0.4605)	(–2.2755)		(–2.2752)
Export-import – news		–0.0355**	–0.0355**		–0.0060	0.0061
		(–2.2113)	(–2.2110)		(–0.9302)	(–0.9444)
Consumer Confidence Index	–0.0048			–0.0031		
	(–1.3307)			(–0.4347)		
Foreign Reserve	–0.0029			–0.0075		
	(–1.0717)			(–1.5885)		
Money Supply	–0.0055			0.0077		
	(–1.0279)			–1.5263		
Motorcycle Sales	0.0386***			0.0048		
	(4.4662)			(0.3256)		
Wholesale Price Index	0.007			0.0837***		
	–0.6935			–3.1831		
FOMC target rate	–0.0054		–0.0052	–0.0148		–0.0148
	(–1.0692)		(–1.0475)	(–1.6450)		(1.6450)
FOMC target rate – news		0.1404	0.1224			
		(0.4965)	(0.4391)			
Dummy subsample periods	Yes	Yes	Yes	Yes	Yes	Yes
Dummy month	Yes	Yes	Yes	Yes	Yes	Yes
Dummy day	Yes	Yes	Yes	Yes	Yes	Yes
Observations	68,856	68,856	68,856	12,382	12,382	12,382
R-squared	0.8666	0.8666	0.8666	0.8172	0.8172	0.8172

Note: The table reports the estimation results of equation (5.1), (5.2) & (5.3) using OLS with robust t-statistics in parentheses. The table demonstrates the impact of macroeconomic announcements and news on volatility of LQ45 returns. Dummies for sub sample periods, month of the year and days of the week are also included in the model. ***,**, and * suggest significance at 1%, 5%, and 10%, respectively. The data are from January 2006 to December 2012 and represented 10^4 times actual figures

Moreover, Table 5.4 indicates that there is no significant impact of BI rate announcements and surprises on volatility of returns during Friday**.** These results are mainly due to insufficient Friday announcement data. From four BI rate announcements made on Friday, three were released during non-trading hours and only one was released during trading hours. In fact, most BI rate announcements were made on Tuesday or Thursday (Bank Indonesia 2013b).

The regression results provided in Table 5.4 also show that inflation announcements, proxied by CPI, do not significantly impact on the volatility of returns if the announcements were released on Mondays to Thursdays, but negatively impact and significantly impact (at five per cent level of significance) on volatility when released on Fridays. That negative and significant relationship between inflation and volatility is also reported in by Andritzky, Bannister and Tamirisa (2007) for the emerging bond market and by Moura and Gaião (2014) for the Brazilian interest rate derivatives market.

In addition, Table 5.4 shows that the Gross Domestic Product (GDP) announcements have no significant impact on volatility during the sample period. This could be because the GDP data are released quarterly and, therefore, have been sufficiently anticipated by market analysts and market participants. The table 5.3 also shows that the GDP announcement surprise has negative impact on volatility if the GDP announcements were on Fridays. The negative relationship between GDP news component and intraday volatility is consistent with Andritzky, Bannister and Tamirisa (2007) who suggest it is due to a calming effect as the increase in GDP tends to lower the volatility of the spreads in emerging bond markets.

Table 5.4 also shows that the announcements of percentage changes in the Export-import impact on volatility and are significant at five per cent level if the announcements were released on Friday. However, the announcement surprises resulted from unexpected Export-import data have negative impact on volatility from Monday to Thursday. These findings are consistent with previous studies such as Andritzky, Bannister and Tamirisa (2007), Smales (2013), and Moura and Gaião (2014), who suggest that countries with a trade surplus tend to have lower volatility, and countries with higher exports indicate a cooling domestic economy. From the macroeconomic perspective, it has been argued that the healthy trade account helped Indonesia to deal with the 2008 financial crisis so that its impact was not as severe as during its 1998 crisis (Ashcroft & Cavanough 2008; Basri 2013; Sangsubhan & Basri 2012).

In addition, there is evidence that some of macroeconomic announcements such as the Consumer Confidence Index (CCI), foreign reserves, and money supply announcements do not impact on volatility[17]. This finding is surprising given empirical evidence that consumer confidence can be a proxy for economic growth, forecast the bull or bear trends of stock markets, and can affect stock returns (Chen 2011; Jansen & Nahuis 2003). These findings are inconsistent with other studies such as by Andersen, Bollerslev, Diebold and Vega (2003) in the context of US foreign exchange market and by Bollerslev, Cai and Song (2000) in the U.S. Treasury bonds market that CCI announcements positively impact on volatility of returns.

Similarly to CCI announcements, as provided in Table 5.4, foreign exchange reserve announcements do not have a statistically significant impact on the volatility of stock returns.[18] Although there are not many studies looking at the impact of foreign reserve announcements on volatility,[19] that finding is different with Thenmozhi and Nair (2014) that the foreign exchange reserve factor inversely related with bond returns in India and Brazil, but positively related with German bonds' returns.

As is similar to foreign reserve announcements, as shown in Table 5.4, there is no evidence that the announcements of money supply (M2) have a statistically significant impact on volatility. This is probably because, in the case of Indonesia, that money supply measure has no longer been considered as an effective operational target for inflation targeting. Therefore Bank Indonesia, like other emerging central banks in the region, has applied the new inflation targeting framework policy by using the 1 month Bank Indonesia Certificate (SBI) rate since July 2005 until July 2008, before finally using the overnight interest rates as operational target (Sahminan 2008).

The regression results of retail sales announcements on volatility of returns are presented in Table 5.4. Regarding the retails sales data, this study follows Bloomberg News which classifies motorcycle sales and local auto sales as retail and wholesale sales indicators.

[17] The Bloomberg database uses the CCI as a cyclical indicator of the economy collected through a survey to customers about the future economic conditions, from job opportunities to expected family income in the next six months.
[18] Previous studies show that foreign reserve is of importance in the economies of emerging countries such as to ease external financing requirements and reduce exchange rate volatility (Choi, Sharma & Strömqvist 2009; Mohanty & Turner 2006).
[19] This is because most studies on high-frequency impact of macroeconomic announcements on volatility conducted in the context of developed markets which do not take into account the announcements of foreign reserves (for example, Andersen, Bollerslev, Diebold & Vega 2003; Ederington & Lee 1993)

Motorcycle sales data were used in this study because it has higher annual sales than auto sales which more reflecting the behaviour of Indonesian low- and middle-income consumers (Credit Suisse 2012).[20] Table 5.4 depicts that the announcements of motorcycle sales positively impact on volatility, significant at one per cent level when the sales data are announced from Monday to Thursday. This finding is consistent with Smales (2013) which finds that retail sales announcements impact positively on volatility of returns of 90 day bank bill, 3 Year bond and 10 Year bond in the Australian interest rate futures market.

Furthermore, Table 5.4 shows that the Wholesale Price Index announcements impact positively on volatility and significant at one per cent level only if the announcements released on Friday. This finding supports previous studies that state announcements relating to the wholesale price index impact positively on returns in markets, such as the Australian interest rate futures contracts market (Smales 2013).

Finally, this section presents the regression results of the U.S. Federal Reserve's announcements impact on volatility. Although a large number of studies has found a negative correlation between U.S. FOMC's announcements and volatility (Nguyen & Ngo 2014), the study finds that the U.S. Fed's announcements and news do not significantly impact on the volatility of Indonesian stock market returns (Table 5.4). This finding is consistent with Nikkinen et al. (2006) that states only developed Asian countries and those Asian countries closely integrated with the U.S. market were significantly affected by the U.S. macroeconomic announcements. The impact of U.S. macroeconomic announcements varies depending on each country's level of international trade, market size, foreign ownership, and the industrial and economic structures.

5.3.2.3 The impacts of the 2008 Global Financial Crisis

Although there is abundance of research examining the volatility of both emerging and developed markets during a crisis (for example, Korkmaz, Cevik & Atukeren 2012; Schwert 1989, 2011), there is a dearth in the literature showing how and to what extent that macroeconomic announcements during the 2008 GFC impact on the volatility of returns in an emerging market such as Indonesia.

[20] Based on annual average number of motor vehicles (by types) in Indonesia from 1987 to 2012. The data are available from Statistics Indonesia.

Using the volatility data series during the GFC period, this study further investigates the impact of macroeconomic announcements on volatility by running regressions using equation (5.3). Only macroeconomic announcements that have a news component are included in this exercise. Furthermore, only data from Mondays to Thursdays are used to avoid inconsistency in daily window observations due to the differences in trading hours between the Monday to Thursday period and Friday.[21] The results of the regression are presented in Table 5.5.

Table 5.5 shows that all types of scheduled macroeconomic announcements have no statistically significant impact on volatility during the GFC, despite the fact that the volatility of returns increases significantly during this period (Figure 5.2). Studies on the impact on volatility of macroeconomic announcements alone, without including the news component during the GFC, are rare. Therefore, this study attempts to find studies with the closest possible approach with which to compare the finding or, if not possible, by either eliminating the impact of the GFC or taking the surprise component of the announcements.

Table 5.5 also shows that here are only two types of macroeconomic news that have a statistically significant impact on the volatility of returns during the GFC period: the GDP news and the U.S. FOMC announcement news. During the crisis, the GDP news had a positive impact on volatility and was significant at one per cent level. This finding is consistent with previous studies such as Smales (2013) who argues that the increase in volatility during the GFC is caused by the increase in the higher-than-expectation economic growth which results in the increase in asset returns. Moreover, this finding is consistent with Moura and Gaião (2014) in the sense that the GFC has contributed to the changes of direction and magnitude of the impact of macroeconomic news on volatility. Before the GFC, the GDP news negatively impacted on volatility at 1 per cent significant level. However, after the GFC, the GDP news has had no significant impact on volatility.

Table 5.5 also reports that the U.S. FOMC announcement news had a positive impact on volatility during the GFC, significant at five per cent level. The significant impact of the FOMC news on volatility is plausible when the market would be substantially responsive to surprises in monetary policy during the crisis. The positive impact of the U.S. FOMC announcement news on volatility could mean that the higher than expected interest rate

[21] Most macroeconomic announcements were released between Monday and Thursday during the GFC period. Therefore, when we ran regression using Friday only datasets, the results show no figures for all types of macroeconomic announcements and news except for the BI interest rate announcement.

announcements during the GFC resulted in increasing prices and the exchange rates. As a result, the volatility of domestic stock market increases. After the GFC, the U.S. FOMC news has also impacted on volatility but in the opposite direction. However, the findings of the current thesis contrasts with that of Moura and Gaião (2014) who contend that in an emerging market such as Brazil, the GFC is reducing the effect of changes in monetary policy surprises because the crisis has created an economic recession worldwide, including in emerging countries. Therefore, the market has to some extent anticipated and become more agile with changes in the directions of domestic monetary policy (Basri 2013).

Table 5.5 Regression results of the impact of macroeconomic announcements and surprises during the full sample and around the GFC periods (Monday to Thursday)

	Period			
Variables	**Full**	**Before**	**GFC**	**After**
Constant	0.0042***	0.0056***	0.0171***	0.0038***
	(0.0010)	(0.0021)	(0.0046)	(0.0006)
Lag volatility	0.8640***	0.8787***	0.8611***	0.8418***
	(0.0196)	(0.0366)	(0.0253)	(0.0196)
BI interest rate	0.0066*	–0.0018	0.0042	0.0108*
	(0.0040)	(0.0026)	(0.0096)	(0.0059)
BI interest rate — news	–0.0933**		–0.0158	–0.1329***
	(0.0379)		(0.0166)	(0.0479)
Inflation	0.0023	0.0005	0.0021	0.0024
	(0.0028)	(0.0054)	(0.0109)	(0.0018)
Inflation — news	–0.0250	–0.0306	–0.0227	–0.0237
	(0.0219)	(0.0231)	(0.1061)	(0.0182)
GDP	0.0006	–0.0083**	0.0099	0.0012
	(0.0022)	(0.0034)	(0.0204)	(0.0020)
GDP — news	0.0010	–0.0388***	0.6908***	0.0002
	(0.0033)	(0.0138)	(0.0577)	(0.0018)
Export-import	0.0013	-0.0000	–0.0017	0.0024
	(0.0027)	(0.0050)	(0.0098)	(0.0018)
Export-import — news	–0.0355**	–0.0251	–0.0751	–0.0207
	(0.0161)	(0.0270)	(0.0512)	(0.0141)
FOMC target rate	–0.0061	–0.0002	–0.0142	–0.0043*
	(0.0050)	(0.0046)	(0.0176)	(0.0025)
FOMC target rate — news	0.3647		0.7711**	–0.5738***
	(0.4103)		(0.3240)	(0.0481)
Dummy subsample period	yes	yes	yes	yes
Dummy month	yes	yes	yes	yes
Dummy day	yes	yes	yes	yes
Observations	68,856	15,744	16,045	37,067
R-squared	0.8666	0.8660	0.8642	0.8213

Note: The table reports the estimation results of equation (5.1), (5.2) & (5.3) using OLS with robust t-statistics in parentheses. The table demonstrates the impact of the macroeconomic announcements and news on return volatility during the 2008 Global Financial Crisis for Monday to Thursday. Dummies for sub sample periods, month of the year and days of the week are also included in the model. ***,**, and * suggest significance at 1%, 5%, and 10%, respectively. The data are from January 2006 to December 2012 and represented 10^4 times actual figures. For brevity, the coefficients of dummy variables are omitted.

5.4 Conclusion

The volatility of Indonesian stock market returns shows a reverse-J shaped from 2006 to 2012 meaning that highly volatile during the opening hours but low during the middle of the day and closing hours. If observation period of that volatility is decomposed into before, during, and after GFC sub sample, that intraday volatility shows different pattern. Before and after the GFC, the volatility shows a U-shaped pattern. This pattern is consistent with previous findings that volatility is usually high during opening and closing hours and low during the middle of the day. As also depicted by its monthly patterns, the GFC which was occurred in October 2008 has changed the patterns of volatility during intraday.

The results of Model 1 regression show that most major domestic macroeconomic announcements such as the Bank Indonesia interest rate, inflation, export-import, motorcycle sales and wholesale price index, have a significant impact on volatility. However, contrary to the literature, the Indonesian GDP announcements and the U.S. FOMC scheduled announcements do not impact on the volatility during the sample period. Furthermore, all macroeconomic news, except inflation and the U.S. FOMC, have a significant impact on volatility during the same period.

The non-significant impact of GDP announcements on the volatility of returns can be explained by the frequency of its releases. Different to other macroeconomic announcements, the GDP is only announced quarterly, which means that high-frequency announcements and news tended to impact on volatility more as the market was more prepared for the forthcoming announcements.

During the GFC, GDP news and the U.S. FOMC news significantly impact on volatility. These findings are consistent with those of previous studies: that the crisis significantly influences the direction and magnitude of market responses to macroeconomic news.

CHAPTER 6
TRADING VOLUME AND THE VOLATILITY OF RETURNS

6.1 Introduction

Having discussed the impact of patterns of intraday volatility and their reactions to scheduled public information and surprises in Chapter 5, the relationships between trading volume and volatility of returns will be investigated in this chapter. It aims to answer research question 3: What is the relationship between trading volume and volatility of returns?

This chapter is structured as follows: Section 6.2 presents the data and methods used to test the research question, descriptive statistics of volatility and the intraday patterns of trading volume and volatility of returns. The effects of seasonality and the 2008 Global Financial Crisis (GFC) on the relationships are also discussed in this chapter. Section 6.3 presents empirical findings and Section 6.4 concludes the chapter.

6.2 Trading volume and volatility of returns relations

The data and estimation methods of trading volume and volatility of returns were presented in Chapter 4 and will not be discussed again in this chapter. The summary statistics of both trading volume and volatility of returns are provided in the next section, before examining the relationships between trading volume and volatility of returns.

6.2.1 Descriptive statistics

Table 6.1 reports the summary statistics of 30 minute average trading volume and the 30 minute window volatility of the LQ45 index returns from 2 January 2006 to 28 December 2012. The summary statistics are decomposed based on subsample periods, months of the year and days of the week.

Table 6.1 Descriptive statistics of trading volume & realized volatility of LQ45 index

	N	Mean	SD	Min	Max	Skewness	Kurtosis
Panel A: Subsample periods							
Period 1 (pre-GFC)	18,518	0.1723	0.1449	0.0047	1.7525	2.3079	11.8027
		0.0529	*0.1462*	*0.0001*	*5.0747*	*16.8456*	*406.8866*
Period 2 (GFC)	18,968	0.2337	0.1843	0	1.9090	1.5509	7.0781
		0.1539	*0.3525*	*0*	*13.0125*	*11.7984*	*260.9552*
Period 3 (post-GFC)	43,754	0.2876	0.2962	0	5.1117	3.7906	29.5158
		0.0489	*0.1252*	*0.0001*	*12.4114*	*40.7012*	*3,285.4200*
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 2 Jan 2006 to 28 Dec 2012. Trading volume is measured as 30 min average of shares traded using five minute trading data. Realized volatility is measured as the sum of squared five minute returns over a 30 min window. Panel A shows the statistics by subsample periods: pre-GFC (2 Jan 2006 to 31 July 2007), GFC (1 Aug 2007 to 31 Mar 2009), and post-GFC (1 Apr 2009 to 28 Dec 2012). Panel B shows the statistics by month of the year and Panel C is by day of the week. For brevity, the data of Mean, SD, Min, and Max values of the trading volume are expressed in hundred-million (100,000,000) shares. Realized volatility values are shown in italics. Table of Means, SD, Min, Max, Skewness and Kurtosis of realized volatility is 10^4 times actual figures.

Panel A of Table 6.1 shows that there are increases in both trading volume and volatility during the GFC compared to previous period.[22] The average trading volume increases from 17.123 million shares before the GFC to 23.37 million shares during the GFC. Similar to trading volume, the mean intraday volatility also increases from 0.0529 before the GFC into 0.01539 during the GFC. After the GFC, the average trading volume increases to 28.76 million shares while the volatility decreases drastically to 0.0489 during the same period.

Panel B of Table 6.1 shows that August is a month when the shares of LQ45 index constituents are heavily traded (34.6 million shares) although the volatility during that month is not the highest (0.0706). That high in trading volume continued over the following months from September until November. Similarly, the volatility of the LQ45 returns during September to November is higher than other months of the year. Those considerable increases in trading volume and volatility coincide with the GFC which emerged in August 2008.

In addition, Panel C of Table 6.1 reports that Friday is the day when the trading activity is low (22.5 million shares) although the volatility is high (0.00849). However, on a day when the volatility is low, such as Thursday (0.0663), it is not necessarily followed by high trading volume. Furthermore, stock trading can be very active in a day when the level of volatility is moderate (0.0726) such as Wednesday (26.4 million shares).

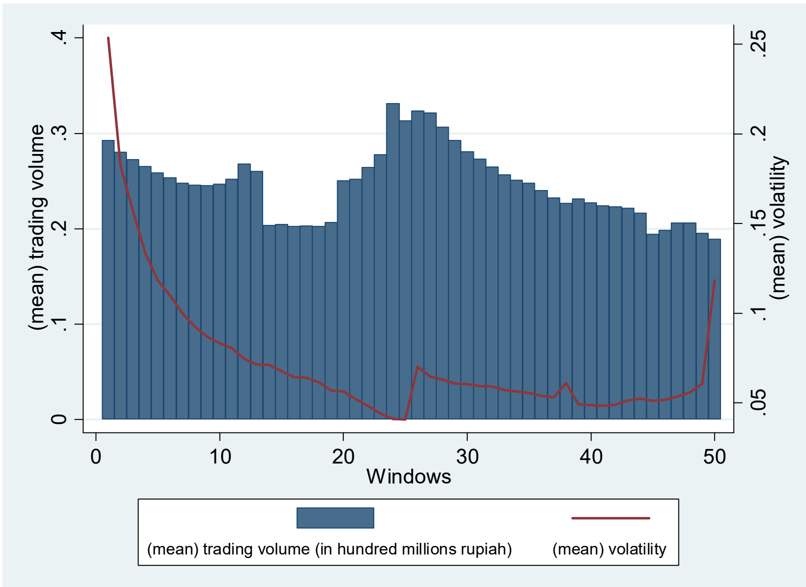
The next section will discuss the patterns of trading volume and volatility during intraday trading. The dynamic and causal relationships between trading volume and volatility will also be reported in the next section.

6.2.2 The intraday patterns of trading volume and volatility

In a similar way to the presentation of statistics summary in Table 6.1, the graphical patterns of trading volume and volatility during intraday trading are decomposed into subsample periods, months of the year and days of the week.

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

Figure 6.1 Intraday patterns of 30 minute window trading volume and volatility



Note: The figure shows the intraday patterns of trading volume and realized volatility. The intraday pattern of trading volume is shown by the bar graph and is reported in hundred million shares. The intraday pattern of realized volatility is shown by the line graph.

Figure 6.1 shows the intraday patterns of both trading volume and volatility of returns during the full sample period. The X-axis represents the number of window intervals during the trading day. The left axis shows the five minute average of shares traded whilst the right axis shows the realized volatility.

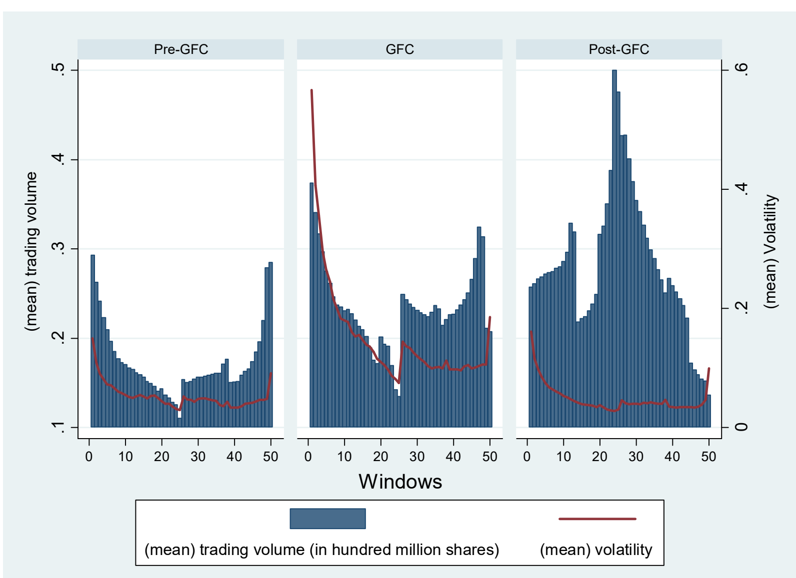
The figure shows that both trading volume and volatility of returns are high following the market opening. Furthermore, soon after the opening, both trading volume and volatility decrease. However, the patterns of decrease in trading volume and volatility are different. Trading volume decreases gradually before it reverses to increasing near the closing of the morning trading session. In the afternoon session, trading volume shows a similar pattern after opening but keeps declining until closing time. This pattern contrasts with that of volatility which increases substantially both before and around market closing. Volatility drops drastically after market opening and throughout the day before it bounces back during market closing times.

The study further investigates the intraday patterns of trading volume and volatility if the observations are decomposed by: subsample periods, months of the year and days of the week. This study finds different patterns of trading volume when the observations are divided into subsample periods. Figure 6.2 shows that, before the GFC, both trading volume and volatility show U-shaped patterns due to high trading activities during opening and closing hours. In this period, trading volume and volatility move in the same direction.

Figure 6.2 also shows that, during the GFC, trading volume moves differently from volatility, particularly during market opening hours when the decrease of volatility is steeper than trading volume. It means that the volatility is substantially high during opening hours and then declines drastically around the middle of the day. During the middle of the day and closing hours, both trading volume and volatility move in the same direction.

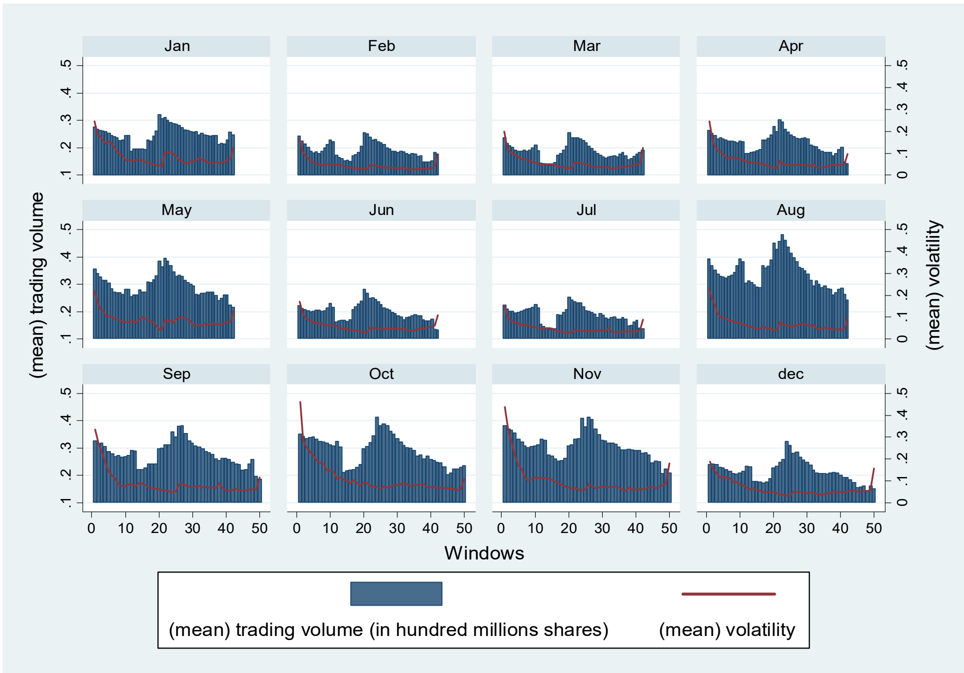
Figure 6.2 depicts that trading volume has considerably different intraday patterns during the GFC than in the previous two periods. Trading volume increases and moves in the opposite direction from the volatility throughout the morning hours. Subsequently, trading volume decreases consistently for the rest of the day whilst volatility jumps close to the market close. This finding is similar to Girard and Biswas (2007) who find negative correlations between trading volume and volatility which are commonly found in studies in the context of emerging markets due to their informational inefficiency.

Figure 6.2 Intraday patterns of 30 minute window trading volume and volatility by subsample periods



Note: The figure shows the intraday patterns of trading volume and realized volatility. The intraday pattern of trading volume is shown by the bar graph and is reported in hundred millions shares. The intraday pattern of realized volatility is shown by the line graph.

Figure 6.3 Intraday patterns of 30 minute window trading volume and volatility by months of the year



Note: The figure shows the intraday patterns of trading volume and realized volatility. The intraday pattern of trading volume is shown by the bar graph and is reported in hundred millions shares. The intraday pattern of realized volatility is shown by the line graph.

Figure 6.3 shows the intraday patterns of trading volume and volatility when the observations are decomposed into months of the year. Trading volume is higher during the opening hours both in the morning and afternoon trading sessions. However, when the trading volume increases before the middle of the day, trading volume continues to decrease in the afternoon trading session until closing. Based on cross-sectional observation, the intraday patterns of trading volume are similar over months of the year except from August to November. Figure 6.3 also shows that the volatility of returns creates a U-shaped pattern during intraday. This pattern is consistent throughout the year, except between September and November. October has an L-shaped pattern of intraday volatility. This finding is not unusual as the 2008 financial crisis occurred in this period and is consistent with Schwert (1989, 2011) who suggests that volatility changes over time and is usually higher during financial crises.

Figure 6.4 Intraday patterns of 30 minute window trading volume and volatility by days of the week

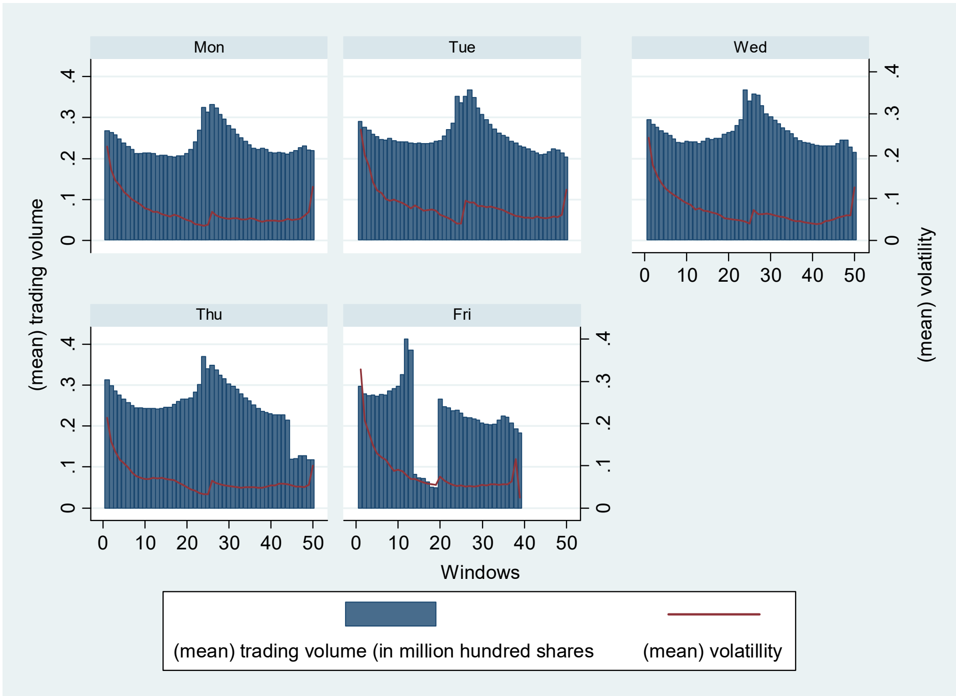


Figure 6.4 depicts the intraday patterns of trading volume and volatility over the days of the week. From Monday to Wednesday, trading volume shows a W-shaped pattern due to the high intensity of trading during opening and closing hours in both trading sessions. The figure shows that during Thursday and Friday, there are heavy trading activities during the opening and the closing of morning trading session. However, in the afternoon session, trading volume consistently decreases until the closing of the market. The light trading activity during the middle of the day is because all information has been publicly available in the marketplace. Furthermore, Figure 6.4 shows a U-shaped intraday pattern of volatility over days of the week except Friday. The volatility during morning hours is higher on Fridays than on other days of the week. Consequently, the decline of volatility on Fridays is substantially steeper than on any other day.

Having discussed the intraday patterns of trading volume and volatility, it is then worth conducting a correlation test to examine the types of relationships between variables in a systematic way. The positive correlation means that the increase in one variable leads to an increase in the other while a negative correlation means that when one variable increases, the other decreases. Finally, uncorrelated correlation means that when there are no relationships between variables.

6.2.3 Correlation test of trading volume and volatility

To examine the relationships between trading volume and volatility, this study conducted a correlation test to estimate the direction and strength of the relationships between trading volume and volatility. The results of the correlation test are shown in Table 6.2 and are provided by categories provided by subsample periods, months of the year and days of the week.

Table 6.2 Correlation matrix of trading volume and volatility

		Trading volume	**Volatility**
	Trading volume	1	
	Volatility		
Panel A: Subsample periods	Pre-GFC	0.2612	1
	GFC	0.1830	
	Post-GFC	0.0237	
Panel B: Month	Jan	0.1204	
	Feb	0.1152	
	Mar	0.1690	
	Apr	0.1590	
	May	0.0990	
	Jun	0.0186	
	Jul	–0.0150	
	Aug	0.0681	
	Sep	0.0619	
	Oct	0.0324	
	Nov	0.0344	
	Dec	0.0975	
Panel C: Day	Mon	0.0988	
	Tue	0.0953	
	Wed	0.0465	
	Thu	0.0986	
	Fri	0.0768	

Note: The table reports the correlation matrix between trading volume and volatility decomposed by subsample periods, months of the year, and days of the week.

Table 6.2 shows that there are positive correlation between trading volume and volatility of returns in almost all categories. The positive correlation means that the increase in one variable leads to an increase in the other while a negative correlation means that when one variable increases, the other decreases. Panel A of Table 6.2 shows that the highest positive correlation between trading volume and volatility is reported during the pre-GFC period (0.2612) and the lowest positive correlation between those variables is during post-GFC period (0.0237). In addition, the correlation between trading volume and volatility was reported positive over months of the year with the highest correlation in the month of March (0.16900). A marginally negative correlation between trading volume and volatility was reported in July (-0.0150). Mondays, Tuesdays, Thursdays and Fridays are days when the correlation between trading volume and volatility is high whilst Wednesday is the day when the correlation between the variable is low (0.0465). The results in Table 6.2 suggest that there is a weak or no relationship between the trading volume and the volatility of the Indonesian equity market returns over the sample period.

The correlation test, however, only indicates any statistical relationships between trading volume and volatility, and is not intended to measure the causal relation between those variables. The next section discusses a model to measure the causal relationships between trading volume and volatility of returns.

6.3 The relationships between trading volume and volatility: Models and empirical findings

This study follows the approach of Brailsford (1996) and Shahzad et al. (2014) who use five minute data to examine the relationships between trading volume and the volatility of LQ45 returns. Furthermore, this study conducts two tests to measure the relationships between trading volume and volatility: (1) a test to identify the contemporaneous impact of trading volume on volatility, and (2) a test to identify on the causal relationship between trading volume and volatility. The results and discussion of the tests will be provided following each approach.

6.3.1 Contemporaneous relationships between trading volume and volatility

The tests of the contemporaneous impact of trading volume on volatility aim to verify the results of correlation matrix, shown in Table 6.2, by investigating the impact of trading volume on volatility during the day using equation (6.1). The relationships are estimated using Ordinary Least Square (OLS) regression with robust standard errors.

The impact of trading volume on volatility of returns is examined by subsample periods, months of the year and days of the week, months, and using a model as follows:

$$RV_{t,h} = a_o + a_1 RV_{t-1} + a_2 AV_{\mathrm{t}} + \sum_{i=1}^{2} a_3 dsubs_i + \sum_{j=1}^{11} a_4 dmonth_j + \sum_{k=1}^{3} a_5 dday_k + \varepsilon_t \qquad (6.1)$$

where the dependent variable $RV_{t,h}$ is the intraday volatility in the 30 minute window (j) on day t, a_o *is* positive and significant if the moving average trading volume $AV_{t,h}$ has a positive relationship with volatility, or negative otherwise. Furthermore, following Pisedtasalasai and Gunasekarage (2007), this study uses the first lag of realized volatility $RV_{i,t-1}$ as an independent variable to take into account the autocorrelation process of these high-frequency data. The study also introduces dummies $dsubs_i$ to examine the relationship over different subsample periods, and $dmonth_j$ and $dday_k$ to take account the patterns and relationships during both months of the year and days of the week.

Due to differences in trading hours between Fridays and other days of the week, and to be similar to empirical tests of volatility in Chapter 5, this study separates the regression results based on groups of days of the week: (1) from Monday to Thursday and (2) Friday.

Table 6.3 Results of the contemporaneous impact of trading volume on volatility

	Monday – Thursday			**Friday**		
VARIABLES	**(Pre-GFC)**	**(GFC)**	**(Post-GFC)**	**(Pre-GFC)**	**(GFC)**	**(Post-GFC)**
Lag RV	0.8718***	0.8570***	0.8420***	0.8747***	0.6627***	0.8202***
	(23.2596)	(33.5675)	(42.9064)	(15.6376)	(4.6183)	(12.1158)
AV	0.0338***	0.0585***	–0.0035***	0.0473***	0.0642**	–0.0017
	(5.6923)	(7.3358)	(–4.5974)	(3.9176)	(2.3727)	(–1.0279)
Constant	0.0005	0.0047	0.0047***	–0.0033	0.0453*	0.0064**
	(0.2901)	(1.0856)	(7.6818)	(–1.1556)	(1.8369)	(2.3663)
Observations	15,744	16,045	37,067	2,774	2,923	6,685
R-squared	0.8670	0.8652	0.8214	0.8834	0.7263	0.9259

Note: The table reports the estimation results of equation (6.1) using OLS with robust t-statistics in parentheses. The table demonstrates regression results of 30 min average trading volume (AV) on volatility decomposed by subsample periods and days of the week. For brevity, the table does not show the results of dummies of subsample period and days of the week. ***,**, and * suggest significance at 1%, 5%, and 10%, respectively. The data are from January 2006 to December 2012. For brevity, the regression results for $dsubs_i$, $dsubs_i$, and $dsubs_i$ are not presented in this table.

Table 6.3 shows the regression results of trading volume and volatility. The table shows that there is a positive and statistically significant impact of trading volume on volatility in the periods before and during the GFC. However, the impact of the trading volume on volatility during the GFC is higher than the period before. This finding is not only reported from

Monday to Thursday but also during Friday. After the GFC, the relationship between volume and volatility is negative and significant from Monday to Thursday (–0.0035), but not significant during Friday.

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 from1990 to 2004 due to the increase of informational efficiency in the markets. Previous studies also find that the positive correlation between volume and volatility is caused by unexpected trading volume made by noise traders and speculative traders (Girard & Biswas 2007) or due to increased foreign transactions (Wang 2007a).

Furthermore, Girard and Biswas (2007, p.431) suggest that the negative relation between expected trading volume 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 markets where information is asymmetrically distributed.

Having presented the results of the first test on the relationships between trading volume and volatility, next the relationships between trading volume and volatility will be examined using Grange-causality test and provided in the following sections.

6.3.2 Causal relationships between trading volume and realized volatility

This section discusses the second approach to examining the relationships between the trading volume and volatility. Following Pisedtasalasai and Gunasekarage (2007), this study employs a Vector Autoregressive (VAR) model of a Granger-causality test to examine whether the relationship between trading volume and volatility is uni- or bi-directional.

Despite criticism of the model's lack of economic meaning, and the risk of a loss of a degree of freedom, the VAR model is chosen for several reasons (Asteriou & Hall 2007, pp. 279–83). First, the model is simple but helps measure the causality between variables. With this model, both trading volume and volatility can be treated symmetrically. This means that the trading volume can be affected by volatility and, simultaneously, volatility can be affected by trading volume. Second, the estimation is also simple and can be completed using the usual

OLS method. Last, according to Asteriou and Hall (2007, pp. 279–283), this model forecasts better than does the simultaneous equation model.

The Granger-causality test used in this study is conducted in two steps. Assuming that both trading volume and realized volatility data series are stationary, the first step is to estimate the VAR model. The Granger-causality test then checks the significance of the coefficients resulting from the estimation and applies variable deletion tests (Asteriou & Hall 2007, p. 282).

The VAR model used in this Granger-causality test is shown as follows:

$$RV_{t,h} = \alpha_0 + \sum_{i=1}^{k} \alpha_i RV_{t-i} + \sum_{i=1}^{k} \beta_i AV_{t-i} + \varepsilon_{1_t} \tag{6.2}$$

$$AV_t = \varphi_0 + \sum_{i=1}^{k} \varphi_i RV_{t-i} + \sum_{i=1}^{k} \gamma_i AV_{t-i} + \varepsilon_{2_t} \tag{6.3}$$

where the dependent variable $RV_{t,h}$ is the intraday volatility in the 30 minute window (j) on day t, a_o *is* positive and significant if the moving average trading volume $AV_{t,h}$ has a positive relationship with volatility, or negative otherwise. Following Pisedtasalasai and Gunasekarage (2007), this study uses the first lag of realized volatility RV_{t-1} as an independent variable to take into account the autocorrelation process of the data. The model is used to test either H_0: $\beta_1 = \beta_2 = \ldots = \beta_k = 0$ against the alternative that the trading volume Granger-causes the volatility, or H_0: $\varphi_1 = \varphi_2 = \ldots = \varphi_k = 0$ against the alternative that the volatility of returns Granger-causes the trading volume. This study utilizes a standard t-test to examine Granger-causality between trading volume and realized volatility. To take account the effects of seasonality, the results of the estimation are decomposed into subsample periods across days of the week.

Before estimating the VAR model, a test of stationarity is conducted and the number of lags to be used in the test is determined. A study by Pisedtasalasai and Gunasekarage (2007) found that the Indonesian stock returns series is stationary from lag 0 up to lag 13, whilst for trading volume the data series is stationary from lag 9 to lag 25. However, more recent studies, such as Shahzad et al. (2014), use the 5 lags based on the Schwarz Bayesian criterion to conduct the test of stationarity.

Following Pisedtasalasai and Gunasekarage (2007), this thesis conducted stationarity tests for both realized volatility and trading volume variables using the Augmented Dickey-Fuller

(ADF) and Phillips-Perron (PP) unit-root tests. The test uses 6 lags level in the stationarity tests because the lag number is within the range of the lag numbers that were found stationary based on similar tests conducted by Pisedtasalasai and Gunasekarage (2007). Moreover, the 6 lags data represent a 30 minute observation when the impact of information arrivals on prices is completed (Andersen, Bollerslev, Diebold & Labys 2003).

Table 6.4 Tests for unit-roots for realized volatility and trading volume

Variables		Lag (n)	ADF	PP
Panel A: Full sample period				
Volatility	RV_t	6	–85.854***	–156.595***
		12	–42.225***	–155.857***
Volume	AV_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	AV_t	6	–35.302***	–47.987***
		12	–28.996***	–44.177***
Panel C: GFC period				
Volatility	RV_t	6	–42.012***	–79.055***
		12	–22.300***	–78.501***
Volume	AV_t	6	–31.432***	–49.743***
		12	–23.840***	–45.800***
Panel D: Post–GFC period				
Volatility	RV_t	6	–49.186***	–131.294***
		12	–22.302***	–130.384***
Volume	AV_t	6	–31.157***	–65.717***
		12	–21.302***	–60.548***

Note: The table reports the results of the ADF and PP tests for unit roots. The RV_t and AV_t denote realized volatility and moving average trading volume respectively. Both ADF and PP are computed with trend and divided into full sample and three subsample periods. The number of lags is chosen based on Andersen, Bollerslev, Diebold & Labys (2003) and Pisedtasalasai and Gunasekarage (2007). The null hypothesis of the tests is that the data contain unit–root. For consistency, this study uses 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 6.4 reports the statistics of both ADF and PP unit-root tests for both realized volatility RV_t and trading volume AV_t. Panel A of Table 6.4 shows the results for the full sample period whilst Panels B, C and D of the table report the results for pre-GFC, GFC and post-GFC periods. The ADF statistics suggest rejecting the null hypothesis, meaning that both the realized volatility and the trading volume series follow a stationary process both at full sample and at every subsample period, and all the t-statistics are significant at 1 per cent level. The PP unit-root test results confirm the test results of the ADF.[23]

[23] This study finds similar results when experimenting with 13 lags levels both for the ADF and PP-unit root tests.

Having the results of stationarity tests, the next step is to conduct the Granger-causality test using the VAR model shown in equation (6.2) and (6.3). The results of the Granger-causality test of trading volume and volatility are provided in Table 6.5.

Panel A of Table 6.5 reports the results when realized volatility RV_t is the dependent variable. Furthermore, Panel B of Table 6.5 reports the results of Granger-causality test when trading volume AV_t is the dependent variable. In both panels, the results are presented by full sample and subsample periods, and further decomposed by groups of days of the week.

Panel A of Table 6.5 shows that trading volume Granger-causes volatility only from Mondays to Thursdays of the full-sample period. Trading volume has an 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 per cent and 1 per cent significant levels. These findings are consistent with Pisedtasalasai and Gunasekarage (2007) who find a negative impact of trading volume on volatility at the fifth lag and at 5 per cent level of significance. However, trading volume does not Granger-cause volatility on Friday. This study then conducted the Granger-causality tests of trading volume on volatility if the observations were decomposed into subsample periods and days of the week.

As presented in Panel A of Table 6.5, prior to GFC and during Monday to Thursday, trading volume Granger-causes volatility at the first lag (0.0626) which is significant at 1 per cent level of significance. Similar results are found until the sixth lag level with different impact directions and level of significance during this period. In addition, Friday data show that a significant relationship between trading volume and volatility occurs at first lag level with negative β_{-1} negative coefficient (0.0539) and significant at 5 per cent level.

Table 6.5 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. 6.2								
Lag(k)								
α_0	0.0075***	0.0040***	0.0085***	0.0107***	0.0096***	0.0093**	0.0051***	0.0077***
	(21.5556)	(6.8006)	(5.7869)	(7.2972)	(10.1650)	(2.5550)	(19.2372)	(8.7764)
α_{-1}	1.0575***	1.1565***	0.9798***	0.9943***	1.0372***	0.9783***	1.2476***	1.1763***
	(242.7049)	(122.9432)	(55.2853)	(114.2243)	(98.9545)	(45.4526)	(175.2829)	(74.0136)
α_{-2}	–0.1295***	–0.1774***	–0.3032***	-0.0924***	–0.1834***	–0.0916***	–0.3654***	–0.2745***
	(–20.8271)	(–12.7997)	(–11.8677)	(-7.6469)	(–12.4803)	(–3.1565)	(–33.1030)	(–11.4179)
α_{-3}	–0.0048	–0.0593***	0.1512***	-0.0016	0.0880***	0.0734***	0.0879***	0.0370
	(–0.8128)	(–4.9204)	(5.8050)	(-0.1377)	(6.1374)	(2.6232)	(8.1126)	(1.5624)
α_{-4}	–0.0484***	–0.0983***	0.1550***	-0.0414***	–0.0406***	–0.0815***	–0.0152	–0.0110
	(–9.0908)	(–8.6942)	(6.0731)	(-4.0062)	(–3.0216)	(–3.0448)	(–1.4968)	(–0.5280)
α_{-5}	–0.0352***	0.0451***	–0.1839***	-0.0334***	–0.0733***	–0.0350**	–0.1146***	–0.1450***
	(–7.1115)	(4.1780)	(–7.6648)	(-3.4594)	(–8.3463)	(–1.9929)	(–12.9902)	(–8.2200)
α_{-6}	0.0335***	0.0145**	–0.0124	0.0259***	0.0371***	0.0268***	0.0641***	0.0923***
	(11.1909)	(2.2113)	(–0.8136)	(4.3824)	(9.7540)	(3.9131)	(12.9936)	(11.1788)
β_{-1}	0.0039	0.0626***	0.1132***	0.0192*	0.0008	–0.0539**	–0.0038*	0.0041
	(1.2253)	(8.8843)	(6.6524)	(1.6864)	(0.1518)	(–2.4293)	(–1.7805)	(1.0242)
β_{-2}	0.0059	–0.0572***	–0.1046***	0.0318	0.0023	0.0682*	0.0051	–0.0046
	(1.1402)	(–5.3531)	(–3.9398)	(1.6315)	(0.2957)	(1.7809)	(1.4611)	(–0.8197)
β_{-3}	0.0040	0.0055	–0.0233	0.0627***	0.0037	0.0949**	–0.0044	–0.0003
	(0.7406)	(0.5155)	(–0.8661)	(2.6978)	(0.4700)	(1.9822)	(–1.2373)	(–0.0437)
β_{-4}	–0.0087	0.0225**	0.0485*	–0.0674***	0.0006	–0.0750	0.0010	0.0015
	(–1.6174)	(2.1397)	(1.8257)	(–2.8181)	(0.0718)	(–1.4673)	(0.2802)	(0.2616)
β_{-5}	–0.0126**	–0.0398***	–0.0535**	–0.0470**	–0.0062	–0.0629	–0.0040	–0.0010
	(–2.4830)	(–3.8599)	(–2.0184)	(1.9917)	(–0.7978)	(–1.2477)	(–1.2272)	(–0.1781)
β_{-6}	0.0092***	0.0178***	0.0316*	0.0276*	–0.0002	0.0565*	0.0047**	–0.0023
	(2.9410)	(2.6377)	(1.8125)	(1.8299)	(0.0392)	(1.7403)	(2.3878)	(–0.5930)
Panel B: Coefficient Estimates of Eq. 6.3								
Lag(k)								
φ_0	0.0165***	0.0181***	0.0210***	0.0192***	0.0276***	0.0223***	0.0182***	0.0259***
	(34.1388)	(23.6407)	(10.6289)	(16.4192)	(14.1637)	(6.0120)	(24.3694)	(7.9655)
φ_{-1}	0.0003	0.0492***	0.0211	0.0113	0.0183	–0.0138	–0.0425**	0.0496
	(–0.0476)	(4.0613)	(0.8825)	(1.6264)	(0.8435)	(–0.6276)	(–2.1252)	(0.8373)
φ_{-2}	–0.0086	–0.0439**	–0.0711**	–0.0184*	–0.0293	–0.0107	0.0874***	–0.0447
	(–0.9939)	(–2.4610)	(–2.0602)	(–1.9151)	(–0.9602)	(–0.3629)	(2.8176)	(–0.4983)
φ_{-3}	–0.0048	–0.0052	0.0438	–0.0052	0.0258	0.0194	–0.0438	0.0755
	(–0.5877)	(–0.3324)	(1.2446)	(–0.5692)	(0.8662)	(0.6818)	(–1.4406)	(0.8545)
φ_{-4}	–0.0041	–0.0115	0.0036	–0.0040	–0.0280	0.0017	0.0121	–0.1275
	(–0.5481)	(–0.7914)	(0.1032)	(–0.4811)	(–1.0039)	(0.0622)	(–0.4233)	(–1.6409)
φ_{-5}	0.0033	0.0058	–0.0280	–0.0006	0.0121	–0.0043	0.0274	0.0569
	(0.4845)	(0.4142)	(–0.8645)	(–0.0832)	(0.6644)	(–0.2421)	(1.1066)	(0.8646)
φ_{-6}	0.0045	0.0102	0.0099	0.0094**	0.0064	0.0020	–0.0046	0.0116
	(1.0796)	(1.2109)	(0.4828)	(1.9932)	(0.8149)	(0.2894)	(–0.3354)	(0.3766)
γ_{-1}	1.1642***	1.1250***	1.1528***	1.0744***	1.0292***	1.0594***	1.1897***	1.0126***
	(264.8038)	(124.0624)	(50.1228)	(118.3723)	(94.4988)	(46.9223)	(197.1923)	(68.3623)
γ_{-2}	–0.1367***	–0.1445***	–0.2322***	–0.1881***	–0.2974***	–0.2524***	–0.1273***	–0.3017***
	(–19.0063)	(–10.5004)	(–6.4700)	(–12.1297)	(–18.6828)	(–6.4754)	(–12.9680)	(–14.2874)
γ_{-3}	–0.0525***	–0.0419***	0.0451	0.0849***	0.1649***	0.1376***	–0.0907***	0.1734***
	(–6.9466)	(–3.0252)	(1.2435)	(4.5860)	(9.9877)	(2.8236)	(–9.0833)	(8.0741)

Var.	Monday-Thursday Full sample	Pre-GFC	GFC	Post-GFC	Friday Full sample	Pre-GFC	GFC	Post-GFC
γ_{-4}	–0.0138*	0.0123	0.0072	–0.0399**	–0.0388**	–0.0217	–0.0105	–0.0440**
	(–1.8432)	(0.9078)	(0.2021)	(–2.0962)	(–2.3463)	(–0.4165)	(–1.0603)	(2.0572)
γ_{-5}	–0.0656***	–0.0665***	–0.0941***	–0.0531***	0.0105	-0.0681	–0.0647***	0.0222
	(–9.2845)	(–5.0093)	(–2.6247)	(–2.8271)	(0.6508)	(–1.3261)	(–7.0755)	(1.0662)
γ_{-6}	0.0376***	0.0087	0.0170	0.0228*	–0.0354***	0.0211	0.0405***	0.0386***
	(8.6665)	(1.0075)	(0.7200)	(1.8976)	(–3.2368)	(0.6390)	(7.3213)	(–2.6903)
Obs.	52,273	11,964	1,898	12,187	8,457	1,998	28,122	4,561

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

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

$$AV_t = \varphi_0 + \sum_{i=1}^{k} \varphi_i RV_{t-i} + \sum_{i=1}^{k} \gamma_i AV_{t-i} + \varepsilon_{2t}$$

where RV_t and AV_t are realized volatility and moving average volume respectively. The Granger-causality tests are decomposed by subsample periods to capture the effect of the 2008 GFC, and by day groups of the week to examine the causality relationships between realized volatility and trading volume. We select the optimal lag length (k) in the VAR model based on Andersen, Bollerslev, Diebold and Labys (2003) and Pisedtasalasai and Gunasekarage (2007). 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 average trading volume Granger-causes intraday realized volatility. Panel B reports the results when average trading volume AV_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 on Granger-causality tests of trading volume and volatility are reported during the GFC. From Mondays to Thursdays in the GFC period, trading volume had a positive impact on volatility at the first lag level with positive β_{-1} (0.1132) coefficient and 1 per cent level of significance, which is higher than that during the pre-GFC period (0.0626). In addition, during Fridays of the GFC period, trading volume negatively causes volatility at the first lag level (–0.0038) and is significant at the 5 per cent level. Nevertheless, different results between groups of days of the week are found for the test during the post-GFC period. After the GFC and from Mondays to Thursdays, trading volume Granger-causes volatility at the first lag level (0.0192) and is significant at the 1 per cent level. However on Fridays, trading volume does not Granger-cause volatility.

Having reported the results of Granger-causality tests of trading volume on volatility, the following section discusses the test results of the trading volume as the dependent variable.

In Panel B of Table 6.5 this study shows the results of the tests of the null hypothesis that the volatility does not Granger-cause the trading volume. The table shows that, during the full sample period, volatility does not Granger-cause trading volume, both for Mondays to

Thursdays and Fridays. The table shows different results when the observation is decomposed into subsample periods. The volatility Granger-causes trading volume only during the pre-GFC period and from Mondays to Thursdays at the first lag level with φ_{-1} coefficient (0.0492) which is significant at 1 per cent level. During the GFC, volatility has a negative impact on trading volume at the second lag level (–0.0711) with 5 per cent significant level. However, that significant impact is only reported during Mondays to Thursdays. A similar finding is reported also during the post-GFC period when the volatility Granger-causes trading volume with negative ϕ_{-2} coefficient (–0.0184) which is significant at 1 per cent level. These findings are similar with Pisedtasalasai and Gunasekarage (2007) who find strong evidence that the volatility of returns Granger-causes trading volume with positive coefficient and significant at 1 per cent level.

Overall, the Granger-causality tests suggest that trading volume has significant effects on volatility, particularly from Mondays to Thursdays. Before the GFC, the impact of trading volume on volatility is evidenced throughout the week. Similar to these findings, the effect of trading volume on volatility also exists during the GFC period but with a greater magnitude. However, the test of Ganger-causality during post-GFC suggests that the impact of trading volume on volatility can only be observed from Mondays to Thursdays.

6.4 Conclusion

This chapter examined the contemporaneous and causal impact of trading volume on the volatility of Indonesian stock returns from 2006 to 2012 using five minute data. Although there are several empirical studies providing evidence on the relationship between trading volume and volatility, studies on the relationship between the two variables in the Indonesian stock market using high-frequency data are rare.

Consistent with the literature, this study finds that trading volume and volatility increase during the GFC. It also finds different patterns of intraday trading volume and volatility before, during and after the GFC. Furthermore, there is 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, tests on the degree and direction of causality between trading volume and volatility show mixed results.

This study has 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 GFC. The practical implication of the study is that it will provide additional measures when analysing the impact of information arrival in the market by looking at changes in patterns of its proxies: trading volume and volatility.

CHAPTER 7
CONCLUSION

7.1 Introduction

The objective of this thesis has been to examine the degree of informational efficiency of the Indonesian stock market (IDX) by measuring the impact of public information arrivals on the volatility of market returns. To be more specific, this study used scheduled macroeconomic announcements as proxies for public information and measured the impact of the announcements on the volatility of the returns of the LQ45 market index. In order to achieve this objective, three main research questions were addressed. These questions were derived from gaps in the literature and from the mixed results of previous empirical studies and, for convenience, are re-stated as follows: (1) What is the pattern of intraday volatility of returns of the Indonesian stock market? (2) How and to what extent is the intraday volatility of stock market returns affected by the arrival of public information? and (3) How and to what extent that volatility correlate with trading volume?

There were three main components that were used to address the research questions: volatility of returns, macroeconomic announcements and trading volume. The volatility was estimated using historical market index prices taken every five minutes and calculated using the realized volatility model. There are two sources of macroeconomic announcements used in this thesis: the U.S. macroeconomic announcements and the Indonesian macroeconomic announcements. The U.S. Federal Reserve's target interest rates were used as a proxy for the U.S. macroeconomic announcements. In addition, there are nine Indonesian scheduled macroeconomic announcements used in this study: the BI interest rate, inflation, GDP, export-import, foreign reserves, consumer confidence index, money supply, consumer confidence index, motorcycle sales and wholesale price index. The last variable used in this study is trading volume, which was calculated as the moving average of the number of shares traded in every thirty minutes. The period of the study is from 2 January 2006 to 31 December 2012.

There are two reasons for using volatility as a measure of market efficiency in this study. First, the data of volatility are stationary and have zero mean and variance, which means that issues with negative movements and net-off response can be avoided. Second, there is scant research using volatility as a measure of market informational efficiency, particularly in the context of the Indonesian stock market. Investigations into the informational efficiency of the market were conducted by looking at the impact of macroeconomic announcements on the volatility and the relationships between volatility and trading volume.

7.2 Summary of results and discussion

The intraday volatility of the IDX returns showed a reverse J-shaped pattern during the sample period. Although the pattern is common in previous studies, this pattern was mainly influenced by the high fluctuations of stock returns during the 2008 Global Financial Crisis (GFC). When the observations of volatility were decomposed into subsample periods: before, during and after the GFC, the volatility showed two different intraday patterns. Before and after the GFC, the intraday volatility of the Indonesian stock market returns showed a U-shaped pattern. This pattern is consistent with previous studies in the literature which showed that the volatility is high following market opening and before market closing, and low during the middle of the day. During the GFC, the intraday volatility showed a reverse J-shaped pattern. These patterns indicate that the returns of the IDX were substantially more volatile during the GFC than before or after it. These findings also imply that the GFC has influenced the magnitude and patterns of intraday volatility of returns. Consequently, analysis of long-term stock market returns and risks in Indonesia, and probably in other markets, should take into account the impact of financial crises.

Scheduled macroeconomic announcements have been widely applied to measure the informational efficiency of an equity market. Additionally, tests on the impact of macroeconomic news have revealed various impacts depending on the types and periods of the released announcements.

Consistent with the literature, this thesis shows that the volatility of the Indonesian stock market returns was affected by major macroeconomic announcements and news related to Bank Indonesia interest rates, inflation, export-import figures, motorcycle sales and wholesale price index data during the sample period. Furthermore, macroeconomic announcements and news with higher frequency tended to affect volatility more than those of lower frequency as the market was better prepared for the forthcoming announcements. However, contrary to the literature, the Indonesian GDP announcements and the U.S. FOMC scheduled announcements did not affect the volatility during the sample period. During the GFC, all scheduled macroeconomic announcements and news had no statistically significant impact on volatility although volatility increased substantially during this period. Only GDP news and the U.S. FOMC news had significant impact on volatility during the crisis.

Previous research has established that trading volume has been widely used to explain the process of price discovery because it carries new information into the market. This thesis shows that there were positive correlations between trading volume and volatility in all observation periods. Trading volume and volatility also increased during the GFC. The highest positive relation between trading volume and volatility was reported at particular times, namely, during the pre-GFC period, in March and April and on Mondays, Tuesdays and Thursdays.

Two tests were conducted to further examine the relationships between trading volume and volatility. The first test was a test to measure the contemporaneous impact of trading volume on volatility. The test showed the positive and statistically significant impact of trading volume on volatility before and during the GFC. However, the impact of that before the GFC was higher than that during the GFC. After the GFC, trading volume negatively impacted on volatility.

Another test used to examine the relationships between trading volume and volatility was a Granger-causality test. Its results supported the previous test on the relationship between trading volume and volatility. The test showed bi-directional relationships between trading volume and volatility. However, in contrast to the previous test, the relationship between trading volume and volatility was more significant during the GFC period than in other periods.

7.3 Implications and recommendation

Having summarized the results and discussions, this section presents the practical and policy implications of these findings to both market participants and regulators.

Some market participants view volatility as an opportunity to make profits by conducting particular trading strategies. Others consider volatility as risk when equity returns become uncertain or do not meet expectations. From a different perspective, market regulators view excessive volatility as threats to the fairness, efficiency and integrity of the market due to substantial and rapid price movements. Failure to achieve fairness, efficiency and integrity leads to withdrawals of investors and firms from the market, and eventually affects the general economy. Therefore, a deeper understanding of high volatility can better equip regulators to develop mechanisms to reduce its impact. For OJK, for example, this study helps enhance the understanding of intraday volatility patterns either during a financial crisis, months of the year or days of the week, and whether the changes of intraday volatility are due to reactions to scheduled macroeconomic announcements or due to trading activities. Given the important economic impact of information, OJK should increase the enforcement of information disclosure regulations to ensure the quality and speed of information released to the market.

The results of this study will provide at least three benefits for market participants. First, the patterns of intraday volatility presented in this thesis suggest two different trading strategies for two types of market participants. Market participants with moderate or conservative risk levels would be able to reduce risks by taking positions only during the time when the volatility is low which suggest all information has been incorporated in prices. This recommendation is supported with the finding that trading volume was large during time intervals when the volatility was low. In addition, the findings suggest that the returns data series and the volatility data series were autocorrelated, meaning that opportunities emerged for moderate and aggressive market participants to construct profitable trading strategies.

Second, most (if not all) foreign and domestic macroeconomic announcements and news significantly impact on the volatility of IDX returns. This finding emphasizes the importance of the macroeconomic announcements and news to which market participants should pay attention. Furthermore, these findings indicate that the market participants should be able to identify other factors impacting on volatility during the day for the announcements with no significant impact.

Finally, the realized model of volatility estimation with high-frequency data used in this thesis was chosen with the motivation that the model could be easily replicated by unsophisticated market participants for similar purposes: for example, to estimate intraday volatility and draw its patterns for stocks of different industries or for different asset classes.

There are additional implications of this study for market regulators. First, the U-shaped pattern of intraday volatility found during pre- and post-GFC and the reverse J-shaped pattern during the GFC, are consistent with the literature. These empirical findings suggest that the patterns of intraday volatility of the IDX returns have not been substantially different from those of other markets. Furthermore, the market regulators, using intraday volatility pattern, should be able to identify when the market is at risk of a crisis.

Second, the results of the autocorrelation test in this thesis suggest that both the volatility of returns and the trading volume of the IDX were correlated at certain lag levels which means that there was predictability in both volatility and in the trading volume data series. The pattern of autocorrelation in the data series indicates that the Indonesian stock market is not informationally efficient despite evidence of volatility reactions to most macroeconomic announcements. The implication of these findings for market regulators, as proposed by Ederington and Lee (1993), is that volatility patterns can be used to measure the degree of market as information arrives.

Third, the results of this thesis reinforce the importance of macroeconomic announcements and news on the volatility of stock market returns. This is likely to be of interest to government policy makers and market regulators who need to be cognizant of their effects on the volatility of asset returns in financial market.

Having discussed the fact that informational efficiency is critical for maintaining market stability in the short-term, and ensuring growth in the longer term, there are three recommendations for market regulators to consider. These recommendations are relevant to the market regulators' objectives 'to become a competitive and credible world-class exchange' (Indonesia Stock Exchange 2013a, p. 1) and lead the industry to become 'a stable, resilient and liquid industry' as mandated in the Capital Market and Non-Bank Financial Institutions Master Plan 2010–2014 (Bapepam-LK 2010, p. 100).

The first recommendation is to increase the level of market's informational efficiency by improving the quality and equality of access to public information. This recommendation should be related but not limited to scheduled macroeconomic announcements, both for institutional and individual investors. So far, only those with sufficient resources can get excess profit by having such public information early and leaving the others with poor resources, especially individuals, few or no benefits from that information. To ensure that quality and equality of access to that public information, marker regulators including the OJK and BEI should identify the best mechanism for publishing the information in timely and economical ways so that investors have equal (or nearly equal) opportunity to access and utilize the information for investment decision-making. The regulators should work with other stakeholder agencies such as the central bank and the Statistics Indonesia to achieve this objective.

The next recommendation is to utilize the volatility indicator as an additional tool to judge whether the market is in a condition of abnormal volatility. The empirical results of this thesis have shown that volatility increases considerably and creates unusual intraday pattern during a financial crisis.

The last recommendation is that market regulators can use the models in this thesis, particularly the volume-volatility relationship model, as a tool to detect unusual market activities and irregular intraday price patterns. There has been abundant empirical research and theory supporting this relationship. This function is becoming more important particularly because of the application of high-frequency data amidst the gradual shifts of trading avenues from conventional broker-based trading systems to enhanced algorithmic trading systems.

7.4 Limitations

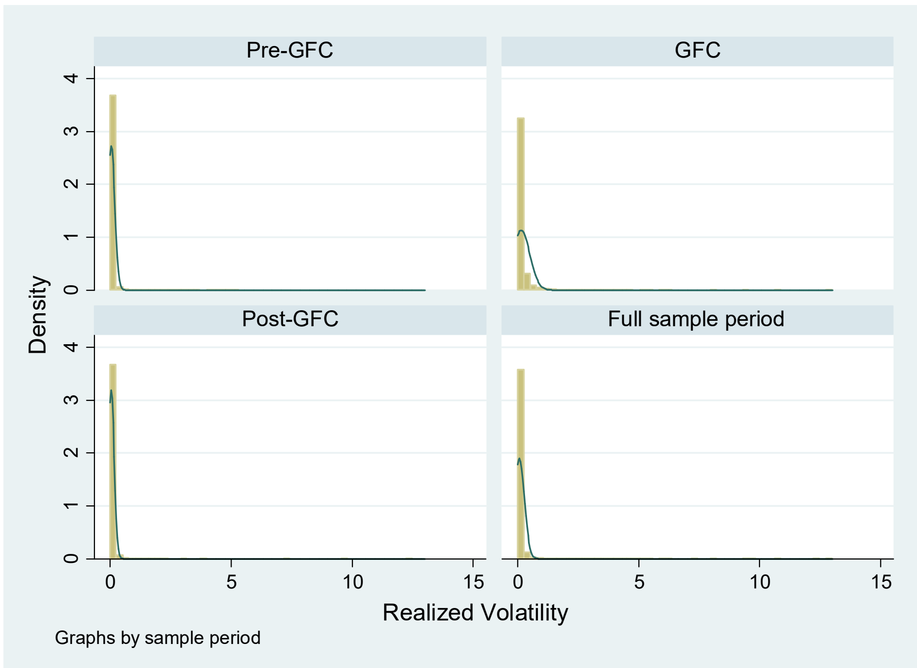
This thesis has several limitations due to the data used. The announcement times of each macroeconomic event were varied and inconsistent which cause difficulties in drawing the pattern of volatility speed and persistence during the announcements. The thesis also employed a market index data of the top 45 most liquid stocks. Although the use of the most liquid stocks ensured the availability of data for analysis, this application has several limitations. First, the data cannot capture the patterns of volatility of the whole market or of illiquid stocks which, according to the Exchange, account for about 25 per cent of the total market capitalisation. In addition, the data cannot accurately capture the impact of particular macroeconomic announcements which tend to have more impact on certain stocks or industries. For example, the announcements of interest rates impact more on financial stocks than on mining stocks due to short-term impacts on those stocks' income and revenues.

7.5 Suggestions for further research

Previous sections have presented the importance of the study of volatility and why this is useful to measure market efficiency. However, further research regarding the speed and persistence of the impact of macroeconomic announcements on the volatility of Indonesian stock market returns is warranted. Additionally, investigation of the patterns of intraday volatility and the impact of macroeconomic announcements on volatility at the company level, or using sectoral indices, may provide further valuable insights. Another possible direction for future research could to be compare the patterns and the impact of macroeconomic news between emerging markets in the region.

APPENDICES

Appendix 1 The distribution of Realized Volatility



Appendix 2 Tests for Unit-roots of Realized Volatility

Variables		Lag (n)	ADF	PP
Full sample period				
Volatility	RV_t	6	–85.854***	–156.595***
		12	–42.225***	–155.857***
Pre-GFC period				
Volatility	RV_t	6	–52.533***	–47.314***
		12	–23.689***	–46.800***
GFC				
Volatility	RV_t	6	–42.012***	–79.055***
		12	–22.300***	–78.501***
Post-GFC period				
Volatility	RV_t	6	–49.186***	–131.294***
		12	–22.302***	–130.384***

This table presents the results of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests for unit roots of stationarity for Realized Volatility (RV_t). Both ADF and PP are computed with trend and divided into full sample and three subsample periods. The number of lags is chosen based on Andersen, Bollerslev, Diebold & Labys (2003) and Pisedtasalasai and Gunasekarage (2007). The null hypothesis of the tests is that the data contain unit-root. For consistency, this study uses 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.

Appendix 3 The Breusch-Godfrey LM and the Durbin-Watson Tests for Autocorrelation

```
. estat bgodfrey, lags(1 2 3 4 5 6)

Number of gaps in sample:  3422

Breusch-Godfrey LM test for autocorrelation
```

lags(p)	chi2	df	Prob > chi2
1	282.078	1	0.0000
2	558.771	2	0.0000
3	667.256	3	0.0000
4	712.758	4	0.0000
5	767.629	5	0.0000
6	2826.485	6	0.0000

```
                         H0: no serial correlation

. estat dwatson

Number of gaps in sample:  3422

Durbin-Watson d-statistic( 16, 81238) =  1.644916
```

This table presents the results of Breusch-Godfrey LM test for autocorrelation. The results show that the statistics are high and the p-value is less than 0.05 which indicate to reject the null hypothesis and conclude that there is serial correlation in the volatility data series. The results of the Durbin-Watson test support the previous results as the *d*-statistic (1.64) is less than 2 which indicate a positive autocorrelation in the volatility data series.

REFERENCES

Adam, S & Hamlin, K 2013, 'Capital flows back to U.S. as markets slump across Asia', *Bloomberg*, 20 August, viewed 7 September 2013, <http://www.bloomberg.com/news/2013-08-19/clouds-gather-over-asian-economies-as-capital-flows-back-to-u-s-.html>.

Admati, AR & Pfleiderer, P 1988, 'A theory of intraday patterns: Volume and price variability', *The Review of Financial Studies*, vol. 1, no. 1, pp. 3–40.

Aggarwal, R, Inclan, C & Leal, R 1999, 'Volatility in emerging stock markets', *Journal of Financial and Quantitative Analysis*, vol. 34, no. 1, pp. 33–55.

Aggarwal, RK & Wu, G 2006, 'Stock market manipulations', *Journal of Business*, vol. 79, no. 4, pp. 1915–53.

Aït-Sahalia, Y, Andritzky, J, Jobst, A, Nowak, S & Tamirisa, N 2012, 'Market response to policy initiatives during the global financial crisis', *Journal of International Economics*, vol. 87, pp. 162–77.

Allford, J & Soejachmoen, MP 2013, 'Survey of recent developments', *Bulletin of Indonesian Economic Studies*, vol. 49, no. 3, pp. 267–88.

Altman, EI & Schwartz, RA 1970, 'Common stock price volatility measures and patterns', *Journal of Financial and Quantitative Analysis*, vol. 4, no. 5, pp. 603–25.

Andersen, TG 1996, 'Return volatility and trading volume: An information flow interpretation of stochastic volatility', *Journal of Finance*, vol. 51, no. 1, pp. 169–204.

Andersen, TG & Bollerslev, T 1998, 'Deutsche-Mark Dollar volatility: Intraday activity patterns, macroeconomic announcements, and longer run dependencies', *Journal of Finance*, vol. 53, no. 1, pp. 219–65.

Andersen, TG, Bollerslev, T & Cai, J 2000, 'Intraday and interday volatility in the Japanese stock market', *Journal of International Financial Markets, Institutions & Money*, vol. 10, no. 2, pp. 107–30.

Andersen, TG, Bollerslev, T & Das, A 2001, 'Variance-ratio statistics and high-frequency data: Testing for changes in intraday volatility patterns', *Journal of Finance*, vol. 56, no. 1, pp. 305–27.

Andersen, TG, Bollerslev, T, Diebold, FX & Ebens, H 2001, 'The distribution of realized stock return volatility', *Journal of Financial Economics*, vol. 61, no. 1, pp. 43–76.

Andersen, TG, Bollerslev, T, Diebold, FX & Labys, P 1999, 'Understanding, optimizing, using and forecasting) realized volatility and correlation', *Unpublished work*, Northwestern University, Duke University and University of Pennsylvania.

Andersen, TG, Bollerslev, T, Diebold, FX & Labys, P 2003, 'Modeling and forecasting realized volatility', *Econometrica*, vol. 71, no. 2, pp. 579–625.

Andersen, TG, Bollerslev, T, Diebold, FX & Vega, C 2003, 'Micro effects of macro announcements: Real-time price discovery in foreign exchange', *The American Economic Review*, vol. 93, no. 1, pp. 38–62.

Andritzky, JR, Bannister, GJ & Tamirisa, NT 2007, 'The impact of macroeconomic announcements on emerging market bonds', *Emerging Markets Review*, vol. 8, no. 1, pp. 20–37.

Aragó-Manzana, V & Fernández-Izquierdo, MA 2003, 'Monthly seasonality of the returns and volatility of the IBEX-35 index and its futures contract', *Applied Economics Letters*, vol. 10, no. 3, p. 129.

Arestis, P, Demetriades, PO & Luintel, KB 2001, 'Financial development and economic growth: The role of stock markets', *Journal of Money, Credit and Banking*, vol. 33, no. 1, pp. 16–41.

Arin, KP, Molchanov, A & Reich, O 2013, 'Politics, stock markets, and model uncertainty', *Empirical Economics*, vol. 45, no. 1, pp. 23–38.

Ashcroft, V & Cavanough, D 2008, 'Survey of recent development', *Bulletin of Indonesian Economic Studies*, vol. 44, no. 3, pp. 335–63.

ASIC 2014, *Glossary,* viewed 2 May 2014, <https://www.moneysmart.gov.au/glossary/v>.

Asteriou, D & Hall, SG 2007, *Applied econometrics : A modern approach using EViews and Microfit*, Rev. edn, Palgrave Macmillan, Basingstoke.

Australian Stock Exchange 2014, *Historical price volatility*, viewed 2 May 2014, <http://www.asx.com.au/prices/historical-price-volatility.htm>.

Bae, KH, Chan, K & Ng, A 2004, 'Investibility and return volatility', *Journal of Financial Economics*, vol. 71, no. 2, pp. 239–63.

Bandi, FM & Russell, JR 2006, 'Separating microstructure noise from volatility', *Journal of Financial Economics*, vol. 79, no. 3, pp. 655–92.

Bandi, FM & Russell, JR 2008, 'Microstructure noise, realized variance, and optimal sampling', *The Review of Economic Studies*, vol. 75, no. 2, pp. 339–69.

Bank Indonesia 2013a, *Indonesian financial statistics - statistik ekonomi dan keuangan Indonesia*, viewed 12 May 2014, <http://www.bi.go.id/en/statistik/seki/terkini/eksternal/Contents/Default.aspx#>.

Bank Indonesia 2013b, *Monetary policy framework*, viewed 1 November 2013, <http://www.bi.go.id/en/moneter/kerangka-kebijakan/Contents/Default.aspx>.

Bank Indonesia 2013c, *Financial system stability forum*, viewed 1 November 2013, <http://www.bi.go.id/en/moneter/kerangka-kebijakan/Contents/Default.aspx>.

Bank Indonesia 2014, *Financial stability review*, Bank Indonesia, Jakarta.

Bapepam-LK 2010, *Master plan pasar modal dan industry keuangan non bank 2010 - 2014 (Master plan capital market and non bank financial institutions 2010 - 2014)*, Indonesian Capital Market and Financial Institutions Supervisory Agency, Bapepamlk, Jakarta.

Bapepam 1999, *History of Indonesian capital market*, viewed 14 February 2014, <http://www.bapepam.go.id/old/old/e_profile/history/index.htm>.

Barndorff-Nielsen, OE & Shephard, N 2002, 'Estimating quadratic variation using realized variance', *Journal of Applied Econometrics*, vol. 17, no. 5, pp. 457–77.

Bartram, SM & Bodnar, GM 2009, 'No place to hide: The global crisis in equity markets in 2008/2009', *Journal of International Money and Finance*, vol. 28, no. 8, pp. 1246–92.

Basri, MC 2013, *A tale of two crises: Indonesia's political economy*, JICA-RI Working Paper No. 57, Tokyo: JICA Research Institute.

Basri, MC 2016, *The Fed's tapering talk: A short statement's long impact on Indonesia*, Ash Center Occasional Paper, June, Cambridge: Harvard Kennedy School.

Baur, DG 2012, 'Financial contagion and the real economy', *Journal of Banking & Finance*, vol. 36, no. 10, pp. 2680-92.

Bekaert, G, Erb, CB, Harvey, CR & Viskanta, TE 1998, 'Distributional characteristics of emerging market returns and asset allocation', *The Journal of Portfolio Management*, vol. 24, no. 2, pp. 102–16.

Bekaert, G & Harvey, CR 1995, *Emerging equity market volatility*, NBER Working Paper No. 5307, Cambridge, Massachusetts: National Bureau of Economic Research.

Bekaert, G & Harvey, CR 1997, 'Emerging equity market volatility', *Journal of Financial Economics*, vol. 43, no. 1, pp. 29–77.

Bekaert, G & Harvey, CR 2000, 'Foreign speculators and emerging equity markets', *Journal of Finance*, vol. 55, no. 2.

Bekaert, G & Harvey, CR 2002, 'Research in emerging markets finance: Looking to the future', *Emerging Markets Review*, vol. 3, no. 4, pp. 429–48.

Bekaert, G, Harvey, CR & Lundblad, CT 2003, 'Equity market liberalization in emerging markets', *Journal of Financial Research*, vol. 26, no. 3, pp. 275–99.

Bennett, M 1995, 'Banking deregulation in Indonesia', *University of Pennsylvania Journal of International Economic Law*, vol. 16, no. 3, pp. 443–81.

Biais, B, Glosten, L & Spatt, C 2005, 'Market microstructure: A survey of microfoundations, empirical results, and policy implications', *Journal of Financial Markets*, vol. 8, no. 2, pp. 217–64.

Białkowski, J, Gottschalk, K & Wisniewski, TP 2008, 'Stock market volatility around national elections', *Journal of Banking & Finance*, vol. 32, no. 9, pp. 1941–53.

Black, F & Scholes, M 1972, 'The valuation of option contracts and a test of market efficiency', *Journal of Finance*, vol. 27, no. 2, pp. 399–417.

Bodie, Z, Kane, A & Marcus, AJ 2008, *Investments*, 7th edn, McGraw-Hill/Irwin, Boston.

Bollerslev, T 1986, 'Generalized autoregressive conditional heteroskedasticity', *Journal of Econometrics*, vol. 31, pp. 307–27.

Bollerslev, T, Cai, J & Song, FM 2000, 'Intraday periodicity, long memory volatility, and macroeconomic announcement effects in the U.S. treasury bond market', *Journal of Empirical Finance*, vol. 7, no. 1, pp. 37–55.

Bollerslev, T, Chou, RY & Kroner, KF 1992, 'ARCH modeling in finance - a review of the theory and empirical-evidence', *Journal of Econometrics*, vol. 52, no. 1–2, pp. 5–59.

Booth, AE 1979, 'The Indonesian economy: Looking towards Repelita III', *Southeast Asian Affairs*, pp. 119–33.

Brailsford, TJ 1994, 'Stock market volatility: A review essay', *Accounting Research Journal*, vol. 7, pp. 40–60.

Brailsford, TJ 1996, 'The empirical relationship between trading volume, returns and volatility', *Accounting & Finance*, vol. 36, no. 1, pp. 89–111.

Broto, C & Ruiz, E 2004, 'Estimation methods for stochastic volatility models: A survey', *Journal of Economic Surveys*, vol. 18, no. 5, pp. 613–49.

Brownlees, CT & Gallo, GM 2006, 'Financial econometric analysis at ultra-high frequency: Data handling concerns', *Computational Statistics and Data Analysis*, vol. 51, no. 4, pp. 2232–45.

Cahyafitri, R 2013, 'Rupiah passes 11,000 per US dollar', *The Jakarta Post*, 23 August, viewed 7 September 2013, <http://www.thejakartapost.com/news/2013/08/23/rupiah-passes-11000-us-dollar.html>.

Cajueiro, DO & Tabak, BM 2004, 'Ranking efficiency for emerging markets', *Chaos, Solitons and Fractals*, vol. 22, no. 2, pp. 349–52.

Calomiris, CW, Love, I & Peria, MSM 2012, 'Stock returns' sensitivities to crisis shocks: evidence from developed and emerging markets', *Journal of International Money and Finance*, vol. 31, no. 4, pp. 743–65.

Campbell, JY, Lo, AW & MacKinlay, AC 1997, *The econometrics of financial markets*, Princeton University Press, Princeton.

Central Intelligence Agency 2014, *The world fact book, country comparison : Stock of direct foreign investment - abroad*, viewed 1 May 2014, <https://www.cia.gov/library/publications/the-world-factbook/geos/us.html>.

Chan, K, Chung, YP & Johnson, H 1995, 'The Intraday behavior of bid-ask spreads for NYSE stocks and CBOE options', *Journal of Financial and Quantitative Analysis*, vol. 30, no. 3, pp. 329–46.

Chang, RP, Ghon Rhee, S & Soedigno, S 1995, 'Price volatility of Indonesian stocks', *Pacific-Basin Finance Journal*, vol. 3, no. 2–3, pp. 337–55.

Chaudhuri, K & Koo, K 2001, 'Volatility of stock returns: Importance of economic fundamentals', *Economic and Political Weekly*, vol. 36, no. 40, pp. 3852–6.

Chen, S-S 2011, 'Lack of consumer confidence and stock returns', *Journal of Empirical Finance*, vol. 18, no. 2, pp. 225–36.

Chiang, SM, Chung, H & Huang, CM 2012, 'Volatility behavior, information efficiency and risk in the S&P 500 index markets', *Quantitative Finance*, vol. 12, no. 9, pp. 1421–37.

Choi, W-G, Sharma, S & Strömqvist, M 2009, *Net capital flows, financial integration, and international reserve holdings: The recent experience of emerging markets and advanced economies*, IMF Staff Papers vol. 56, no. 3, pp. 516–40, Washington, D.C.: International Monetary Fund.

Ciupac-Ulici, M 2012, 'The analysis of stock market volatility by rolling windows', *Quality - Access to Success*, vol. 13, no.3, pp. 101–8.

Cole, DC & Slade, BF 1996, *Building a modern financial system: The Indonesian experience*, Cambridge University Press, New York.

Cole, DC & Slade, BF 1998, 'Why has Indonesia's financial crisis been so bad?', *Bulletin of Indonesian Economic Studies*, vol. 34, no. 2, pp. 61–6.

Comerton-Forde, C 1999, 'Do trading rules impact on market efficiency? A comparison of opening procedures on the Australian and Jakarta Stock Exchanges', *Pacific-Basin Finance Journal*, vol. 7, no. 5, pp. 495–521.

Copeland, TE 1976, 'A model of asset trading under the assumption of sequential information arrival', *Journal of Finance*, vol. 31, no. 4, pp. 1149–68.

Credit Suisse 2012, *Global emerging consumer survey*, Zurich: Credit Suisse.

Cross, F 1973, 'The behavior of stock prices on Fridays and Mondays', *Financial Analysts Journal*, November-December, pp. 67–9.

Dacorogna, MM, Gençay, R, Muller, UA, Olsen, RB & Pictet, OV 2001, *An introduction to high-frequency finance*, Academic Press, San Diego.

Darrat, AF, Zhong, M & Cheng, LT 2007, 'Intraday volume and volatility relations with and without public news', *Journal of Banking & Finance*, vol. 31, pp. 2711–29.

De Santis, G & Imrohoroglu, S 1997, 'Stock returns and volatility in emerging financial markets', *Journal of International Money and Finance*, vol. 16, no. 4, pp. 561–79.

Du Toit, C & Conradie, WJ 2006, 'A realized volatility measurement using quadratic variation and dealing with microstructure effects', *Orion*, vol. 22, no. 2, pp. 117–29.

Ederington, LH & Lee, JH 1993, 'How markets process information: News releases and volatility', *The Journal of Finance*, vol. 48, no. 4, pp. 1161–91.

Ederington, LH & Lee, JH 2001, 'Intraday volatility in interest-rate and foreign-exchange markets: ARCH, announcement, and seasonality effects', *Journal of Futures Markets*, vol. 21, no. 6, pp. 517–52

Engle, RF 1982, 'Autoregressive conditional heteroscedascity with estimates of the variance of United Kingdom inflation', *Econometrica*, vol. 50, no. 4, pp. 987–1007.

Engle, RF 2002, 'Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models', *Journal of Business and Economic Statistics*, vol. 20, no. 3, pp. 339–50.

Engle, RF, Ghysels, E & Sohn, B 2013, 'Stock market volatility and macroeconomic fundamentals', *Review of Economics and Statistics*, vol. 95, no. 3, pp. 776–97.

Engle, RF & Patton, AJ 2001, 'What good is a volatility model?', *Quantitative Finance*, vol. 1, pp. 237–45.

Epps, TW 1976, 'The stochastic dependence of security price changes and transaction volumes in a model with temporally dependent price changes', *Journal of The American Statistical Association*, vol. 71, no. 356, pp. 830-34.

Epps, TW & Epps, ML 1976, 'The stochastic dependence of security price changes and transaction volumes: Implications for the mixture-of-distributions hypothesis', *Econometrica*, vol. 44, no. 2, pp. 305–21.

Erb, CB & Harvey, CR 1996, 'Political risk, economic risk, and financial risk', *Financial Analysts Journal*, vol. 52, no. 6, pp. 29–46.

Errunza, V & Hogan, K 1998, 'Macroeconomic determinants of European stock market volatility', *European financial management*, vol. 4, no. 3, pp. 361–77.

Fama, EF 1970, 'Efficient capital markets: A review of theory and empirical work', *The Journal of Finance*, vol. 25, no. 2, pp. 383–417.

Fama, EF 1991, 'Efficient capital markets: II', *The Journal of Finance*, vol. 46, no. 5, pp. 1575–617.

Fedorova, E, Wallenius, L & Collan, M 2014, 'The impact of Euro area macroeconomic announcements on CIVETS stock markets', *Procedia Economics & Finance*, vol. 15, p. 27.

Foster, FD & Viswanathan, S 1994, 'Strategic trading with asymmetrically informed traders and long-lived information', *The Journal of Financial and Quantitative Analysis*, vol. 29, no. 4, pp. 499–518.

French, KR 1980, 'Stock returns and the weekend effect', *Journal of Financial Economics*, vol. 8, pp. 55–69.

French, KR & Roll, R 1986, 'Stock return variances: The arrival of information and the reaction of traders', *Journal of Financial Economics*, vol. 17, pp. 5–26.

FKSSK 2015, FKSSK perkuat koordinasi kebijakan untuk menjaga stabilitas sistem keuangan – FKSSK to strengthen coordination in policies to maitain financial system stability, *Press Release,* Forum Koordinasi Stabilitas Sistem Keuangan, viewed 17 August 2015, <http://www.fiskal.kemenkeu.go.id/2010/edef-konten-view.asp?id=20150813171031591655933>.

Gaoxiang, W & Lim, C 2010, 'Effects of macroeconomic factors on share prices', *Journal of International Finance & Economics*, vol. 10, no. 2, pp. 113–23.

Ghon Rhee, S & Wang, J 2009, 'Foreign institutional ownership and stock market liquidity: Evidence from Indonesia', *Journal of Banking and Finance,* vol. 33, no. 7, pp. 1312–24.

Gibbons, MR & Hess, P 1981, 'Day of the week effects and asset returns', *Journal of Business*, vol. 54, no. 4, pp. 579–96.

Giles, C 2014, 'China poised to pass US as world's leading economic power this year', *Financial Times*, 30 April, viewed 1 May 2014, <http://www.ft.com/cms/s/0/d79ffff8-cfb7-11e3-9b2b-00144feabdc0.html#axzz30R0PBTQh>.

Girard, E & Biswas, R 2007, 'Trading volume and market volatility: Developed versus emerging stock markets', *Financial Review*, vol. 42, no. 3, pp. 429–59.

Glosten, LR & Milgrom, PR 1985, 'Bid, ask and transaction prices in a specialist market with heterogeneously informed traders', *Journal of Financial Economics*, vol. 14, pp. 71–100.

Goldstein, DG & Taleb, NN 2007, 'We don't quite know what we are talking about: When we talk about volatility', *The Journal of Portfolio Management*, vol. 33, no. 4, pp. 84–6.

Gorton, G 2009, 'The subprime panic', *European Financial Management*, vol. 15, no. 1, pp. 10–46.

Gorton, G 2010, 'E-coli, repo madness, and the financial crisis', *Business Economics*, vol. 45, no. 3, pp. 164–73.

Gropp, R & Kadareja, A 2012, 'Stale information, shocks, and volatility', *Journal of Money, Credit and Banking*, vol. 44, no. 6, pp. 1117–49.

Grossman, SJ & Stiglitz, JE 1980, 'On the impossibility of informationally efficient markets', *The American Economic Review*, vol. 70, no. 3, pp. 393–408.

Hadad, MD, Hall, MJB, Kenjegalieva, KA, Santoso, W & Simper, R 2011, 'Banking efficiency and stock market performance: An analysis of listed Indonesian banks', *Review of Quantitative Finance and Accounting*, vol. 37, no. 1, pp. 1–20.

Hamada, M 2003, *Transformaton of the financial sector in Indonesia*, Research Paper No. 9, Chiba: Institute of Developing Economics (IDE).

Hameed, A & Ashraf, H 2009, 'Stock market volatility and weak-form efficiency: Evidence from an emerging market', *International Journal of Business and Emerging Markets*, vol. 1, no. 3, pp. 249–63.

Hanousek, J, Kočenda, E & Kutan, AM 2009, 'The reaction of asset prices to macroeconomic announcements in new EU markets: Evidence from intraday data', *Journal of Financial Stability*, vol. 5, no. 2, pp. 199–219.

Hansen, PR & Lunde, A 2006, 'Realized variance and market microstructure noise', *Journal of Business & Economic Statistics*, vol. 24, no. 2, pp. 127–61.

Harris, L 1986, 'A transaction data study of weekly and intradaily patterns in stock returns', *Journal of Financial Economics*, vol. 16, no. 1, pp. 99–117.

Henker, T & Husodo, ZA 2010, 'Noise and efficient variance in the Indonesia Stock Exchange', *Pacific-Basin Finance Journal*, vol. 18, no. 2, pp. 199–216.

Herron, MC 2000, 'Estimating the economic impact of political party competition in the 1992 British election', *American Journal of Political Science*, vol. 44, no. 2, p. 326.

Hill, H 2000, 'Indonesia: The strange and sudden death of a tiger economy', *Oxford Development Studies*, vol. 28, no. 2, pp. 117–39.

Hill, H & Shiraishi, T 2007, 'Indonesia after the Asian crisis', *Asian Economic Policy Review*, vol. 2, no. 1, pp. 123–41.

Hossain, AA 2013, *Macroeconomic and monetary policy issues in Indonesia*, Routledge Studies in the Growth Economies of Asia, Hoboken: Taylor and Francis.

Indonesia Stock Exchange 2006, *Fact book 2006*, Jakarta: Indonesia Stock Exchange.

Indonesia Stock Exchange 2008, *Fact book 2008*, Jakarta: Indonesia Stock Exchange.

Indonesia Stock Exchange 2009a, *Annual report 2008*, Jakarta: Indonesia Stock Exchange.

Indonesia Stock Exchange 2009b, *Fact book 2009*, Jakarta: Indonesia Stock Exchange.

Indonesia Stock Exchange 2011, *Fact book 2011*, Jakarta: Indonesia Stock Exchange.

Indonesia Stock Exchange 2012, *Fact book 2012*, Jakarta: Indonesia Stock Exchange.

Indonesia Stock Exchange 2013a, *Annual report 2012,* Jakarta: Indonesia Stock Exchange.

Indonesia Stock Exchange 2013b, *Fact book 2013*, Jakarta: Indonesia Stock Exchange.

Indonesia Stock Exchange 2014a, *Annual report 2013,* Jakarta: Indonesia Stock Exchange.

Indonesia Stock Exchange 2014b, *Fact book 2014*, Jakarta: Indonesia Stock Exchange.

Inflation Monitoring and Control Coordination Team 2011, *Task fulfillment report year 2011*, Jakarta: Inflation Monitoring and Control Coordination Team.

International Monetary Fund 2010, *Indonesia: Financial system stability assessment*, Washington, D.C.: International Monetary Fund.

International Monetary Fund 2014, *Impact of Fed tapering announcements on emerging markets*, IMF Working Paper No. 14/109, pp. 1–34.

Jacquier, E, Polson, NG & Rossi, PE 1994, 'Bayesian analysis of stochastic volatility models', *Journal of Business & Economic Statistics*, vol. 12, no. 4, pp. 371–89.

Jain, PC & Joh, G-H 1988, 'The dependence between hourly prices and trading volume', *The Journal of Financial and Quantitative Analysis*, vol. 23, no. 3, pp. 269–83.

Jakarta Stock Exchange 2006, *Annual report*, Jakarta: Jakarta Stock Exchange.

James, GA & Karoglou, M 2010, 'Financial liberalization and stock market volatility: The case of Indonesia', *Applied Financial Economics*, vol. 20, no. 6, pp. 477–86.

Jansen, WJ & Nahuis, NJ 2003, 'The stock market and consumer confidence: European evidence', *Economics Letters*, vol. 79, no. 1, pp. 89–98.

Kalev, PS, Liu, W-M, Pham, PK & Jarnecic, E 2004, 'Public information arrival and volatility of intraday stock returns', *Journal of Banking & Finance*, vol. 28, pp. 1441–67.

Karpoff, JM 1987, 'The relation between price changes and trading volume: A survey', *Journal of Financial & Quantitative Analysis*, vol. 22, no. 1, pp. 109–26.

Kim, EH & Singal, V 2000, 'Stock market openings: Experience of emerging economies', *Journal of Business*, vol. 73, no. 1, pp. 25–66.

Kim, JH & Shamsuddin, A 2008, 'Are Asian stock markets efficient? Evidence from new multiple variance ratio tests', *Journal of Empirical Finance*, vol. 15, no. 3, pp. 518–32.

Kim, O & Verrecchia, RE 1991, 'Trading volume and price reactions to public announcements', *Journal of Accounting Research*, vol. 29, no. 2, pp. 302–21.

Kim, S & Nguyen, D 2008, 'The reaction of the Australian financial markets to the interest rate news from the Reserve Bank of Australia and the U.S. Fed', *Research in International Business and Finance*, vol. 22, no. 3, pp. 378–395.

Korkmaz, T, Cevik, EA & Atukeren, E 2012, 'Return and volatility spillovers among CIVETS stock markets', *Emerging Markets Review*, vol. 13, no. 2, p. 230.

Kung, JJ, Carverhill, AP & McLeod, RH 2010, 'Indonesia's stock market: Evolving role, growing efficiency', *Bulletin of Indonesian Economic Studies*, vol. 46, no. 3, pp. 329–46.

Kyle, AS 1985, 'Continuous auctions and insider trading', *Econometrica*, vol. 53, no. 6, pp. 1315–35.

Lee, B-S & Suh, J 2005, 'What drives volatile emerging stock market returns?', *Pacific-Basin Finance Journal*, vol. 13, no. 4, pp. 367–85.

Leeves, G 2007, 'Asymmetric volatility of stock returns during the Asian crisis: Evidence from Indonesia', *International Review of Economics and Finance*, vol. 16, no. 2, pp. 272–86.

LeRoy, SF & Porter, RD 1981, 'The present-value relation: Tests based on implied variance bounds', *Econometrica*, vol. 49, no. 3, pp. 555–74.

Levine, R 1997, 'Financial development and economic growth: Views and agenda', *Journal of Economic Literature*, vol. 35, no. 2, pp. 688–726.

Levine, R & Zervos, S 1998a, 'Capital control liberalization and stock market development', *World Development*, vol. 26, no. 7, pp. 1169–83.

Levine, R & Zervos, S 1998b, 'Stock markets, banks, and economic growth', *The American Economic Review*, vol. 88, no. 3, pp. 537–58.

Lumley, T, Diehr, P, Emerson, S & Chen, L 2002, 'The importance of the normality assumption in large public health data sets', *Annual Review Public Health*, vol. 23, pp. 151–69.

Madhavan, A 2000, 'Market microstructure: A survey', *Journal of Financial Markets*, vol. 3, no. 3, pp. 205–58.

Malkiel, BG 2003, 'The efficient market hypothesis and its critics', *The Journal of Economic Perspectives*, vol. 17, no. 1, pp. 59–82.

Martens, M, van Dijk, D & de Pooter, M 2009, 'Forecasting S&P 500 volatility: Long memory, level shifts, leverage effects, day-of-the-week seasonality, and macroeconomic announcements', *International Journal of Forecasting*, vol. 25, pp. 282–303.

Matsumoto, Y 2007, *Financial fragility and instability in Indonesia*, Routledge, London.

McInish, TH & Wood, RA 1992, 'An analysis of intraday patterns in bid/ask spreads for NYSE stocks', *Journal of Finance*, vol. 47, no. 2, pp. 753–64.

McKeon, R & Netter, J 2009, 'What caused the 1987 stock market crash and lessons for the 2008 crash', *Review of Accounting and Finance*, vol. 8, no. 2, pp. 123–37.

McCredie, B, Docherty, P, Easton, S & Uylangco, K 2014, 'The differential impact of monetary policy announcements and explanatory minute releases on the Australian interest rate futures market', *Pacific-Basin Finance Journal*, vol. 29, pp. 261–271.

Ministry of Finance of the Republic of Indonesia & University of Indonesia 2012, *A study on bilateral cooperation Indonesia and the U.S. in economy and finance - Kajian kerjasama bilateral Indonesia - Amerika di bidang Ekonomi dan keuangan*, Jakarta: Ministry of Finance of the Republic of Indonesia & University of Indonesia.

Ministry of Trade of the Republic of Indonesia 2014, *Economic profile*, viewed 11 May 2014, <http://www.kemendag.go.id/en/economic-profile/indonesia-export-import>.

Mishkin, FS & Eakins, SG 2012, *Financial markets and institutions*, 7th edn, Pearson, Boston.

Mitchell, ML & Mulherin, JH 1994, 'The impact of public information on the stock market', *Journal of Finance*, vol. 49, no. 3, pp. 923–50.

Mohanty, MS & Turner, P 2006, 'Foreign exchange reserve accumulation in emerging markets: What are the domestic implications?', *BIS Quarterly Review*, pp. 39–52.

Moura, ML & Gaião, RL 2014, 'Impact of macroeconomic surprises on the Brazilian yield curve and expected inflation', *North American Journal of Economics and Finance*, vol. 27, pp. 114–44.

MSCI 2011, *Indexes*, viewed 24 April 2014, <http://www.msci.com/products/indexes/>.

Mudrajad, K, Tri, W & Ross, HM 2009, 'Survey of recent developments', *Bulletin of Indonesian Economic Studies*, vol. 45, no. 2, p. 151.

Muller, UA 1993, 'Statististics of variables observed over overlapping intervals', *Unpublished work*, the O&A Research Group.

Muller, UA, Dacorogna, MM, Dave, RD, Olsen, RB, Pictet, OV & von Weizsacker, JE 1997, 'Volatilities of different time resolutions - Analyzing the dynamics of market components', *Journal of Empirical Finance*, vol. 4, pp. 213–39.

Mulyadi, MS 2009, 'Volatility spillover in Indonesia, USA, and Japan capital market', *Unpublished work,* Munich Personal RePEc Archieve.

Nanto, DK 2009, 'The global financial crisis: Analysis and policy implications', *Congressional Research Service: Issue Brief*, p. 1–105.

Nelmida, Nassir, AM & Hassan, T 2009, 'The impact of new information regime on the Jakarta Stock Exchange', *International Research Journal of Finance and Economics*, no. 33, pp. 154–67.

Nguyen, T & Ngo, C 2014, 'Impacts of the U.S. macroeconomic news on Asian stock markets', *Journal of Risk Finance*, vol. 15, no. 2, p. 149.

Nikkinen, J, Omran, M, Sahlstrom, P & Aijo, J 2006, 'Global stock market reactions to scheduled U.S. macroeconomic news announcements', *Global Finance Journal*, vol. 17, no. 1, pp. 92–104.

Nikkinen, J, Omran, M, Sahlstrom, P & Aijo, J 2008, 'The effects of US macroeconomic news announcements on emerging stock markets in the Asia-Pacific region', *Asia Pacific Journal of Economics and Business*, vol. 12, no. 1, pp. 3–14.

Nikkinen, J & Sahlström, P 2004, 'Scheduled domestic and US macroeconomic news and stock valuation in Europe', *Journal of Multinational Financial Management*, vol. 14, no. 3, pp. 201–15.

Nowak, S, Andritzky, J, Jobst, A & Tamirisa, N 2011, 'Macroeconomic fundamentals, price discovery, and volatility dynamics in emerging bond markets', *Journal of Banking & Finance*, vol. 35, no. 10, pp. 2584–97.

O'Hara, M 1996, *Market microstructure theory*, Blackwell Publishers, Cambridge.

Öğüt, H, Mete Doğanay, M & Aktaş, R 2009, 'Detecting stock-price manipulation in an emerging market: The case of Turkey', *Expert Systems With Applications*, vol. 36, no. 9, pp. 11944–9.

Ozenbas, D, Pagano, MS & Scwartz, RA 2010, 'Accentuated intra-day stock price volatility', *The Journal of Portfolio Management*, vol. 36, no. 3, pp. 45–55.

Pisedtasalasai, A & Gunasekarage, A 2007, 'Causal and dynamic relationships among stock returns, return volatility and trading volume: Evidence from emerging markets in South-East Asia', *Asia-Pacific Financial Markets*, vol. 14, no. 4, pp. 277–97.

Poon, S-H & Granger, CWJ 2003, 'Forecasting volatility in financial makets: A review', *Journal of Economic Literature*, vol. 41, no. 2, pp. 478–539.

Rangel, JG 2011, 'Macroeconomic news, announcements, and stock market jump intensity dynamics', *Journal of Banking & Finance*, vol. 35, no. 5, pp. 1263–76.

Reilly, FK & Brown, KC 2012, *Investment analysis and portfolio management*, 10 edn, Thomson/South-Western, Mason, Ohio.

Republic of Indonesia 1995, Indonesian Capital Market Law.

S&P Dow Jones Indices 2014, *Indices by asset classes*, viewed 24 April 2014, <http://au.spindices.com/>.

Sabirin, S 1991, 'Indonesia's financial reforms: Challenges in the 1990s for its banking and financial markets', *Journal of Asian Economics*, vol. 2, no. 2, pp. 383–97.

Sadka, R & Sadka, G 2009, 'Predictability and the earnings–returns relation', *Journal of Financial Economics*, vol. 94, no. 1, pp. 87–106.

Sahminan, S 2008, *Effectiveness of monetary policy communication in Indonesia and Thailand*, BIS Working Paper No. 262, Basel: Bank for International Settlements.

Samarakoon, LP 2011, 'Stock market interdependence, contagion, and the U.S. financial crisis: the case of emerging and frontier markets', *Journal of International Financial Markets, Institutions & Money*, vol. 21, no. 5, p. 724.

Sangsubhan, K & Basri, MC 2012, 'Global financial crisis and ASEAN: Fiscal policy response in the case of Thailand and Indonesia', *Asian Economic Policy Review*, vol. 7, no. 2, pp. 248–69.

Santoso, W 2000, *Indonesia's financial and corporate sector reform*, Research Paper, Jakarta: Banking Research and Regulation Directorate, Bank Indonesia.

Schwert, GW 1989, 'Why does stock market volatility change over time?' *Journal of Finance*, vol. 44, no. 5, pp. 1115

Schwert, GW 2011, 'Stock volatility during the recent financial crisis', *European financial management*, vol. 17, no. 5, pp. 789–805.

SEC 2012, *SEC approves proposals to address extraordinary volatility in individual stocks and broader stock market*, viewed 2 May 2014, <http://www.sec.gov/News/PressRelease/Detail/PressRelease/1365171482422#.U2N93KKZFZJ>.

Segara, L & Sagara, R 2007, 'Intraday trading patterns in the equity warrants and equity options markets: Australian evidence', *Australasian Accounting Business & Finance Journal*, vol. 1, no. 2, p. 42.

Shahzad, H, Duong, HN, Kalev, PS & Singh, H 2014, 'Trading volume, realized volatility and jumps in the Australian stock market', *Journal of International Financial Markets, Institutions and Money*, vol. 31, pp. 414–30.

Shiller, RJ 1987, 'The volatility of stock market prices', *Science*, vol. 235, no. 4784, pp. 33–7.

Shiller, RJ 2003, 'From efficient markets theory to behavioral finance', *The Journal of Economic Perspectives*, vol. 17, no. 1, pp. 83–104.

Smales, LA 2012, 'RBA monetary policy communication: The response of Australian interest rate futures to changes in RBA monetary policy', *Pacific-Basin Finance Journal*, vol. 20, no. 5, pp. 793–808.

Smales, LA 2013, 'Impact of macroeconomic announcements on interest rate futures: High-frequency evidence from Australia', *Journal of Financial Research*, vol. 36, no. 3, pp. 371–88.

Soesastro, H & Basri, MC 2005, 'The political economy of trade policy in Indonesia', *ASEAN Economic Bulletin*, vol. 22, no. 1, pp. 3–18.

Statistics Indonesia 2013, *Economic growth of Indonesia quarter IV-2012 (Pertumbuhan Ekonomi Indonesia Triwulan IV-2012)*, viewed 18 March 2013, <http://www.bps.go.id/eng/aboutusw1.php?news=1&nl=1>.

Stephan, JA & Whaley, RE 1990, 'Intraday price change and trading volume relations in the stock and stock option markets', *Journal of Finance*, vol. 45, no. 1, pp. 191–220.

Stiglitz, JE 2004, 'Capital-market liberalization, globalization, and the IMF', *Oxford Review of Economic Policy*, vol. 20, no. 1, pp. 57–71.

Storkenmaier, A, Wagener, M & Weinhardt, C 2012, 'Public information in fragmented markets', *Financial Markets and Portfolio Management*, vol. 26, no. 2, pp. 179–215.

Syurkani 2010, 'Inflation dynamics and monetary policy in Indonesia', PhD thesis, Victoria University, Melbourne.

Thenmozhi, M & Nair, KS 2014, 'Impact of changes in macroeconomic factors on treasury bond returns: Evidence from emerging and developed markets', *Amity Global Business Review*, vol. 9, pp. 24–37.

Tsay, RS 2006, 'Multivariate volatility models', *IMS Lecture-Notes Monograph Series, Time Seris and Related Topics*, vol. 52, pp. 210–222.

Wang, GJ, Yourougou, P & Wang, YD 2012, 'Which implied volatility provides the best measure of future volatility?', *Journal of Economics & Finance*, vol. 36, no. 1, pp. 93–105.

Wang, J 2007a, 'Foreign equity trading and emerging market volatility: Evidence from Indonesia and Thailand', *Journal of Development Economics*, vol. 84, no. 2, pp. 798–811.

Wang 2007b, 'Foreign ownership and volatility dynamics of Indonesian stocks', *Asia-Pacific Financial Markets*, vol. 14, no. 3, pp. 201–10.

Wood, RA, McInish, TH & Ord, JK 1985, 'An investigation of transactions data for NYSE stocks', *Journal of Finance*, vol. 40, no. 3, pp. 723–39.

World Bank 1994, *Indonesia stabililty, growth and equity in repelita VI*, World Bank, <http://www-wds.worldbank.org/external/default/WDSContentServer/WDSP/IB/1994/07/20/000009265_3961006022434/Rendered/PDF/multi0page.pdf>.

World Bank 2014, *World Databank*, viewed 1 May 2014, <http://databank.worldbank.org/data/home.aspx>.

World Federation of Exchanges 2010, *Members*, World Federation of Exchanges, viewed 18 March 2015, < http://www.world-exchanges.org/member-exchanges/key-information>.

World Federation of Exchanges 2011, *Statistics*, World Federation of Exchanges, viewed 18 March 2015, <http://www.world-exchanges.org/statistics/annual-query-tool>.

Wurgler, J 2000, 'Financial markets and the allocation of capital', *Journal of Financial Economics*, vol. 58, no. 1–2, pp. 187–214.

YahooFinance 2014, *Jakarta Composite Index Historical Price*, Yahoo Finance, viewed 27 February 2014, <http://finance.yahoo.com/q/hp?s=%5EJKSE+Historical+Prices>.