ESSAYS ON STOCK MARKET BEHAVIOUR

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ABSTRACT

This thesis consists of three empirical essays on certain aspects of the behaviour of the stock market. The first study measures the impact of political reform on stock market volatility in Southeast Asian countries using a GARCH-family of model. We find that these major political changes have positive impact on the stability of the stock market. The second study employs an Autoregressive Distributed Lag model and Toda–Yamamoto (1995) Granger causality test to assess the interaction between Thailand's stock market and macroeconomic variables. We find long-run and short-run interactions exists between the stock market index and macro variables. The third study provides another look at the volatility of the stock exchange through variance decomposition. With a short-length dataset from Thailand, we find that discount rate news and cash flow news are equally important.

Keywords: Political reform, GARCH, Autoregressive distributed lag model, Granger causality, Variance decomposition.

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CHAPTER 1

INTRODUCTION

1.1 Research background

1.1.1 The theoretical background of the stock market

The stock market is an important part of the economy. It is a place where stocks, bonds, and other sorts of securities are exchanged; its main function is to facilitate the flow of capital between the buyer and seller of securities. The stock market takes on a vital role in the economic growth and overall development of a nation. Therefore, it is of interest to governments, policy makers, as well as investors. The main functions of the stock market are as follows.

Facilitating resources

The first and fundamental function of the stock market is to allocate resources efficiently. To be more specific, the stock market helps transfer capital from surplus units to deficit ones, across time and space (Merton and Bodie, 1995). By providing a wide range of financial instruments, stock markets allow individual savers to select the investments that fit their risk appetite and liquidity needs. The better the mobilisation of savings, the higher the saving rate is (Levine and Zervos, 1998). In other words, a well-functioning stock market can generate a higher savings rate and improve the quantity and quality of investments (Singh, 1997).

Facilitating risk amelioration

The second function of the stock market is to facilitate risk amelioration. Indeed, the stock market and institutions may arise to facilitate the trading, pooling, and hedging of liquidity and downside risk, given the specific transaction and information costs (Levine, 1997). Liquid capital markets are markets where financial instruments are traded relatively inexpensively, with little uncertainty about the settlement and timing. By making trades more straightforward, stock markets allow investors to hold financial assets that can be sold easily and in a timely manner, in case the investors seek access to the savings. Firms also benefit from the permanent and long-term resources provided by the initial investor.

Acquiring investment information and allocating resources

As Carosso (1970) notes, it is costly and difficult for individual investors to evaluate firms and market conditions. That is why individual investors may not have sufficient time, capability, and means to collect and assess information on firms, their administration, and the relevant economic conditions. The lack of reliable information makes investors more reluctant to make investment decisions. This problem increases the information costs, keeping capital away from the most promising and applicable projects.

The introduction of stock markets and financial intermediaries is believed to reduce information acquisition costs (Diamond, 1984; Boyd and Prescott, 1986). Financial intermediaries and stock markets with sufficient data are believed to be better at evaluating a firm's value than individual savers. Therefore, such intermediaries can facilitate capital allocation (Greenwood and Jovanovic, 1990). An efficient stock market can also reduce the costs of information through the acquisition and diversification of firm-specific information embedded in the stock prices. Indeed, when stock markets become bigger and more liquid, it is less costly for market participants to acquire information about investment opportunities and then allocate their resources more efficiently.

Supervising managers and exerting firm control

Another function of the stock market is to monitor firm managers and promote corporate governance (Jensen and Meckling, 1976). After financing a firm, investors may demand the information acquisition and the supervision of corporate control. Indeed, the public trading of stocks efficiently reflects the information about firms and therefore allows investors to link managerial compensation to stock prices. In addition, in highly developed stock markets, poorly managed firms are easy to be taken over, followed by the firing of their current managers. Thus, better stock markets can improve corporate governance.

1.1.1 The development of the stock market in Thailand and other Southeast Asian countries

The Stock Exchange of Thailand (SET) was established on 30 April 1975 as the National Stock Exchange of Thailand. Beginning with 21 securities in 1975, it has expanded rapidly during the past 40 years, especially during the 1980s and 1990s. Specifically, the SET market has become an exchange with 454 listed securities in 1996 (before the Asia financial crisis of 1997), 501 listed securities in 2003 and 744 listed companies by the end of 2017, which are categorised into eight industrial groups[1].

The SET has witnessed a significant growth in recent decades. From 2001 to 2016, the SET's compound annual growth rate is 12.9%, and the listed companies' net profit increased 13.8% per year. In comparison, SET's growth rate is approximately twice the GDP growth rate, which is approximately 7.3% per year[2]. The SET also experienced significant growth in size. Its capitalisation has increased considerably from approximately 2,559 billion Baht (US$98.5 billion) in 1996 to approximately 15,000 billion Baht (US$432.96 billion) by the end of 2016, except for the period of the Asian crisis and the global financial crisis in which the market cap remained stable. The ratio of stock market capitalisation to gross domestic product (GDP) shares the same pattern: It increases gradually except during times of crisis, having reached a ratio of more than 100% at the end of 2016.

The Ho Chi Minh Stock Exchange (HOSE) is the largest stock exchange of Vietnam. The HOSE was established in July 2000, late compared with other stock exchanges. Starting with only two equity issues listed, the number of listed companies on the HOSE increased to 247 as of July 2010, with a market capitalisation of US$28.28 billion. Since 2010, HOSE market capitalisation has witnessed a steady average increase of 11.49% per year. With 388 listed companies as of July 2017, the size of HOSE is approximately US$100 billion, accounting for more than half of Vietnam's total GDP value.

[1] These include agro and food industry, consumer products, financials, industrials, property and construction, resources, services and technology.
[2] Source: SET, Office of the National Economic and Social Development Board.

The Vietnam stock market is highly promising. The price to earnings ratio (P/E) in the Vietnam stock market is among the lowest among other regional indices. As of July 2017, the average P/E of Vietnam was 16.5, which is the lowest compared with the P/E of China (17.1), Japan (19.2), and Indonesia (24.9). It is only higher than the P/E of Thailand (16.0). Moreover, the Vietnam stock market has been taking advantages of new government policies, which were expected to strengthen the economy with the sale of stakes in state-owned companies, the stable exchange rate, and low inflation rate. Based on these advantages, the Vietnam stock index hit a 10-year high in 2017, making it one of the hottest markets in Asia.

Indonesia is the largest economy in Southeast Asia and one of the G20 major economies. Their national stock exchange, IDX, is also one of the oldest stock markets in Asia. It was originally established in 1912 under the Dutch colonial government and reopened in 1977, after several closures during World Wars I and II. In the recent decades, the Indonesian economy has witnessed substantial growth with the average annual GDP growth rate of approximately 5%. Taking advantage of this, the Indonesia Stock Exchange index has soared with an average annual growth rate of 71.6% from January 2001 to December 2016[3]. As of the end of 2016, the market capitalisation of IDX was approximately US$490 billion, which was the highest in Southeast Asia.

The first stock exchange of the Republic of the Philippines was established in 1927 during the American colonial period under the name of the Manila Stock Exchange (MSE). The operations of the MSE ceased during the Japanese occupation

[3] The author's computations are based on Datastream data.

during World War II and recovered after Japan's surrender in 1945, with only 14 listed companies. In 1963, the Makati Stock Exchange (MkSE) was set up and started trading the same stocks as on the MSE. Only in 1992, the Philippines Stock Exchange (PSE), the national stock exchange of the Republic of the Philippines, was incorporated with the unification of the MSE and the MkSE. At the end of 2016, 265 listed companies were traded in the PSE, with a total market capitalisation of approximately US$240 billion.

In Figure 1.1, we present the market capitalisation of the four countries from 1990 to 2016; the ratio of market capitalisation over GDP is shown in Figure 1.2. It can be seen that all series experienced a volatile period before the 2007–2009 global financial crisis. However, the market capitalisation of these countries grew steadily after the crisis, from a moderate level in the case of Vietnam to very high levels in the cases of Thailand and Indonesia. In size, the market capitalisations of SET and IDX are all above US$400 billion, which is nearly double the size of the PSE. Regarding Vietnam's stock exchange, although the stock market has witnessed significant growth in recent years, its market capitalisation and market cap to GDP ratio are still relatively low.

Figure 1.1: Market capitalisation

Market capitalisation of the stock indices of Thailand, Indonesia, the Republic of the Philippines, and Vietnam in US$ billion. Owing to the shortage of information on the stock market index of the Philippines, only data from 1996 has been included in the figure.

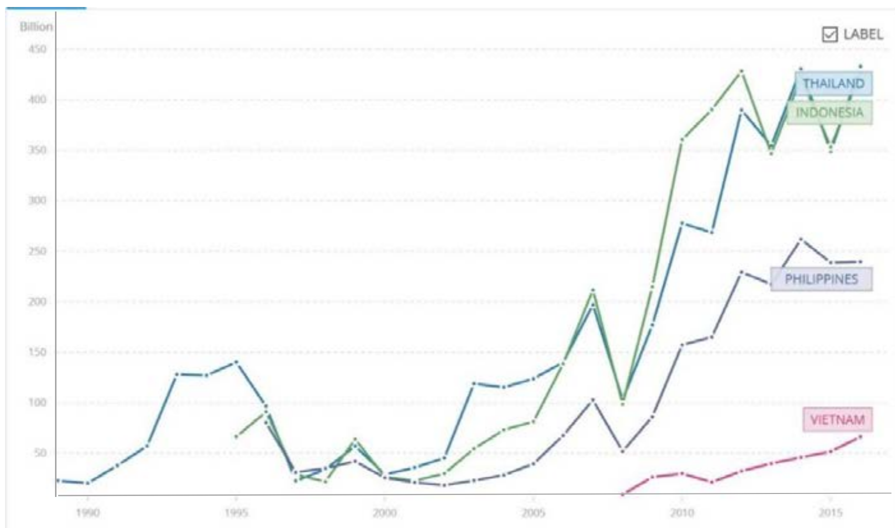
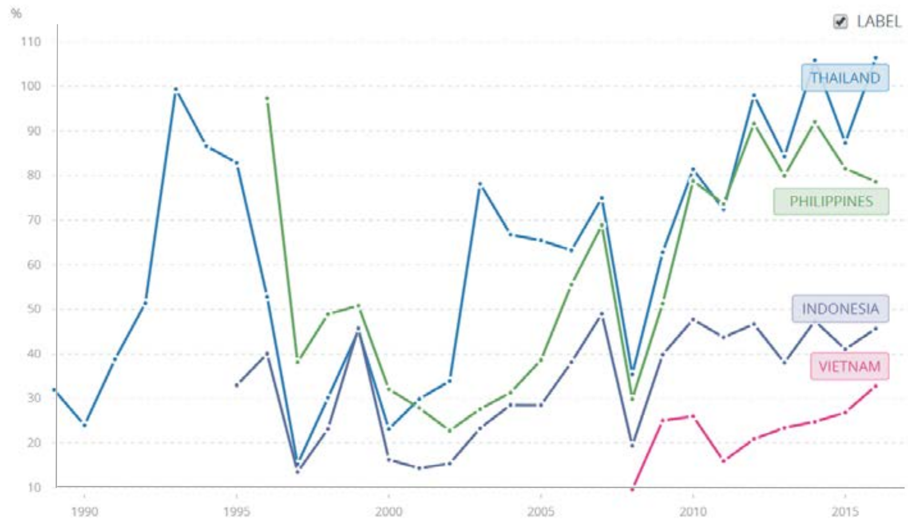


Figure 1.2: Market cap to GDP ratio

The ratios market capitalisation over GDP of Thailand, Indonesia, the Republic of the Philippines, and Vietnam in US$ billion. The data were collected from the World Bank.



1.2 Research motivations and research questions

Motivated by the significant development of the stock market in the region, together with its role in the economy, this thesis provides empirical assessments of the behaviour of the stock market.

The first empirical study (Chapter 2) measures the impact of political reform on stock market volatility in the Southeast Asian region. It aims to answer the questions: Does political reform have a positive or negative impact on the volatility of the stock markets in Southeast Asia? This question arises because of the prevailing situation of extreme political change worldwide, including recent significant changes in the politics of Southeast Asian nations: Thailand, the Philippines, Vietnam, and Indonesia. Moreover, the rapid development of the stock market in these nations together with ASEAN's advancing role in the global economy make the research more necessary.

Chapter 2 employs the conditional volatility approach on a set of daily broad market indices. Specifically, we incorporate the GARCH specifications with multiplicative dummy variables proxying political events. Coefficients related to dummies are evaluated on whether the introduction of a new government increases the volatility of stock markets or not. If a statistically significant positive coefficient is found, the political reforms are believed to increase stock market volatility. In contrast, if the coefficient is negative, the stock market becomes more stable after the reform. In this chapter, we also account for the robustness check by employing different dummies or different model specifications.

The second study (Chapter 3) focuses on another aspect of stock market behaviour: the long-term relationship between macro variables and stock prices. It emerges because macroeconomic variables reflect the state of the economy and the systematic risk. Thus, their changes will affect the economy's pricing operator as well as the dividends, two important factors determining stock prices. Over the past decades, several studies have measured these relationships, but no consistent results were found. Our study, therefore, provides another look at the relationship, using a Thailand dataset to answer two questions in emerging market condition: (i) Is there a long-term relationship between the stock market index and macroeconomic variables? and (ii) Is there any Granger causality between the stock market and macroeconomic variables?

A set of stock price index and macro variables (industrial production, money supply, exchange rate, prime lending interest rate, and the MSCI global index) is collected on a monthly basis and transformed into logarithmic form. To answer the first question, we employ the autoregressive distributed lag (ARDL) cointegration technique, which is valid regardless of whether the series is integrated of order one or stationary. Once cointegration exists, the second question will be examined using the Toda–Yamamoto Granger non-causality technique (TYDL). These two methodologies are hoped to perform better and more efficiently in a mixture of stationary and non-stationary variables, which are determined by both the traditional unit root tests and the advanced ones allowing for structural break.

In the third study, we continue to employ the dividend discounted model with two elements, dividend and discount rate, to reflect the price and return of the stock market. However, we consider it in the aspect of stock-return variance decomposition in Thailand. We aim to answer the question whether the usual findings about the dominant role of discount rate news are still true in the Thailand's case.

To answer this question, the chapter follows Campbell's (1991) variance decomposition, but considers three specific cases: (i) the baseline model resembling Campbell's (1991) approach, (ii) the modified model with the inclusion of macroeconomic variables, and (iii) the modified model with the inclusion of both macroeconomic variables and global factors. Apart from the baseline model, the two modified versions are proposed to answer criticisms of model specification errors. A large set of local macroeconomic information is extracted using the principal component methodology, and the MSCI global index is employed to reflect the global factors. The main target – the reaction of the stock return to cash flow news and discount rate news – is calculated in each case employing VAR estimation.

CHAPTER 2

MEASURING THE IMPACT OF POLITICAL REFORM ON STOCK MARKET VOLATILITY IN ASEAN COUNTRIES USING A CONDITIONAL VOLATILITY MODEL

2.1 Introduction

Stock market volatility is one of the most important risk indicators in financial markets. An increase or decrease in the volatility of the stock market price index can be attributable not only to financial and macroeconomic variables, but also to political factors (Schwert, 1989). In recent decades, several political events have had major impacts on the financial markets, e.g. the EU referendum on European Membership, the US presidential election, and the Middle East and North African civil uprisings. Significant changes in political regimes are also documented in Asia, with the most noticeable events being the political reforms of the Association of the Southeast Asian Nations (ASEAN), including Thailand, Vietnam, Indonesia, and the Philippines. With the rapid growth of ASEAN as the new hot spot and new driving force of global economic growth, a formal study investigating the impact of political reform on stock market volatility of these countries becomes necessary. Our research, therefore, aims to answer the following questions: What is government reform in ASEAN, and how does it influence the stability of financial markets within the countries? To be more specific, does this political reform have a positive or negative impact on ASEAN stock market volatility?

The topic of measuring the link between politics and stock market movement has not been uncommon in the literature. From a theoretical aspect, Pastor and Veronesi (2013) made the first attempt at accounting for the response of asset prices to political news, using the political uncertainty index. Political uncertainty refers to uncertainty about the future path of government policy. It may include uncertainty about monetary or fiscal policy, tax, regulatory regime, or election outcomes. Political uncertainty is considered to have a positive impact on stock market volatility through decision rules in their general equilibrium model time. At any point, rational investors observe the political signals and reset their beliefs about future government actions. The stock market price, therefore, responds to political uncertainty: a stronger reaction when uncertainty is greater. In other words, stock price volatility and political uncertainty should move in the same direction according this theory. As for empirical analysis, mixed results have been found, depending on specific countries, events, or sectors. The most usual finding is greater volatility in the short run, owing to the effect of political uncertainty (Bautista, 2003; Mei and Guo, 2004; Bialkowski, 2008).

This chapter aims to understand the influence of the most recent and noticeable political events on ASEAN stock market volatility. The political events in this study – political reforms – share the same special characteristics: a new government system, which is considered an extreme political event. They can take two forms in our dataset: political regime (Indonesia, Vietnam, and the Philippines) and military coup (Thailand). These changes may lead to more political uncertainty, but could also reduce it.

We use the conditional volatility model to capture special characteristics of the financial dataset: leptokurtic and volatility clustering. The three most popular forms of general autoregressive conditional heteroscedasticity (GARCH) have been employed, including the plain vanilla GARCH model (GARCH(1,1)), exponential GARCH (EGARCH(1,1)) and asymmetric GARCH (GARCH-GJR(1,1)). To model political reform, we add multiplicative dummy variables to these specifications. Additive dummy variables, together with BEKK specification proposed by Baba, Engle, Kraft, and Kroner (Baba *et al.*, 1995) capturing the volatility spillover effect, are used for a robustness check.

Using daily data for four countries within ASEAN, including Thailand, Vietnam, Indonesia, and the Philippines from January 2010 to February 2017, our research concludes that lower volatility owing to political reform is found in the cases of the three countries: Thailand, Vietnam, and Indonesia. In other words, the new government creates a beneficial impact on the stock market. Robustness tests, using additive dummy variable and the BEKK specification confirm these results.

In addition to be the latest attempt at discovering the effect of politics on the stock market, this study is the first research that concentrates on the impact of political reform on the stock market in four ASEAN member countries. Extensive employment of univariate and multivariate GARCH models with a daily dataset have demonstrated that political events in ASEAN do bring stability to the financial market – expressed by the reduction in stock-return volatility.

The chapter is organised as follows. After this introduction (Section 2.1), there is a literature review that includes a short introduction about the economy.

The background on government reforms and related literature are presented in Section 2.2. Section 2.3 provides a data description. Section 2.4 conveys the methodology employed, and Section 2.5 provides the empirical part. The final section contains a quick summary about the research motivation and the overall conclusions.

2.2 Literature review

2.2.1 Background on government reform of the Southeast Asian countries

Founded in 1967, ASEAN now consists of 10 member states located in the southeast of the Asian continent. It has become a common market of more than 600 million people, dwarfing NAFTA's 400 million and the EU's 500 million. ASEAN is playing a vigorous role in the Asian economy and has become a driver of global economic growth. At its current growth rate, ASEAN is expected to become the fourth largest market by 2030, after the EU, US, and China. For that reason, any potential political and economic factor that is believed to influence the ASEAN economy should be considered carefully. As far as politics is concerned, it can be seen clearly that remarkable changes have taken place recently in government administration (political reform) in several key ASEAN countries, including Thailand, Indonesia, the Philippines, and Vietnam. We present the brief background of the economy and political reform below to provide an overview of the countries.

- **Thailand**

Over the past few decades, Thailand has recorded remarkable growth in economic development, changing from a low-income to an upper-middle-income country (ranked in 2011). The country grew at an average of 7% annually throughout the boom period 1960–1996. After the crisis period 1997–1999, economic growth in Thailand rebounded quickly, growing at an average of 5% annually during the period 1999–2005 and approximately 3.5% during the period 2005–2015. Thailand is now on the path to recovery, with economic growth of 3.9% in 2017, and is forecast to reach 4% in 2018. It is often cited as one of the most successful economic development stories in the world.

Thailand is a mixed economic system in which both the private sector and the government are key stakeholders. The government provides infrastructure and regulation and gives the private sector the chance to own businesses. The country relies heavily on exports and is ranked 20th among the largest exporting countries in the world. The two major sectors of the economy are industry and services, each contributing nearly half of total GDP.

Regarding politics, the government system was changed from absolute monarchy to institutional monarchy in June 1932. Since then, Thailand has been embroiled in chaos, with a total of 23 military coups and coup attempts. In 2001, Thaksin Chinnawat Shinawatra, a telecommunication billionaire, became prime minister. He is the first prime minister to have twice won in landslide elections, in 2001 and 2005, with better-than-ever performance of his government. With the philosophy of populism and a focus on channelling more funds into rural areas, termed Thaksinomics, the Thai economy has recovered largely from the 1997 crisis. Nevertheless, there was still a coup against this popular, dynamic, and decisive leader, resulting from a series of his mistakes, such as undermining the media, implementing an anti-drug campaign that resulted in approximately 2,500 deaths, which is unacceptable to the Buddhist society. There was also the so-called Finland Plan to turn Thailand into republic and the abuse of the system of checks and balances of the Thai government to benefit his family's business. He was overthrown in September 2006 in a military coup, supported by the Bangkok-based establishment. The new government tried to return stability to Thailand on one hand. On the other, it continued to press charges against Thaksin. Since then, Thailand has been deeply divided into pro-Thaksin "red shirts" and pro-elite or anti-Thaksin "yellow shirts". "Red-shirt" protests occur at regular intervals, creating a volatile political situation in the country.

In 2011, Yingluck Shinawatra, the sister of the ousted Thai leader, was elected as prime minister. Massive protests against her government have occurred, with the aim of removing Thaksin's influence on Thai politics. Yingluck was removed from office by a court ruling in 2014, for transferring an officer to another post, after she became prime minister in 2011.

Prayut Chan-o-Cha, the powerful army chief launched a coup on 22 May 2014, after a series of protests and conflicts among rival parties. The coup d'état was believed to dissolve the disagreement between rival parties, particularly benefit-related conflicts between the rural areas and urban middle classes, therefore bringing an end to the turmoil.

- **Indonesia**

Indonesia is the largest economy in Southeast Asia, ranking 16th among global economies by nominal GDP, and ranking in the top ten by price-adjusted GDP (GPP). After the Asian economic and financial crisis in mid-1997, Indonesia undertook reforms in the financial sector to mitigate key risk elements of the crisis. Since then, Indonesia has achieved recovery with impressive growth of approximately 5% annually, reaching a peak of 6.5% in 2011. The key growth drivers are recovery in household consumption, which makes up more than half of GDP (World Bank data), investment, and net exports, which were fuelled by a commodities boom in the 2000s.

Like Thailand, Indonesia is a mixed economic system in which the government regulates private enterprise. The service sector contributes 46% of GDP, industry accounts for approximately 40% of GDP, and agriculture makes up approximately 14%, employing 32% of the population.

Holding the office for more than 31 years (1967–1998), Suharto instituted a policy called New Order, which helped boost economic development and reduced the inflation rate from 630% in 1966 to less than 9% by 1972. The living standard and level of education have improved substantially over the whole period, but the nation's wealth has been distributed inequitably. A small proportion of the elite have received large shares of the development. In the 1990s, corruption was at the highest level, and Suharto became the most corrupt leader according to Transparency International's corrupt leader list. As a result, riots in 1998 forced Suharto's resignation and paved the way for democracy in Indonesia, one of the most populous countries in the world.

During the post-Suharto period, known as the reformation period, important structural changes have been made including a two-term limit on the presidency and decentralisation of power to the regions. Several policies for the financial sector have been adopted to rebuild and move Indonesia towards a modern financial system. Economic growth, therefore, has been improved considerably.

The most recent election, which was held on 9 July 2014, brought President Joko Widodo into office for a five-year term. It marked a new chapter in Indonesian politics, as Widodo is the first Indonesian president without a high-ranking military or political background. President Widodo's win is widely regarded as reflecting the hope for a new type of leader, rather than the old-style Indonesian politician. Widodo's main priorities are improving the ease of doing business and transparency, as well as the development of the infrastructure. Fuel subsidies take up approximately one-third of the national budget. The subsidies are planned to be reduced or eliminated, and the savings will be redirected to priorities such as infrastructure, healthcare, education, and agriculture.

- **Philippines**

The Philippines is the 13th largest economy in Asia and ranks third in the ASEAN economy after Thailand and Indonesia. The average economic growth increased considerably from approximately 4.5% between 2000 and 2009 to an average of 6.3% between 2010 and 2016, moving the Philippines from a lower-middle-income country to an upper-middle-income country. The country's growth dynamism is rooted in strong domestic demand supported by greater economic growth, increased public spending on infrastructure, and higher employment and rising remittances. The composition of GDP is divided into three main sectors: agriculture (15%), the industrial sector (31%), and the service sector (57.5%). Although employing approximately 30% of the population, agriculture accounts for a small proportion of GDP, shifting the Philippines from an agrarian to an industrial and service-oriented country.

As for politics, the Philippines became a self-governing commonwealth in 1935. After being under Japanese and US control, the Republic of Philippines gained independence. Ferdinand Marcos ruled the country for 20 years and was widely criticised for his dictatorship, as well as his failure to prevent government bribery and corruption. Corazon Aquino led the country next (1986–1992). Her government survived several coup attempts, suggesting that resilience was one of her leadership qualities. Fidel Ramos, Joseph Estrada, and Gloria Macapagal Arroyo became presidents in the periods 1992–1998, 1998–2004, and 2004–2010, respectively. Under their governance, the Philippines experienced greater GDP growth and significant progress on economic reforms and was among the few countries that experienced no economic contraction following the global financial crisis. The presidency of Benigno Aquino III, 2010–2016, witnessed an increase in economic growth, although political and economic conditions were more volatile. His administration is remembered for its good governance, transparency, and improvements in education, agriculture, and infrastructure.

Rodrigo Duterte became the 16th president of the Philippines on 9 May 2016, after a controversial campaign. His governing ability has been questioned and doubt has been expressed about his ability to steer one of Asia's leading economies, especially because the economy was doing very well during his predecessors' terms. Duterte focuses on deadly anti-drug and anti-corruption campaigns rather than politics. His drug war kills thousands of people while ignoring the rise of ISIS and allowing a major city, Marawi, be taken by ISIS. Since President Duterte entered office, a large amount of foreign funds has been pulled out of the Philippines. The peso performed worse than the US dollar, and the Philippines stock market is the worst performer among major Asian stock markets. Duterte's leadership style, which is unpredictable, is leading to the risk of sovereign downgrade and investor concern.

- Vietnam

After more than 30 years of Doi Moi reform, the economy of Vietnam has experienced considerable growth from one of the world's poorest nations to a lower-middle-income group. The GDP per capita growth was approximately 7.9% in the 2000s, 6.5% in 2010, and approximately 6.4% in 2016. Exports have been a major source of Vietnam's revenue.

Among the agricultural, industrial, and service sectors, the service sector accounts for the largest proportion of the economy's business activity (45.5%), followed by the industrial sector (36.4%) and the agricultural sector (18.1%). Industry is mainly driven by textile, plastic, paper, and food exports; the service sector is largely composed of tourism and telecommunications.

As for politics, Vietnam is a one-party Communist state. The platform for the economy and politics is set up by the National Congress of the Communist Party. The National Congress, summoned every five years, discusses long-term policy. The Congress elects the Central Committee and the Politburo, the country's top two decision-making bodies. Under the leadership of the ninth-tenure Politburo and Prime Minister Phan Van Khai in the period 2000–2006, Vietnam achieved prosperity: rapid expansion of GDP and financial markets, large FDI inflow, and the acceleration of privatisation. The stock market, which took up less than 1% of GDP by 2000, increased its share to 22.7%. The bright outlook caused by joining the WTO kept the market rising even when the risk of a huge bubble was triggered.

In contrast, under the two-term presidency of the successor Nguyen Tan Dung, seven conglomerates, which were established to propel the economy, have degenerated into problems such as corruption, interest groups, and crony capitalism. State-owned enterprises enjoyed massive investment (70% social investment, 50% state investment, 60% ODA), but created only 10% employment and ended up with large debt. In Vietnam, loans were granted to these unprofitable sectors, based on political connections, impeding the impact of finance on the economy's development.

The 12th National Congress, held on 22 Jan 2016, was seen as a milestone after 20 years from the start of the "open policy" to the market economy. The event witnessed (i) an unexpected re-election of the current General Secretary[4], who is famous for his anti-corruption campaigns and (ii) the retreat of the Prime Minister. The re-elected General Secretary called the Party Congress a new milestone in national construction and defence. A new image of creativity and integrity are key focuses of the new government after facing many difficulties, such as corruption and budget deficits left over from the previous administration.

[4] Before the event, the General Secretary was 72 years old, the supposed age of retirement. Conventionally, the top leader of the country must be younger than 67 years old to be re-elected.

To sum up, the Southeast Asia economies have improved significantly during the past two decades regardless of the political chaos and different political regimes. All major political events in ASEAN are related to the changes in government regimes: replacing one government regime with another. They can be carried out through domestic protest (coup d'état in Thailand) or formal election (Vietnam, the Philippines, and Indonesia). Regardless of the regime changes employed, unexpected domestic protest, or periodic elections, the new governments share the same special characteristics: a new style of government compared with the past.

2.2.2 Related literature

Understanding the volatility of the stock market is crucial in finance decision-making. Several studies have targeted political uncertainty and its significant impact on stock market volatility. This literature review will provide a very short theoretical framework, together with the previous empirical analysis, about this relationship.

When it comes to the theoretical framework, not much guidance has been given on the relationship between politics and the finance market. Models covering the reaction of asset price to political variables are rarely found in finance theory. Pastor and Veronesi (2012, 2013) try to fill this gap by using a political uncertainty index to represent the political environment. They propose a general equilibrium model in which the profitability of any firm (agent) follows a stochastic process with the mean influenced by prevailing government policies. At any point, the government makes endogenous policy decisions about whether to maintain its current policy or to change to a new one. They take investors' profit and political costs, which are uncertain but can be learned through time, into consideration. If the old policy's impact on the firm's profitability is sufficiently unfavourable, it will be replaced. Once there is a change in policy, the agents will adjust their beliefs. Stock prices, therefore, react to political uncertainty: larger fluctuations when political uncertainty is greater. This decision rule suggests the effect of political uncertainty on the stock market: it causes the stock market risk premia and volatility to move in the same direction. To be more specific: higher levels of political uncertainty cause higher stock volatility (Pastor and Veronesi, 2013).

When it comes to the empirical influence of political instability, numerous studies have been conducted, from investigating the need of having political variables in the model to a focus on their impact.

Schwert (1989) made one of the first attempts to consider having variables other than macroeconomics and financial variables in explaining stock-return volatility. Schwert (1989) regresses the S&P 500 stock volatility on the interest rate, leverage ratio, trading volume, and bond volatility. He confirms the role of these variables on stock volatility but specifies their small contribution to the volatility. Especially during the Great Depression, although the macroeconomic variables experienced unexpected high volatility levels, "none increases by a factor of three", as stock volatility did, creating the volatility puzzle. De Long and Becht (1992) and Bittlingmayer (1998) consider the periods of high volatility as "peso problems", problems arising when an unexpected event occurs that affects asset prices – and note that peso problems provide a convincing explanation of excess return volatility. The key thing about peso problems is that the event does not actually have to happen while investors believe that it might, which creates excess volatility. In all of these cases, political instability is the leading cause of especially high volatility together with the group of macroeconomics and finance performance.

Follow-up studies have produced evidence to support the role of political instability (Mei and Guo, 2004; Bialkowski, 2008; Chau *et al.*, 2014; Wisniewski, 2016). Different shapes and forms ranging from major political changes, such as war, to minor changes, for example political elections and political announcements, have been considered. Nevertheless, because our research targets the reform of the four ASEAN countries through domestic protests and elections, this thesis will focus on specific findings related to these two kinds of events.

Domestic protest

Unlike a cross-border conflict, a domestic protest is a conflict happening within the borders of a country. This kind of event has been observed more frequently recently, resulting in a replacement of one government regime by another. Acemoglu, Hassan, and Tahoun (2014) measure the impact of regime change in Tunisia, Egypt, and Libya on the firm-level stock price in the period 2005–2013. Firms are divided into different categories depending on their relationship with the incumbent party. Nine days after the regime change, highly connected firms are proven to have relatively lower market value than non-connected ones (Acemoglu *et al.*, 2014). Bautista (2003) looks at the impact of regime change on the Philippines but focuses on the broad index from 1987 to 2000. Applying the regime switching model, Bautista concludes that periods of military coup are associated with the destabilisation of the stock market and higher volatility episodes. Chau *et* *al.* (2014) target Middle Eastern countries, as do Acemoglu *et al.* (2014), but focus on the impact on the broad index. Employing the conditional volatility model, Chau *et al.* (2014) indicate that stock market volatility increases significantly after civil uprisings.

The results in the cases of domestic conflict named above are similar to results in the case of armed cross-border conflict reported in Rigobon and Sack (2005) and Wolfers and Zitzewitz (2009): armed protests cause declines and fluctuations in stock prices. However, they contrast with Amihud and Wohl (2004), who argue the positive impact of the conflict and new regime in Iraq on the stock market index in the US. The authors argue that cross-border conflicts are "ultimate negative sum games"; therefore, once the conflict starts, the new regime will put an end to the devastating situation that is happening. Lower expenditure associated with the ending of the wars will lead to a positive impact in this case (Amihud, 2004).

Elections

Apart from the topics focusing on the impact of the dramatic political events, such as armed conflict, the literature on less dramatic events, namely elections, has long been studied. As for periodic elections, their impact on economic growth have been proven (Nordhaus, 1975; Wisniewski, 2016) and on the stock market (Allvine and O'Neill, 1980; Huang, 1985; Booth and Booth, 2003) with this pattern: lower economic growth / return in the first half of the term and higher growth / return in the second half. Mei and Guo (2004) supplement the impact of presidential cycles on volatility using a sample of 22 emerging countries and estimate probit model and switching regressions. A greater yearly volatility level is observed in most emerging countries during elections and transition periods, even after controlling for business-cycle variables. Bialkowski (2008) examines the broad market index, as do Mei and Guo (2004), for 27 OECD nations. Employing a conditional volatility model to measure the cumulative volatility within a short daily window, Bialkowski finds that within the election framework, the level of volatility is elevated temporarily. Smales (2016) supports Bialkowski in showing the positive relationship between political and stock market uncertainty in the Australian context: a higher uncertainty level around the election leads to greater stock-return volatility.

Fuss and Bechtel (2008) and Boutchkova *et al.* (2012) deviate from the above research, employing a broad stock market index and consider the sectoral-level exposure. Fuss and Bechtel (2008) use a GARCH-type model, which better explains characteristics of finance data: leptokurtic and volatility clustering. They categorise the influence of government partisanship in Germany on firm size: small firms are influenced by the partisanship, whereas politics does not matter to mid- and large-sized firms. The "volatility-reducing effect" of electoral uncertainty is corroborated in this research, explained by the special characteristics of the political system in Germany. Because Germany has a system of proportional representation, any electoral uncertainty will make coalitions more likely, which would imply the lower possibility of significant change in policy. Future economic stability, therefore, is expected, leading to lower stock volatility. Boutchkova *et al.* (2012) specify inconsistent reactions to a large set of different sectors in developed and developing countries, as do Fuss and Bechtel (2008). Using a panel regression of annual volatility on the political and economic variables, the authors identify a positive impact with the magnitudes differing greatly among industries.

2.2.3 Further comments on the literature and suggestions for research

The analyses of Schwert (1989) and Bittlingmayer (1998) are typical of the literature, which suggests the need for political variables in explaining greater stock-return volatility. Different methodologies have been employed to measure the impact of political events on the stock market, including events studies, panel regression and conditional volatility models. Most of them target the influence on the volatility within a short window of several days around the events (see Acemoglu *et al.*, 2014; Bialkowski, 2008; Smales, 2016). Several studies aim at the longer term impact by employing yearly volatility measurement (see Mei and Guo, 2004; Boutchkova *et al.*, 2012). Chau *et al.* (2014) provide another look at the long-term influence when dividing the dataset into only two periods: before and after the event.

As for the results, different regime changes are proven to have different impacts on stock-return volatility. Regime change deriving from armed conflicts usually cause increased stock market volatility (see Acemoglu *et al.*, 2014; Bautista, 2003; Chau *et al.*, 2014; Wolfers and Zitzewitz, 2009), but they can also lower the volatility level by putting an end to the disorder situation (Amihud *et al.*, 2004). Election-related regime changes, on one hand, are considered volatility-increasing factors (see Mei and Guo, 2004; Bialkowski, 2008; Smales, 2016); on the other, they are listed as volatility-reducing factors (Fuss and Bechtel, 2008), or are considered as having inconsistent roles (Boutchkova *et al.*, 2012).

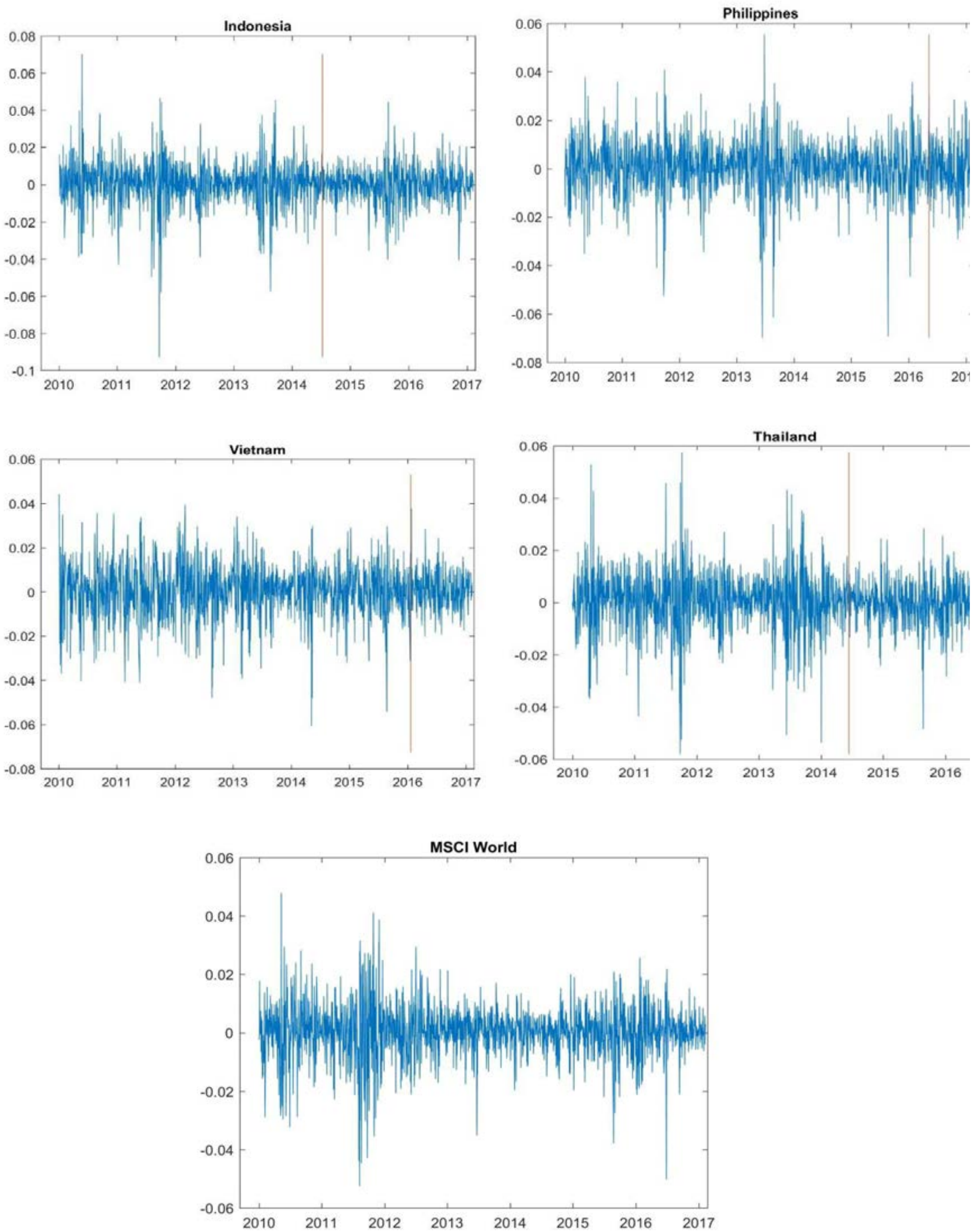
Overall, the above findings seem to suggest that the influence of regime change on volatility depends on the nature of the events: different regime changes have different impacts on different states. Most of them measure the impact around the event. To the best of my knowledge, no study has focused on the long-term impact of regime change on ASEAN countries. This chapter, therefore, aims to fill the gap by employing the conditional volatility GARCH-family models with daily data, as Fuss and Bechtel (2008) and Chau *et al.* (2014), to cover the special characteristics of a finance dataset (lepturkotosis and volatility cluster), which cannot be covered in an annual volatility measurement, as in Mei and Guo (2004) or Boutchkova (2012). We aim to answer the questions whether the new style of government brings long-term stability to the stock market.

2.3 Data

Our dataset contains the daily aggregate stock market index of four countries (Thailand, Indonesia, Vietnam, and the Philippines) and the MSCI world index; all were collected from Datastream between 2010 and 2017. These countries were chosen because they all underwent political reforms, according to our definition of a new style of government, during the sample period. Furthermore, their stock markets have been established long enough to supply sufficient data for reliable results. Myanmar, although it has experienced political revolution, was not considered because the Myanmar stock exchange has been trading for less than two years. Thus, we work with the data of only four countries: Thailand, the Philippines, Indonesia, and Vietnam. Data before 2010 was not collected to avoid any potential impact of the global financial crisis, 2007–2009, on stock market volatility.

Figure 2.1: Plots of the return series of stock indices

The return series of the stock indices of Indonesia, the Philippines, Thailand, Vietnam, and the MSCI world index January 2010–February 2017. The red line marks the date of the political event.



Suppose P_t is the price of the stock market for each country at the end of trading day t. Continuous compound return series take the form $r_t = \ln(\frac{P_t}{P_{t-1}})$. Figure 1 illustrates the daily return of the four national indices of Indonesia, the Philippines, Vietnam, Thailand, and the global MSCI world index from January 2010 to February 2017, with a considerable amount of dispersion around the zero-average daily return. The level of dispersion, moreover, is not constant over time. Some periods display low volatility followed by low values, whereas high volatility is followed by high values, displaying a volatility clustering phenomenon in the daily return of these countries.

Table 2.1: Descriptive statistics of daily return of countries' stock indices

The descriptive statistics of daily return of the stock indices of Vietnam, Thailand, the Philippines, and Indonesia from January 2010 to February 2017. The last column presents the test statistics of the Jarque–Bera (JB) test.

	Mean	Min	Max	Standard deviation	Skewness	Kurtosis	JB-test stats
Vietnam	0.00019	−0.0605	0.044	0.0115	−0.3734	4.8059	281.333**
Thailand	0.00041	−0.0581	0.057	0.0102	−0.3012	7.2712	1437.31**
Philippines	0.00048	−0.0699	0.055	0.0107	−0.6222	7.3686	1531.22**
Indonesia	0.00043	−0.093	0.070	0.0113	−0.5893	8.8936	2623.48**
MSCI world	0.00021	−0.0526	0.047	0.0089	−0.4705	7.2299	1383.26**

Table 2.1 shows that Thailand, the Philippines, and Indonesia share the same level of the average daily stock return, approximately 0.04%. The stock exchange of Vietnam shows the lowest average daily return, but the highest volatility compared with the other countries. Compared with the global index MSCI, ASEAN stock markets generally experience greater returns and greater volatility than globally.

Kurtosis values larger than 3 indicate that the series exhibits fat-tails in the distribution of returns. There is a good possibility of larger positive or negative stock returns than the normal distribution. Skewness coefficients of these series are all negative, indicating the asymmetric distribution of the market return series: the value to the left of the mean is fewer, but farther from it than the value to the right of the mean.

2.4 Methodology

2.4.1 Univariate models

Our research employs the generalised autoregressive conditional heteroskedasticity (GARCH) framework of Engle (1982) and Bollerslev (1986) to answer the question of how political reform events influence the stability of the stock market in the Asian region. Specifically, the empirical analysis proceeds with the three-step approach presented below:

2.4.1.1. Data filtering

The purpose of this step is to filter out any global movements and potential autocorrelation from the local stock return. We follow Gulen and Mayhew (2000) and Chau, Deesomsak, and Wang (2014), illustrating the pattern of stock return by the autoregressive model:

$$R_t = \omega + \alpha_w R_{w,t-1} + \sum_{i=1}^{5} \alpha_i R_{t-i} + \sum_{t=MON}^{THU} \beta_t DAY_t + u_t,$$

in which

R_t = daily return of stock index on day t;

$R_{w,t}$ = daily return of world market index on day t;

R_{t-1} = lagged daily return of the stock index;

DAY_t = day-of-the-week dummies for Monday to Thursday.

In this equation, the day-of-the-week effect, which is corroborated in some previous research (French, 1980; Keim and Stambaugh, 1984; Barone, 1990; Aggarwal and Rivoli, 1989; Wong, Hui and Chan, 1992), has been accounted for by adding dummy variables for Monday through Thursday. Lagged return is also added to the equation to remove any predictability of stock return induced by non-synchronous trading. Non-synchronous trading is a situation of low frequency trading. It is a possible source of autocorrelation in a stock index because the index is calculated each day from the closing prices of different stocks, which have not been established at the same time (Lo and Mackinlay, 1988; Nelson, 1991). The greater the variance at closing times, the greater the correlation. Therefore, lagged of stock return is included up to 5 lags to remove any possibility of autocorrelation. It is then confirmed by the Ljung–Box test for autocorrelation among residuals.

The MSCI world index is another independent variable in this whitening procedure. It is used to remove the effect of global factors on stock market volatility. Owing to the difference in time zones, the contemporaneous impact of global factors is reflected through the lagged value. The MSCI world index is preferred over a regional index, such as the MSCI Asia index, because of its comparatively higher integration level with East Asian economies (Devereux, Lane, Park and Wei, 2011).

2.4.1.2 Model selection

The output of the whitening procedure, the residual series, is an input in this model selection part. According to Alexander (2001), choosing the appropriate

GARCH-type model is necessary to reduce the convergence problem – a situation in which the likelihood function may become very flat and the gradient search algorithms fall off a boundary. If the model describes the data well, the convergence issue will be mitigated. Therefore, the most effective way to deal with the problem is to select the best fit model (Alexander, 1998).

The GARCH-type model, proposed by Engle (1982) and developed by Bollerslev (1986), has received great interest of both academia and practitioners in modelling volatility of economic and financial series. A variety of GARCH-type models has been proposed to deal with specific features, including: exponential GARCH (EGARCH) of Nelson (1991), asymmetric GARCH (GJR-GARCH) of Glosten, Jagannathan and Runkle (1993), asymmetric power GARCH (APGARCH) of Ding, Granger, and Engle (1993), and the threshold ARCH (TARCH) of Zakoian (1994). GARCH(1,1), the most frequently used model, is used as a benchmark for the conditional volatility model. The other two forms, EGARCH(1.1) and GJR-GARCH, are also tested because of their ability to capture stylised facts not covered in the GARCH(1,1) model.

The GARCH(1,1)

This is the simplest form among GARCH-type models. GARCH(1,1) is normally preferred because of its simplicity and efficiency. It is hardly outperformed by other specifications, even more complicated versions (Hansen and Lunde, 2006). The form of GARCH (1,1) is:

$r_t = \varepsilon_t$ [5]

$\varepsilon_t = z_t \sigma_t \quad z_t \xrightarrow{i.i.d} \mathrm{N}\,(0,1)$

$\sigma^2{}_t = \omega_t + \alpha\varepsilon^2{}_{t-1} + \beta\sigma^2_{t-1}$

in which $\omega_t > 0$, $\alpha > 0$, $\beta > 0$, and $\alpha + \beta > 1$ and r_t is the return series, ε_t is residuals, z_t is standardised residuals. The first equation illustrates sources of the input dataset, which is the residuals of the previous step or a whitened series. They are very close to zero; therefore, for simplicity, we assume that the return process follows the first equation of the system.

The $\sigma^2{}_t$ presents the conditional variance at time t of the residual series. This conditional volatility depends on its one-period lagged value and squared of last-period return (last-period residuals). The model can be written in ARCH format using the iteration:

$$\sigma^2{}_t = \omega_t + \alpha\varepsilon^2{}_{t-1} + \beta\sigma^2_{t-1}$$

$$\sigma^2{}_t = \omega_t + \alpha\varepsilon^2{}_{t-1} + \beta(\omega_{t-1} + \alpha\varepsilon^2{}_{t-2} + \beta\sigma^2_{t-2})$$

$$= \omega_t + \alpha\varepsilon^2{}_{t-1} + \beta\omega_{t-1} + \beta\alpha\varepsilon^2{}_{t-2} + \beta^2(\omega_{t-2} + \alpha\varepsilon^2{}_{t-3} + \beta\sigma^2_{t-3})$$

………

$$= \frac{\omega_t}{1-\beta} + \alpha \sum_{i=0}^{\infty} \varepsilon^2_{t-1-i}\,\beta^i$$

In this format, the conditional variance at time t depends on the weighted value of past residuals.

[5] We estimate the mean of daily return of the stock indices of all ASEAN countries; they are very close to zero; therefore, we assume that the return process follows the equation ($r_t = \varepsilon_t$).

The GJR-GARCH(1,1)

GJR-GARCH(1,1) extends the GARCH(1,1) by adding a leverage effect (asymmetric effect) to the model. GJR-GARCH(1,1) helps quantify the observed asymmetric characteristics of the stock market that bad news increases volatility more than good news does (Engle *et al.*, 1990; Basher and Sadorsky, 2016). If stock prices fall, the ratio of debt over equity will increase, giving the firm great leverage with more uncertain conditions, which then increases stock price volatility. However, the same increase in stock prices reduces the debt over equity ratio, and so, does not create the same positive impact on volatility. These situations confirm the necessity of using asymmetric GARCH in capturing the asymmetric response of conditional volatility in the equity market.

GARCH(1,1) specifications:

$$r_t = \varepsilon_t$$

$$\varepsilon_t = z_t\sigma_t \qquad z_t \xrightarrow{i.i.d} \mathrm{N}\ (0,1)$$

$$\sigma^2{}_t = \omega_t \ + \alpha \varepsilon^2{}_{t-1} \ + \beta\sigma^2{}_{t-1} + \xi I_{t-1}[\ \varepsilon_{t-1} < 0]\ \varepsilon^2{}_{t-1}$$

in which $I_{t-1} = 1$ if $\varepsilon_{t-1} < 0$, and $I_{t-1} = 0$ otherwise. In other words, I is a dummy variable taking the value of 1 in response to bad news and 0 in case of good news. The coefficient ξ connected to dummy I can be used to differentiate the impact between positive and negative shocks. To be more specific, if $\xi > 0$, any negative shocks will have a greater impact than the positive ones, even at the same level.

The EGARCH(1,1)

Nelson (1991) argues that the non-negativity constraints of parameters in the linear GARCH specification are too restrictive. He proposes another model in the form, namely EGARCH(1,1), with no restrictions in the parameters (different from the requirements α and β to be non-negative in GARCH(1,1)). This model also captures the asymmetric response of volatility to shocks and takes the following form:

$$r_t = \varepsilon_t$$

$$\varepsilon_t = z_t\sigma_t \qquad z_t \xrightarrow{i.i.d} \mathrm{N}\ (0,1)$$

$$\log(\sigma^2{}_t) = \omega_t + \alpha\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \chi\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta\log(\sigma^2{}_{t-1})$$

Which model best fits the dataset?

To select the model, we apply three criteria: the log-likelihood function, the Akaike information criterion (AIC), and the Heteroskedastic mean squared errors (HMSE).

- The log-likelihood function

The function's value comes from the probability density function and has the form called the likelihood, as below. GARCH-type models should be chosen so that the log-likelihood function, denoted by lnL, has the highest value.

$$lnL = -\frac{N}{2}\,log(2\pi) - \frac{1}{2}\left(\sum_{i=1}^{N} log(\sigma^2{}_t) - \frac{\varepsilon^2{}_t}{\sigma^2{}_t}\right)$$

- The Akaike information criterion

This is a measure of fit in which the preferred value is the lowest one. AIC is defined as: $AIC = 2k - 2lnL$.

- **Heteroskedastic mean squared error**

This is a loss function in which the preferred value is the smallest one. The formula is below (Bollerslev and Ghysels, 1996).

$$HMSE = \frac{1}{N}\sum_{i=1}^{N}([\frac{\sigma_t}{\widehat{\sigma_t}}]^2 - 1)$$

The chosen model will be the one satisfying at least two among the three criteria (Gulen and Mayhew, 1999, 2000).

2.4.1.3 Measuring the impact of political turmoil on stock-return volatility

Following Gulen and Mayhew (2000), two options can be used to measure the impact of political reform on stock volatility under the univariate framework. The first is to divide the period into two sub-periods (before and after the reform), and then compare the estimated coefficients together to clarify the question about the difference in the reaction of broad index volatility. The second option is to estimate the full sample in one regression with the inclusion of dummy variable D, gauging the reform. We follow Gulen and Mayhew (2000) and Chau *et al.* (2014), choosing D, so that D equals unit after the reform, which takes on the value of zero before the change. Because our dataset and two sub-periods are short, which can lead to difficulty in obtaining a reliable GARCH estimator in the first option, the second option is preferred.

Incorporating dummy variable D into each of the three GARCH-types, we have new customised models:

GARCH(1,1): $\sigma^2{}_t = (1+\lambda\mathrm{D})(\omega + \alpha\varepsilon^2{}_{t-1} + \beta\sigma^2{}_{t-1})$

GJR-GARCH(1,1): $\sigma^2{}_t = (1+\lambda\mathrm{D})(\omega + \alpha\varepsilon^2{}_{t-1} + \beta\sigma^2{}_{t-1} + \xi I[\,\varepsilon_{t-1} < 0]\,\varepsilon^2{}_{t-1})$

EGARCH(1,1): $\log(\sigma^2{}_t) = (1+\lambda\mathrm{D})(\omega + \alpha\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \chi\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta\log(\sigma^2{}_{t-1}))$

The dummy variable D is included as a multiple dummy on the assumption that the patterns of change of each component are similar to each other, following Gulen and Mayhew (2000) and Chau *et al.* (2014). The coefficient λ is used to evaluate whether the impact of political reform increases the market's volatility or not. If $\lambda>0$, the stock market will experience greater volatility after the reform; if $\lambda<0$, the government reform will mark a new period of low volatility.

2.4.2 Models for robustness test

2.4.2.1 The univariate approach with an additive dummy variable

In the previous section, political reform is incorporated into the model using the multiplicative dummy, which assumes the same proportional change of each element to the event. In this section, we aim to perform a robustness check using an additive dummy variable in the GARCH specifications.

The additive dummy versions of GARCH, GJR-GARCH, and EGARCH are as follows, respectively:

GARCH(1,1): $\sigma^2{}_t = (1+\vartheta\mathrm{D})\omega + \alpha\varepsilon^2{}_{t-1} + \beta\sigma^2_{t-1}$

GJR-GARCH(1,1): $\sigma^2{}_t = (1+\vartheta\mathrm{D})\omega + \alpha\varepsilon^2{}_{t-1} + \beta\sigma^2{}_{t-1} + \xi I[\,\varepsilon_{t-1} < 0]\,\varepsilon^2{}_{t-1})$

EGARCH(1,1): $\log(\sigma^2{}_t) = (1+\vartheta\mathrm{D})\omega + \alpha\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \chi\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta\log(\sigma^2{}_{t-1})$

Here, D is an additive dummy variable taking the value of 1 on the day and after the reform, while taking the value of 0 otherwise. If ϑ is statistically significant and has the same sign with the λ estimated in the previous section, we can conclude that the previous results are robust.

2.4.2.2 The multivariate model with a dummy variable

The univariate GARCH models are successful at capturing the cluster in volatility of high-frequency finance data, but not the cluster in correlation among them. Correlation clustering refers to the tendency of asset prices to move in the same direction, each asset having its own time-varying conditional variance as well as time-varying conditional covariance with the other asset. When government reform takes place, the conditional covariance will change significantly, probably leading to biased results in the previous univariate model. For that reason, this section will employ the multivariate GARCH framework, specifically the bivariate GARCH to cover for the volatility interaction within each pair of local stock index and the MSCI global index. This framework will be used to test the robustness of the previous results.

The bivariate GARCH has the following specification:

$$\sigma^2{}_{1t} = \omega_1 + \alpha_1 \varepsilon^2{}_{1,t-1} + \beta_1 \sigma^2{}_{1,t-1}$$

$$\sigma^2{}_{2t} = \omega_2 + \alpha_2 \varepsilon^2{}_{2,t-1} + \beta_2 \sigma^2{}_{2,t-1}$$

$$\sigma_{12,t} = \omega_3 + \alpha_3 \varepsilon_{1,t-1} \varepsilon_{2,t-1} + \beta_3 \sigma_{12,t-1}$$

$$\begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix} \mid I_{t-1} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2{}_{1t} & \sigma_{12,t} \\ \sigma_{12,t} & \sigma^2{}_{2t} \end{pmatrix} \right).$$

Rewriting the system of equation above using matrix notation on setting

$$\varepsilon_t = \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix}$$

$$\mathrm{H}_t = \begin{pmatrix} {\sigma^2}_{1t} & \sigma_{12,t} \\ \sigma_{12,t} & {\sigma^2}_{2t} \end{pmatrix}$$

for the error vector and GARCH covariance matrix, respectively, we have a new equation:

$$vech(\mathrm{H}_t) = diag(\omega_1, \omega_2, \omega_3) + diag(\alpha_1, \alpha_2, \alpha_3) vech\left(\varepsilon_t, {\varepsilon'}_{t-1}\right)$$
$$+ diag(\beta_1, \beta_2, \beta_3) vech(\mathrm{H}_{t-1})$$

Here the notation *vech* represents the half vectorisation constructed by stacking the columns on top of each other, with the first column on top, and the off-diagonal elements are not repeated. I_{t-1} denotes information set at time t-1.

We follow Karoyli (1995), Gulen and Mayhew (2000), and Chau *et al.* (2014) in using the so-called BEKK specification, proposed by Baba, Engle, Kraft, and Kroner (Baba *et al.,* 1995), to parameterise the conditional variance and covariance. This method allows the dynamic interaction between the local index and the world index without requiring estimation of too many parameters (eight coefficients for a bivariate BEKK). Moreover, the positive definiteness of the covariance matrix is ensured with confidence with BEKK. We present the procedure of bivariate BEKK specification as follow:

First, the data filtering process is carried out to remove any predictability of return, including the day-of-the-week effect and the potential autocorrelation, as discussed in the previous section:

$R_{i,t} = \omega_i + \sum_{j=1}^{5} \alpha_j R_{i,t-j} + \sum_{k=MON}^{THU} \beta_k DAY_k + u_{i,t}$

$R_{w,t} = \omega_w + \sum_{j=1}^{5} \alpha_j R_{w,t-j} + \sum_{k=MON}^{THU} \beta_k DAY_k + u_{w,t}$,

in which $R_{i,t}$ = daily return of country stock index *i* on day *t*;

$R_{w,t}$ = daily return of world market index on day *t*;

R_{t-j} = lagged daily return of the stock index;

DAY_k = day-of-the-week dummies for Monday to Thursday.

$u_{i,t}$ and $u_{w,t}$ are error terms having multivariate normal distribution:

$u_t | I_{t-1} \sim N(0, H_t)$

with H_t follow the BEKK specification:

$$H_t = \mathrm{C'C} + \mathrm{A'}\varepsilon_{t-1}\varepsilon'_{t-1}\mathrm{A} + \mathrm{B'}H_{t-1}\mathrm{B}$$

and C, A, and B are matrix of constants, ARCH coefficients, and GARCH coefficients, respectively. It can be expanded as follows:

$$\begin{pmatrix} \sigma_{11,t} & \sigma_{12,t} \\ \sigma_{21,t} & \sigma_{22,t} \end{pmatrix} = \begin{pmatrix} c_{11} & 0 \\ c_{12} & c_{22} \end{pmatrix} \begin{pmatrix} c_{11} & 0 \\ c_{12} & c_{22} \end{pmatrix} + \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix} \begin{pmatrix} \varepsilon^2{}_{1,t-1} & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon^2{}_{2,t-1} \end{pmatrix} \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix}$$

$$+ \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix} \begin{pmatrix} \sigma_{11,t-1} & \sigma_{12,t-1} \\ \sigma_{12,t-1} & \sigma_{22,t-1} \end{pmatrix} \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix}$$

To measure the impact of political reform on the volatility, we add dummy variables to the constant term of the model, following Doan (2013):

$$H_t = (\mathrm{C} + \mathrm{D}^*\mathrm{dt})'(\mathrm{C} + \mathrm{D}^*\mathrm{dt}) + \mathrm{A'}\varepsilon_{t-1}\varepsilon'_{t-1}\mathrm{A} + \mathrm{B'}H_{t-1}\mathrm{B},$$

where C is a lower triangular matrix, *dt* is a dummy variable taking 0 value before the event and 1 on or after the event. The aim of the study is to measure the impact of political reform on local stock market volatility when accounting for the spillover impact of global market movements. The research is not designed to measure how political reform in a single local country affects the global market. Therefore, a dummy variable is not included in the world's conditional covariance, or d_{22} of the D set is 0.

Our modified specification, after adding dummy elements, is:

$$\begin{pmatrix} \sigma_{11,t} & \sigma_{12,t} \\ \sigma_{21,t} & \sigma_{22,t} \end{pmatrix} = \left(\begin{pmatrix} c_{11} & 0 \\ c_{12} & c_{22} \end{pmatrix} + \begin{pmatrix} d_{11} & 0 \\ d_{12} & 0 \end{pmatrix} d_t \right) \left(\begin{pmatrix} c_{11} & 0 \\ c_{12} & c_{22} \end{pmatrix} + \begin{pmatrix} d_{11} & 0 \\ d_{12} & 0 \end{pmatrix} d_t \right) +$$

$$\begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix} \begin{pmatrix} \varepsilon^2{}_{1,t-1} & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon^2{}_{2,t-1} \end{pmatrix} \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix} + \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix} \begin{pmatrix} \sigma_{11,t-1} & \sigma_{12,t-1} \\ \sigma_{12,t-1} & \sigma_{22,t-1} \end{pmatrix} \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix}$$

After estimating these parameters using the maximum likelihood estimation method, the estimators will be assessed similarly to the univariate model's case. If d_{11} is negative, it implies the positive impact of the new government: the volatility of the stock market decreases after the event. If d_{11} is positive, the introduction of the new government is related to greater volatility. Regarding the d_{12} coefficient, a statistical value of d_{12} suggests that the political reform affects the integration of individual local country and the MSCI world index. If not, results from the univariate model remain valuable.

2.5 Empirical analysis

2.5.1 The univariate GARCH

2.5.1.1 The whitening regression

This section carries out separate regressions of stock market returns on its lagged values and global returns together with day-of-the-week effect. The OLS estimation technique is used. Results are presented in Table 2.2.

Table 2.2 shows the significant impact of the global returns index (MSCI index) on all broad indices of ASEAN countries. Coefficients α_w are all positive and statistically significant. Among them, Indonesia's coefficient has the highest value, illustrating the country's highly integrated level of its financial market with the MSCI world index. Vietnam and Thailand share the same level of influence, which is double that of the Philippines.

As for autoregressive coefficients (α_1 to α_5), α_1 is statistically significant for all countries, whereas the other four coefficients (α_2 to α_5) are mostly not significant. These properties illustrate the short memory impact of past returns on today's returns. It can be explained by the non-synchronous trading characteristics in emerging markets as analysed before. Different daily closing times of each component cause autocorrelation in returns of the broad index, frequently at one lag.

Table 2.2: Estimation results of preliminary test

The estimated values and the corresponding *t*-statistics of parameters in data filtering estimation for each country. The signs ***, **, * indicate that the estimated value is statistically significant at 99%, 95%, and 90% levels of confidence.

Vietnam

	Estimated value	t statistics
Constant	-0.0010	-1.807**
α_w	0.2668	8.858**
α_1	0.0937	4.001**
α_2	0.0387	1.651
α_3	0.0283	1.211
α_4	-0.0251	-1.074
α_5	-0.0107	-0.4620
β_{MON}	0.00058	0.6862
β_{TUE}	0.0017	2.052**
β_{WED}	0.00160	1.8992
β_{THU}	-0.04455	2.438**

Thailand

	Estimated value	t statistics
Constant	-0.0007	-1.497
α_w	0.2826	10.16**
α_1	-0.0525	-2.186**
α_2	0.0146	0.6431
α_3	-0.0244	-1.077
α_4	0.0233	1.031
α_5	-0.0175	-0.7768
β_{MON}	0.0013	1.847
β_{TUE}	0.0021	2.992**
β_{WED}	0.0008	1.218
β_{THU}	0.0013	1.799

The Philippines

	Estimated value	t statistics
Constant	-0.0000	-0.0894
α_w	0.1372	5.289***
α_1	0.4635	17.64***
α_2	0.0417	1.9096
α_3	-0.0268	-1.240
α_4	-0.0343	-1.583
α_5	-0.067	-3.110***
β_{MON}	-0.0003	-0.4505
β_{TUE}	0.0016	2.224**
β_{WED}	0.0003	0.4561
β_{THU}	0.0004	0.6136

Indonesia

	Estimated value	t statistics
Constant	-0.00122	-2.1754
α_w	0.4183	14.096**
α_1	-0.0616	-2.581**
α_2	0.0214	0.9427
α_3	-0.122	-5.438**
α_4	-0.0457	-2.012**
α_5	0.0039	0.1747
β_{MON}	0.0022	2.777**
β_{TUE}	0.0036	4.61**
β_{WED}	0.0012	1.508
β_{THU}	0.0011	1.425

Regarding to the day–of–the–week effects, coefficients β_{TUE} of all four indexes are statistically significant, coincide with literature on day – of – the – week effects in both emerging and developed countries (French, 2000; Jaffe and Westerfield, 1985; Choudhry, 2000). Indonesia stock exchange also experience day of the week effect on Monday. Besides, the coefficient α_W is all statistically significant, implying the moving average with global stock index (Gulen and Mayhew, 2000; Khazali, 2008).

Using the residuals of the whitening equation as the new return series, we carry out the following tests to prove the necessity of autoregressive conditional heteroskedasticity (ARCH) effect in measuring volatility. The first test is Ljung – Box test on the residuals following Engle and Ng (1993) to confirm whether the extracted series are free from autocorrelation or not in the residuals. The second test is Ljung – Box test on the squared residuals (a proxy of volatility of daily stock return). The test statistics up to lag twelve are reported in the last two columns of the table:

- On residuals, the Ljung – Box tests revealed that serial autocorrelation in return series is removed in almost all countries: Vietnam, Thailand, Philippines while the test on Philippines stock return is marginally significant. This suggests that the whitening procedure has removed any predictability parts in return.

- On squared residuals, the Ljung – Box tests are remarkably significant in all cases, indicating the existence of the time-varying volatility in the daily returns of all markets as well as the need of having GARCH specification in modelling stock return volatility.

Table 2.3: The Ljung – Box test for the residuals and squared residual

	Vietnam	Thailand	Philippines	Indonesia
LBQ(12) (Levels)	15.9580	8.8743	9.6525	24.300**
LBQ(12) (Squared)	402.84**	391.90**	340.172**	275.114**

**: statistical significance at 95% level of confidence

2.5.1.2 Selecting a GARCH-type model

After doing preliminary regression in the first step, the residual series are saved to be the input of this step. These series become our new return series. Vanilla GARCH(1,1) is compared with EGARCH(1,1) and GJR-GARCH(1,1), using the three mentioned criteria: lnL, AIC, and HMSE. The GARCH-type model will be the one satisfying two of the three criteria below:

- Highest log-likelihood values *lnL*
- Lowest AIC
- Lowest HMSE

In each table, the three information criteria are calculated to show the preferred model. For example, in Vietnam, the log-likelihood value *lnL* gets the highest value for GARCH(1,1), compared with the case of EGARCH(1,1) and GJR-GARCH(1,1). *lnL*, therefore, is in bold in the GARCH(1,1) column and shows the preference for the GARCH(1,1) over other models when LnL information criteria is used. Carrying out a similar process for the other information criteria tests of each country, we can conclude that the GARCH(1,1) is a reasonable model for Vietnam and the Philippines, whereas GJR-GARCH(1,1) is for Thailand and the Philippines.

Overall, GARCH(1,1) and GJR-GARCH(1,1) outperform EGARCH(1,1). Thus, the next step employs both GARCH(1,1) and GJR-GARCH(1,1) to answer the target question.

Table 2.4: Selecting a GARCH-type model using the information criteria

Vietnam

	GARCH(1,1)	EGARCH(1,1)	GJR-GARCH(1,1)
LnL	**−5.5533**	−5.5596	−5.5552
AIC	**1.1113**	1.1127	1.1118
HMSE	**3.4791**	3.6068	3.5211
Selected model	X		

Thailand

	GARCH(1,1)	EGARCH(1,1)	GJR-GARCH(1,1)
LnL	−6.1337	−6.1365	**−6.1018**
AIC	1.2275	1.2281	**1.2213**
HMSE	4.191	**3.4024**	3.6247
Selected model			X

The Philippines

	GARCH(1,1)	EGARCH(1,1)	GJR-GARCH(1,1)
LnL	**−5.8484**	−5.8602	−5.8608
AIC	**1.1703**	1.1728	1.173
HMSE	5.5771	**4.5876**	4.8667
Selected model	X		

Indonesia

	GARCH(1,1)	EGARCH(1,1)	GJR-GARCH(1,1)
LnL	**−5.6441**	−5.6537	−5.6527
AIC	1.1294	1.1315	**1.1283**
HMSE	4.6635	4.5285	**4.4997**
Selected model			X

2.5.1.3 Using a univariate model to measure the impact of political reform on stock market volatility

From the specification test, GARCH(1,1) and GJR-GARCH(1,1) will be used to test the impact of political uncertainty on stock market volatility. We follow Gulen and Mayhew (2000) and Chau *et al.* (2014), using multiplicative dummy variables to represent the two different periods. As mentioned in the methodology section, dummy variable D is chosen to equal 0 before the event and takes on the value of 1 from the event onwards. Dummy D divides our dataset into two periods to have volatility comparison; therefore, choosing it is an essential part of our study.

In line with the literature, the event date is chosen when the news is out. It is the election day in case of the Philippines and Indonesia: When the new government is elected, their vision and proposed plan during the election campaign are taken into consideration, creating two sub-periods with different volatility levels. In the case of Thailand, it is the start date of the new government after the coup d'état, on which political turmoil is expected to end. As for Vietnam, the meeting date of the National Congress, on which key leading people of the country are elected, has been selected. Their visions and economic and political strategies will be immediately taken into consideration, creating a new phase of market volatility.

It is important to note that we follow the literature in choosing the dates above. Although based on different kind of events, these dates share the same characteristics: marking the new period of stock-return volatility. Chau *et al.* (2014) chooses the start date of the civil uprisings in the Arab World to define the dummy, whereas Gulen and Mayhew (2000) choose the introduction day of the equity index to partition the period into two parts for comparison. Therefore, we strongly believe that our method of choosing the date is appropriate, rational, and consistent with the literature.

Table 2.5: Data period

The research period and the dates from which dummy variables take on the value of unit for the four ASEAN countries. The last two columns count the number of days before the event and after the event, called number of observations before the event and after the event).

Country	Data period	Event date	Obs. Pre-	Obs. Post-
Vietnam	4 Jan 2010–10 Feb 2017	22 Jan 2016	1508	261
Thailand	4 Jan 2010–10 Feb 2017	22 May 2014	1159	695
The Philippines	4 Jan 2010–10 Feb 2017	9 May 2016	1599	183
Indonesia	4 Jan 2010–10 Feb 2017	9 July 2014	1108	636

To answer the question whether political reform does raise stock market volatility (if $\lambda > 0$) or decreases volatility (if $\lambda < 0$), coefficients λ, related to dummy D, is assessed.

Table 2.6: Estimation of conditional volatility

The estimated values and the corresponding *t*-statistics (in parentheses) of parameters of GARCH specifications. The sign *** means the estimated parameter is statistically significant at 99% confidence level, and the signs ** and * denote the statistically significant at 95% and 90% confidence levels, respectively.

	Selected model	ω	α	Β	ξ	λ
Vietnam	GARCH(1,1)	0.0000	0.1527	0.7479		−0.0953
		(3.252)***	(5.886)***	(16.719)***		(−2.488)**
Thailand	GJR-GARCH(1,1)	0.0000	0.0061	0.8843	0.1480	−0.0388
		(2.934)***	(0.545)	(37.395)***	(5.295)***	(−2.224)**
The Philippines	GARCH(1,1)	0.0000	0.1071	0.8143		0.0320
		(2.061)**	(3.973)***	(13.999)***		(1.001)
Indonesia	GJR-GARCH(1,1)	0.0000	0.0817	0.7775	0.1495	−0.0537
		(2.828)***	(2.4101)**	(13.667)***	(2.403)**	(−1.896)*

The estimated coefficients ω, α, and β are statistically significant at 1% and 5%, representing the usual conditional volatility dynamic. Among the four countries, Vietnam's stock exchange is the most sensitive to market events, with α above 0.1. The α values of the Philippines and Indonesia are lower than Vietnam's, but still relatively high; approximately 0.1. of Thailand's volatility is least influenced by the market shocks in the group where α is small (α = 0.006) but insignificant. Regarding ξ in the two GJR-GARCH(1,1) specifications for Thailand and Indonesia, they are positive and statistically significant, implying the leverage effect of stock-return volatility: A negative return today has great memory on tomorrow's.

The remaining estimated coefficients λ is the most important coefficient in our research. They are negative for three countries: Thailand, Vietnam, and Indonesia, with the largest coefficient belonging to Vietnam. Coefficients of

Indonesia and Thailand follow Vietnam's. The Philippines' coefficient is at the same level of Thailand, but not statistically meaningful. Overall, the form of new government creates a positive impact on the stock market. In other words, the news decreases volatility in the stock market or increases stability in Thailand, Indonesia, and Vietnam. The finding fits with the economic condition of the countries as analysed in the overview section, and it coincides with the previous literature about the significant impact of politics on stock market return volatility. Any political party that assumes power after getting votes from the public or any forms of armed conflict must carry out the pre-announced policies, suspend projects of the previous government, or re-launch them with new identities. Stock market volatility, therefore, reacts to the changes in government. However, the impact sign in the three ASEAN countries above is opposite to the usual findings about the higher level of volatility following the news in the long run as in Mei and Guo (2004) and Chau *et al.* (2013). The reason is that the new forms of government are considered as positive decisions, bringing an end to the long-standing disorder in these countries and a new hope for the ASEAN economy. As for the Philippines, the coefficients λ is not statistically significant: No statistically structural change in the reaction of the conditional volatility to political reform has been detected.

2.5.2 Robustness tests

2.5.2.1 Alternative specification of the impact of political reform using an additive dummy

Putting the additive dummy variables ϑ into the models specified in the methodology section, we have the following results:

Table 2.7: Estimation of the GARCH specifications with additive dummy variable

The estimated values and the corresponding *t*-statistics (in parentheses) of parameters of GARCH specifications. The sign ** indicates that the estimated value is statistically significant at 95% level of confidence.

	Selected model	ω	α	β	ϑ	ϑ
Vietnam	GARCH(1,1)	0.0001	0.1521	0.7427		−0.4530
		(2.866)**	(5.664)**	(15.457)**		(−4.255)**
Thailand	GJR-GARCH(1,1)	0.0001	0.0039	0.8863	0.1494	−0.4752
		(3.643)**	(0.889)	(48.203)**	(5.847)**	(−4.297)**
The	GARCH(1,1)	0.0001	0.1080	0.8138		0.4851
Philippines		(2.073)**	(3.9269)**	(14.011)**		(0.969)
Indonesia	GJR-GARCH(1,1)	0.0000	0.0795	0.7673	0.1485	−0.3518
		(2.701)**	(2.508)**	(12.419)**	(2.363)**	(−2.508)**

The coefficients ϑ are negative and statistically significant for Vietnam, Thailand, and Indonesia, whereas that for the Philippines is positive but insignificant. They all confirm the robustness of the previous results: The new government reduces stock market volatility.

2.5.2.2 Alternative specification allowing for the joint dynamics of the local index and MSCI global index

This section will employ a multivariate framework to test the robustness of the previous estimation results. Time-varying covariance between emerging countries' returns and the global index is accounted for here. Estimated coefficients are reported in Table 2.8.

Table 2.8: Estimate of the multivariate GARCH with dummy variables

The estimated parameters of the BEKK specification with dummy variables and the corresponding *t*-statistics in parentheses. The sign ** indicates that the estimated value is statistically significant at 95% level of confidence.

	Vietnam	Thailand	The Philippines	Indonesia
c_{11}	0.0049	0.0080	0.0030	0.0039
	(3.6692)**	(8.0506)**	(1.4489)	(5.1350)**
c_{12}	0.0006	0.0042	−0.0008	−0.0007
	(0.4640)	(1.2797)	(−0.3683)	(−0.7588)
α_{11}	0.2343	0.9975	0.2114	0.1168
	(2.6213)	(3.1592)**	(3.9120)**	(0.9714)
α_{12}	0.2136	0.3781	0.0453	−0.0444
	(1.8963)	(3.4460)**	(0.3195)	(−0.1567)
α_{21}	0.0367	−0.3426	0.0483	0.0342
	(0.5922)	(−1.4220)	(0.6477)	(0.3117)
β_{11}	0.8697	0.4280	0.9257	0.9401
	(15.132)**	(1.9384)	(14.792)**	(102.187)**
β_{12}	−0.1137	−0.1553	−0.0478	−0.0150
	(−1.3986)	(−0.3254)	(−0.5920)	(−0.9312)
d_{11}	−0.0080	−0.0135	0.0036	−0.0285
	(−3.3619)**	(−8.2034)**	(1.2676)	(−18.726)**
d_{12}	−0.0014	−0.0071	0.0003	−0.0004
	(−0.6083)	(−0.9981)	(0.4147)	(−0.4086)

The coefficients of interest are d_{11} and d_{12}. Table 2.8 shows that d_{11} takes a negative value and is statistically significant for three countries: Vietnam, Thailand, and Indonesia, implying the positive impact of the political reform on the stock market. They also confirm the findings in the univariate model. d_{12} is not statistically significant for any countries in the sample, meaning that the spillover effect of the MSCI global index's volatility on our emerging countries is not statistically significant. Therefore, the work using the univariate model remains valuable, and they all confirm that government reforms in ASEAN countries help stabilise stock returns.

2.5.2.3 Robustness check when using different dates of political reform

This section tests the sensitivity of the previous results, using alternative dates and re-estimates model parameters. We follow the same procedure. First, we choose the event date dividing the whole sample period into two smaller ones, before and after the event, and then compare the volatility between these two periods. The GARCH-type model with dummy variables is employed to assess whether any significant difference exists in the volatility of the market between pre-event and post-event periods. The statistically significant coefficient associated with the dummy variable indicates the impact of the political reform on market volatility: A positive sign indicates an increase in volatility, and a negative sign indicates lower volatility.

Recall that the GARCH parameters are estimated for the whole period, so it is not ideal to test the sensitivity of the results using alternative dates just several days before or after the event. The results will not change significantly for these dates. Therefore, in this section, we will choose a longer window to test the robustness, 30 days before and after the event. Denote the event date in the previous section is T. In the first scenario, the new event date is 30 days before the event date T, denoted $T-30$. In the second scenario, another new event date is 30 days after the event T, denoted T+30. In each scenario, volatility values are compared using the chosen GARCH specification.

Table 2.9: Estimate of the GARCH models with event date T−30 and T+30

The estimated values and the corresponding *t*-statistics of parameters of GARCH specifications. Panel A is for the scenario T−30, and panel B is for the scenario T+30. The sign ** means the estimated parameter is statistically significant at 95% confidence level, and the sign * denotes the statistically significant at 90% confidence level.

		Parameter estimation with the alternative date T−30				
Panel A	*Selected model*	ω	α	β	ξ	λ
Vietnam	GARCH(1,1)	0.0000	0.1555	0.7484		−0.0836
		3.1898**	6.0186**	16.767**		−2.3051**
Thailand	GJR-GARCH(1,1)	0.0000	0.0965	0.6879	0.2491	−0.0335
		0.6482	0.9110	2.0482**	1.3581	−1.2084
The Philippines	GARCH(1,1)	0.0000	0.1061	0.8188		0.0256
		2.2058**	4.0542**	15.751**		1.0138
Indonesia	GJR-GARCH(1,1)	0.0000	0.0848	0.7763	0.1461	−0.0473
		2.5976**	2.4548**	12.3895**	2.2479**	−1.6985
		Parameter estimation with the alternative date T+30				
Panel B	*Selected model*	ω	α	β	ξ	λ
Vietnam	GARCH(1,1)	0.0000	0.1575	0.7405		−0.0916
		2.9348**	5.7751**	14.747**		−2.0214**
Thailand	GJR-GARCH(1,1)	0.0000	0.0083	0.8839	0.1445	−0.0366
		2.9025**	0.4757	−0.0366	4.5554**	−2.1161**
The Philippines	GARCH(1,1)	0.0000	0.1084	0.8143		0.0265
		1.8776	3.7532**	12.6251**		0.6945
Indonesia	GJR-GARCH(1,1)	0.0000	0.0834	0.7770	0.1482	−0.0557
		2.5571**	2.3919**	12.108**	2.2918**	−1.9796*

Table 2.9 clearly shows that the estimated parameters of GARCH specifications do not change significantly for Vietnam and the Philippines. As for

Vietnam, the estimated coefficient λ is still significant in the T−30 and T+30 scenarios. Its value increases from −0.0953 to −0.0836 when the date T−30 is substituted by the date T and also increases from −0.0953 to −0.0916 when the date T+30 is substituted by the date T. This means that the date T brings the lowest value of the parameter λ compared with the other two alternatives, T−30 and T+30. In other words, the preliminary choice of event date, T, produces a new period with lowest stock market volatility or the stock market is least volatile. In addition, the difference in the estimated value of λ between scenarios T−30 (λ = −0.0836) and T+30 (λ = −0.0916) implies that the market is calmer on the post-event date than the pre-event date.

As for the Philippines, the estimated values of λ are not significant for both scenarios T−30 and T+30. However, the value of λ slightly decreases from the option T to T−30 (from 0.0320 to 0.0256), as well as from the option T to T+30 (from 0.0320 to 0.0265). As in the case of Vietnam, this result implies that the selected date T better supports the conclusions that volatility increases after the government reform in the Philippines.

In the case of Thailand and Indonesia, only the scenario T+30 produces the statistically significant value of λ for both countries. The option T−30 gives λ a not statistically significant value. This means that the market volatility comparison in the two countries is significantly influenced by the date selection, on or after the selected event dates, but not before these. This result reinforces the consistency of our selected date of political reform in the prior section.

Overall, we have tested the robustness of the results using different model specifications: using different kinds of dummy variables (additive dummy instead of multiplicative dummy), allowing for the joint dynamics of the local index and the MSCI global index, and using different dates of political events. All of these confirm the robustness of the previous results as well as the dates highlighting that the government reforms are appropriate.

2.6 Conclusion

It has been commonly reported that financial and economic variables play a small role in stock market volatility, whereas political variables and their changes are attributable to a considerable swing in the price and volatility levels (Schwert, 1989). For this reason, this research aims to test the impact of political variables on the stock indices in four members of ASEAN, which emerged as flashpoints in the world economy. The political variable in this research is restricted to the regime changes sharing the same special characteristic: a new government that is different from the previous one, even if it is formed under protest or periodic elections.

Employing the three most popular forms of GARCH-type models, including GARCH(1,1), EGARCH(1,1), and GARCH-GJR(1,1), with dummy variables separating before- and after-event periods (the reform day), the research has accounted for the following points. First, it accounts for the special characteristics of stock-return-volatility clustering. Second, it employs the most frequent dataset that can be collected, a daily stock index. Third, it covers the volatility spill over effect from the global factors to the stock market using a multivariate GARCH framework. And last but not least, it aims at the measurement of long-term stability rather than the volatility around a short-term window of several days surrounding the events.

Overall, a positive, long-term relationship between stock market volatility and political reform has been found. In other words, the new forms of government in these ASEAN members reduce stock market volatility. This finding coincides with Amihud *et al.* (2004) and Fuss and Bechtel (2008), explained by fact that the reforms bring an end to the disorders taking place for a long time in these countries. They are recognised as milestones in economic development: The new leading system will bring better and more stable economic growth. It may be that the new regimes in Thailand, Vietnam, and Indonesia are seen as more business friendly, offering optimism and transparency to business. In other words, the political reforms in ASEAN Members Countries do bring new hope and raise the level of stability of the financial markets.

The findings above not only indicate the positive relationship between government reform in the three ASEAN countries and stock-return volatility, they also elaborate on the impact of a series of politically related events, such as strikes, riots, assignations, and government changes, on volatility. The findings provide significant benefits for portfolio managers and investors in making investment decisions, and they remind the authorities to be mindful of any considerable change in political decisions. Future studies can calculate the political instability index and its relationship with stock market volatility. A comparative assessment of the similarities and differences in the kinds of political events (elections, wars, riots, assignations) and their impact on stock-return volatility would be an interesting area for future research.

Chapter 3

THE RELATIONSHIP BETWEEN MACROECONOMIC VARIABLES AND THE STOCK MARKET: EVIDENCE FROM THE THAILAND STOCK MARKET INDEX

3.1 Introduction

In the past few decades, the stock market has grown significantly and played an important role in the economic activities of developed and developing countries. Several empirical studies have considered the relationship between the stock market and macroeconomic variables, but there has been no agreement on the relationship. In some studies, several macroeconomic variables are cointegrated with the stock market (Aburgi, 2008; Maysami and Sims, 2002; Diamandis and Drakos, 2011); in other studies, no long-term association is found (Tsouma, 2009; Lin, 2012). Short-term causality results are mixed too, depending on the period and research area. This situation, therefore, raises the necessity of having another research specific to Thailand's market to understand how Thailand's stock market index relates to macroeconomic variables.

Two questions are raised to answer the question, using the most up-to-date dataset from January 2001 to December 2016. First, is there any long-term relationship between macroeconomic variables and the stock market index? Second, do macroeconomic variables Granger affect the Thailand stock exchange and vice versa? These two questions are considered together, because once cointegration exists, there must be Granger causality in at least one direction.

Because the dataset is a mixture of stationary and non-stationary series, an autoregressive distributed lag model (ARDL) bounds test for long-term cointegration is employed rather than the traditional Engle and Granger (1987) and Johansen (1990) cointegration tests. As for the causality, Toda and Yamamoto (1995) Granger non-causality (TYDL) is preferred over a standard test of the coefficients of lagged differenced variables. To the best of my knowledge, this study is the first that combines ARDL and TYDL to answer the aforementioned questions about Thailand's stock market. The entire up-to-date dataset is employed, from January 2001 to December 2016.

Empirical findings verify the existence of a positive long-term relationship between the stock market index and money supply, the exchange rate and MSCI index. They signify the forward-looking information in stock prices and can be used to set an investment strategy for stock traders (improved performance of equity portfolio by considering both local and global factors) and regulation for policy-makers (stabilise the financial market by formulating and regulating the macro economy). As for the short-term interaction, the interest rate variable Granger causes the stock price, whereas the stock price Granger causes the interest rate and the exchange rate. This causality direction supports the portfolio balance theory and implies that a currency crisis can be controlled by stock market regulations.

This chapter is structured as follows. Section 2 reviews empirical studies related to this topic. Section 3 presents the methodology in general, and Section 4 examines both data selection and model specification. Section 5 provides empirical analysis, and the final section concludes the study.

3.2 Literature review

The relationship between the stock market and macroeconomic variables has been studied extensively during the past few decades. Most studies focus on the US and other industrialised markets in Europe, Asia, and Latin America. Only a few studies target developing nations. Different econometric techniques have been applied, such as VAR, VECM, GARCH, and ARDL. The role of each explanatory variable is different in different contexts. This literature survey will review some of the seminal studies in this field in two main perspectives: (i) a long-term relationship using cointegration analysis and (ii) a short-term Granger causality test.

Fama and Schwert (1977) and Nelson (1977) are two of the earliest studies of the relationship between macroeconomics and the stock market. Focusing on the US stock market, the authors confirm that macroeconomic variables have an influence on the stock market return. They base their findings on the arbitrage pricing theory (APT), developed by Ross (1976), which assumes that the equity price is attributed by several factors. Chen, Roll, and Ross (1986) explained that the stock price is determined by the discounted future dividends; thus, any macro variables affecting the dividend flows or the discount rate will be considered in the stock price–macro variables relation. Fama (1970) in the semi-strong form of market efficiency supports this theory, stating that the stock price must convey all available information, so that any macroeconomic variables must be fully reflected in the stock price in the competition among the profit maximising investors. Bilson *et al.* (2000) discusses two models: a model with local factor and a model with both local and global factors. He emphasises the need to add global factors proxied by the world equity return to the set of macroeconomic variables in explaining stock market return. The variables used in his research include: local macro variables (narrow money supply, industrial production, interest rate, exchange rate) and the world market return MSCI index. Aburgi (2008) selects a similar set of predetermined variables based on the theoretical propositions and literature in this field. The author explains that this kind of initial variable selection is an unavoidable problem (Fama, 1981); thus, the researchers can consider previous research and judgements to form the relevant factors.

Using selected macroeconomic variables, Engle and Granger (1987) and Johansen and Juselius (1990) proposed cointegration techniques to determine the long-term relationship between them and the stock market index. There exists a long-term relationship between the variables, equivalent to their cointegration, if they are integrated of same order, and the linear relationship between them is stationary. The long-term relationship implied by cointegration is linked with short-term adjustment through the error-correction model (ECM). Maysami and Sims (2002, 2001a, 2001b) on Asia markets, Maysami *et al.* (2005) on the US and Singapore markets, and Ibrahim (1999), Ibrahim and Aziz (2003) on the Malaysian market, and Diamandis and Drakos (2011) on Latin American countries are some typical papers establishing the long-term cointegration between stock prices and macro variables using these error-correction models.

Maysami and Sims (2002, 2001a, 2001b) examine long-term relationships between macro variables and stock price using an error-correction model in the Asian stock markets. Maysami and Sims (2002) focus on the relationship in Hong Kong and Singapore, Maysami and Sims (2001a) focus on Malaysia and Thailand, and Maysami and Sims (2001b) focus on two developed markets, Japan and Korea. Adopting Hendry's (1986) approach, which examines both short- and long-term relationships, all three studies come to the same conclusion that macroeconomic variables (interest rate, inflation, money supply, exchange rate, and industrial production) affect the stock market index, but the sign and magnitude differ, determined by the structure of the financial system in each country.

Ibrahim (1999) considers the relationship in another Asian country, namely Malaysia. The group of seven variables includes the industrial production index, price index, money supply M1 and M2, exchange rate, credit aggregates, and foreign reserves with the Kuala Lumpur Stock Exchange (KLSE) Composite Index. Cointegrations corroborated between KLSE and the three variables – foreign reserves, credit aggregates, and the price level – suggest that the Malaysian stock exchange is informationally inefficient. The finding contrasts with Habibullah and Baharumshah (1996), who assert the efficiency of the Malaysian stock market in the long term but agree with Ibrahim and Aziz (2003) investigating the relationship between KLSE and four macroeconomic variables (industrial production, exchange rate, money supply, and price level). Humpe and Macmillan (2007) base their study on the error-correction model to understand the long-term movement of stock prices in developed markets, US and Japan. The long-term relationship between the stock price and a set of five macroeconomic variables is corroborated in both countries, although the signs are inconsistent.

Mukherjee and Naka (1995) and Hassan (2003) applied a multivariate cointegration technique to examine the long-term relationship in Japan and the Persian Gulf region, respectively. They confirmed the cointegrating relationship between stock market levels and the macro variables. As for Japan, the coefficient signs are consistent with the *a priori* hypotheses. As for the Persian Gulf region, long-term relationships exist together with the short-term Granger causality.

The application of the error-correction model in identifying the long-term relationships as above is believed to be sensitive to the lag length choice and depend on the order of integration tests, such as the augmented Dickey Fuller (ADF) test and the Phillips–Perron (PP) test but suffers from low power in small samples. For that reason, another cointegration technique, the autoregressive distributed lag model (ARDL), has been proposed by Pesaran *et al.* (2001) to gauge the cointegration between variables without pretesting the order of integration. One can test the long-term relationship among stationary and non-stationary variables using this technique, so that the test does not suffer from the low power problem in a small sample. ARDL, therefore, has become a popular and standard technique examining cointegration among financial variables in general, as well as among finance variables and macro variables specifically.

Several studies have adopted the ARDL approach to measure the relationship. Sharing the same set of macroeconomic variables, Lin (2012), Rushdi, Kim, and Silvapulle (2012), Hassan and Al Refai (2012), and Bekhet and Matar

(2013) follow the ARDL methodology to examine stock market price–macroeconomic variable cointegration. Hassan and Al Refai (2012) and Bekhet and Matar (2013) specify the characteristics of the Jordan macroeconomic dataset (a mixture of stationary and non-stationary) and the suitability of the ARDL model for the research question. Their empirical tests during the periods 1997–2010 and 1978–2010, respectively, suggest that macro variables are important in determining the long-term stock market index in Jordan. Lin (2012) complements the literature by accounting for structural breaks in the model. First, structural breaks in the dataset from 1986 January to 2010 December are accounted for by the Lee and Strazicich's (2001) unit root test with two breaks together with the traditional unit root test to obtain more precise results. Second, structural breaks are also accounted for in the main test, the ARDL bound tests in four separate monthly periods, even when the subsample includes only 24 observations (July 1997–July 1999). Focusing on stock prices and exchange rates in emerging Asian countries, Lin (2012) specifies a different relationship through different phases: the relationship did exist in subsamples with stronger co-movement during crisis periods than during tranquil periods.

Apart from identifying the existence of macroeconomic variables and the stock price interaction, the sign of the interaction term has been indicated in the literature. It can be either positive or negative as corroborated below.

GDP is believed to have a positive impact on stock prices in the long run, corroborated by Maysami and Sim (2002), Mukherjee and Naka (1995), Ibrahim and Aziz (2003), and Ratanapakorn and Sharma (2007). An increase in GDP associates with the greater ability of firms to generate cash flows and higher stock prices.

The money supply can take either positive or negative signs of influence on stock prices in the long run. Bekhet and Matar (2013), Mukherjee and Naka (1995), and Maysami and Sim (2002) document a positive long-term relationship, whereas Fama (1981) and Ibrahim and Aziz (2003) specify a negative one. The interaction between these two variables, money supply and stock price, can be direct or indirect via the output, inflation, and interest rate (Dhakal *et al.*, 1993).

The cointegration between the exchange rate and stock price can be positive (Mukherjee and Naka, 1995; Ibrahim and Aziz, 2003; Bekhet and Matar, 2013) or negative (Ibrahim and Wan, 2001). A decrease in the value of currency will make exports less expensive in the international market. As a result, the volume of export and cash flow will increase, raising the higher stock price. However, it can have a negative impact when the decreases in the exchange rate increases the cost of inputs used in the production.

The interest rate is negatively cointegrated with stock price in Mukherjee and Naka (1995), Abdullah and Hayworth (1993), and Bekhet and Matar (2013). An increase in the interest rate raises the discount rate, which inversely affects the stock price. It also increases the financing cost of corporations, thus, negatively affecting future corporate profitability, as well as the stock price.

The MSCI world index can play a significant role in explaining stock market movement in some countries and be insignificant for other countries (Fifield *et al.*, 2002). A positive sign of interaction between MSCI and the stock market price implies the market is integrated with the world market (Aburgi, 2008).

Once long-term cointegration has been established, there must be Granger causality between the variables in at least one direction. In the long run, the cointegrated series are tied together; thus, in the short run, these series may drift apart but they "must drift back together" (Carol, 2008), creating causality flow called Granger causality. The causality is frequently tested using joint significance tests of differenced variable coefficients in an error-correction model. Kwon and Shin (1999), Nasseh and Strauss (2000), Pan, Fok, and Liu (2007), and Ratanapakorn and Sharma (2007) are some typical papers applying this methodology on unit root I(1) series. Kwon and Shin (1999) and Nasseh and Strauss (2000) prove the causality from macro to stock price, whereas Ratanapakorn and Sharma (2007) observe the impact of stock price on macro ones. Pan, Fok, and Liu (2007) share this disagreement in causality among East Asian nations. Granger (2000) also reports contradictory results when using the bivariate VAR model with stationary variables exchange rate and stock price. The exchange rate is reported to Granger cause stock price in South Korea, but is Granger caused by stock price in other highly industrialised, developed Asian countries.

Lin (2012) implements this Granger causality test, but on a mixture of stationary and non-stationary series instead of using merely stationary or merely non-stationary series as above. However, owing to the absence of cointegration among the series, a standard Granger causality test is still employed. Shan *et al.* (2001) investigate the Granger causality relationship, but using a modified Wald test proposed by Toda and Yamamoto (1995). They support the cointegration relationship as well as the direction of causality from the stock market to the macroeconomic variable, economy growth.

Further comments on the literature and suggestions for our research

From the literature review, it can be clearly seen that extensive studies have been carried out in both developing and developed markets. They generally support the importance of local macro variables and global factors in the stock market–macro variables relationship. Nevertheless, the sign and the magnitude of the response of stock returns to each variable, as well as the Granger causality between them, vary greatly among nations, regions, and continents, and there is a need to update the analysis to include the recent crisis.

For this reason, this research aims to contribute to the literature by examining the relationship between Thailand's stock market and macroeconomic variables, one of the most developed countries in Asia, using a dataset of 16 years from 2001 to 2016. ARDL will be employed to gauge the cointegration instead of the standard Johansen cointegration technique, which is sensitive to the lag length choice and order of integration. The standard Granger causality test, based on joint significance of coefficients of differenced variables, will be replaced by the Toda–Yamamoto (1995) in this research. Moreover, we employ dummy variables to deal with structural breaks during the sample period rather than dividing the sample into very small sets of data analysed in Lin (2012) above. The breakpoints are also allowed for in this study using Zivot and Andrews (1992) and Lee and Strazicich (2001) unit root tests.

3.3 Methodology

This section introduces the methodology used in the research. Owing to the inconclusive results of unit root tests, the ARDL methodology will be employed in the model. ARDL is a new approach testing the long-term relationship between dependent variables and a set of explanatory variables when there is uncertainty about the order of integration of the variables. In the ARDL approach, two new sets of critical values are proposed, to provide "critical value bounds" (Pesaran, 2001). The computed test statistic is compared with the critical bounds to make inferences about the long-term cointegration.

Moreover, the research also aims at measuring short-term Granger causality between them. The research employs the Toda and Yamamoto (1995) methodology, allowing a Granger causality test among stationary and non-stationary variables, rather than the Wald test on parameters of a VAR model, which do not follow a usual asymptotic distribution.

For that reason, this section will cover methodology on: the ARDL bound test and the Toda–Yamamoto Granger causality test. Also introduced is the unit root test, which is the first compulsory test to determine the characteristics of the dataset before applying the ARDL bound test and the Toda–Yamamoto test.

3.3.1 Traditional unit root test with no structural break

Unit root testing is a necessary step before empirical analysis. To determine the stationarity of a series, the following traditional tests are proposed: the

Augmented Dickey-Fuller test (ADF), the Phillips–Peron test (PP), and the Kwiatkowski, Phillips, Schmidt, and Shin test (KPSS).

3.3.1.1 The Augmented Dickey Fuller test

Suppose Y_t is a series of interest, the ADF test means estimating the following equation:

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-i} + \varepsilon_t$$

This is the most general form, allowing for testing unit root with drift and trend. ΔY_t denotes the first difference of the series Y_t, ΔY_{t-i} denotes lagged dependent variables and is added to this augmented specification to remove serial autocorrelation in residuals. β_1 is the constant, β_2 is the time-trend coefficient, and ε_t is the residual. δ is coefficient related to lagged variable Y_{t-1} and is used to test the null hypothesis. t denotes a time trend variable. The lag number is determined by the Schwarz Information criterion (SIC).

A unit root test for stationarity is equivalent with testing the hypothesis:

$H_0: = 0$: unit root (non-stationary series)

$H_1: < 0$: no unit root (stationary series)

Compare the *t*-value of δ – the coefficient of the lag dependent variable calculated from the above equation – with the critical value for ADF (Asteriou and Hall, 2007) to determine whether or not a time series is stationary. If the *t*-value is less than critical value, the series is stationary (no unit root test).

3.3.1.2 The Phillips–Perron test

Although the ADF test removes the serial correlation in errors by adding the lagged value of ΔY, Phillips and Perron (1988) developed a test taking care of the problem using new *t*-statistics without adding lagged difference terms. This is a nonparametric statistical method, advantageous over ADF because: (i) PP tests are robust to the general form of the residuals' heteroskedasticity, (ii) no lag length need be specified in the PP test. However, the PP test still relies on asymptotic theory or a large dataset, which is not popular in developing and transitional countries.

The unit root test regression in Phillips and Perron (1988) has the form:

$$\Delta y_{t-1} = \alpha_0 + \gamma y_{t-1} + \varepsilon_t$$

$H_0: \gamma = 0$: unit root (non-stationary series)

$H_1: < 0$: no unit root (stationary series)

The PP method corrects the *t*-statistics of the coefficient γ to account for the serial correlation in the residuals ε_t. It is considered a modification of the ADF *t*-statistics with the same asymptotic distribution.

3.3.1.3 The Kwiatkowski, Phillips, Schmidt, and Shin test

The ADF and PP tests are criticised as having low power – probability of rejecting the null hypothesis when it is false. Therefore, there is a tendency to accept the null hypothesis rather than what is warranted, indicating that there are several unit root series (Gujarati and Porter, 2009). Kwiatkowski, Phillips, Schmidt, and Shin (1992) develop the reverse null: the series is stationary by default.

ADF/PP	*KPSS*
H_0: y_t ~I(1)	H_0: y_t ~I(0)
H_1: y_t ~I(0)	H_1: y_t ~I(1)

The model of KPSS:

$$y_t = \beta' D_t + \mu_t + u_t$$

$$\mu_t = \mu_{t-1} + \varepsilon_t, \qquad \varepsilon_t \sim \mathrm{N}(0, \sigma_\varepsilon^2)$$

D_t is a deterministic component (constant or constant and trend). μ_t is a pure random walk with variance σ_ε^2 as specified in the above equation. The null hypothesis that $y_t$is stationary is formulated as:

H_0: $\sigma_\varepsilon^2 = 0$: stationary series

H_1: $\sigma_\varepsilon^2 > 0$: non-stationary series

The KPSS *t*-statistic for testing the null against the alternative is calculated by:

$$KPSS = (T^{-2} \sum_{t=1}^{T} \widehat{S}_t^{\,2}) / \hat{s}^2$$

Here $\widehat{S_t} = \sum_{j=1}^{T} \hat{u}_t$, $\hat{u}_t$is the residual of the regression of y_t on D_t. $\hat{s}^2$ is the long-term variance of u_t using $\widehat{u_t}$.

The null hypothesis of stationary is rejected at 100.α% level if the KPSS calculated above is greater than critical value.

3.3.2 Unit root test in the presence of a structural break

A macroeconomic series is usually collected over a long period. Thus, it is likely to have abrupt changes at some points, called structural breaks. Perron

(1989) argues that the conventional unit root tests are biased if the trend data have structural breaks. In the presence of structural breaks, the mentioned traditional unit root tests are thought to have low power: stationary series may be categorised as non-stationary series (Perron, 1989). To overcome this problem, some additional tests allowing for one or two structural breaks have been proposed, such as Zivot and Andrews (1992), Lumsdaine and Papell (1997), Perron and Vogelsang (1992), and Lee and Strazicich (2003). This study will cover two tests that allow for structural breaks: the Zivot and Andrews (1992), in the case of one structural break, and the Lee and Strazicich (2003), a two-break unit root test.

3.3.2.1 Unit root test in the presence of one structural break

Based on Perron (1992), Zivot and Andrews specify three equations for unit root test: (i) Model A, a crash model, which allows for a break in the level (intercept) of a series; (ii) Model B, a changing growth model, which allows for a change in the slope (the growth rate); (iii) Model C, which allows for a change in both the level and slope of a series.

Suppose y_t is a series of interest, we have three specifications corresponding, respectively, to the three Models A, B, and C as below:

$$\Delta y_t = c + \alpha y_{t-1} + \beta t + \gamma DU_t + \sum_{i=1}^{p} d_i y_{t-i} + \varepsilon_t$$

$$\Delta y_t = c + \alpha y_{t-1} + \beta t + \theta DT_t + \sum_{i=1}^{p} d_i y_{t-i} + \varepsilon_t$$

$$\Delta y_t = c + \alpha y_{t-1} + \beta t + \gamma DU_t + \theta DT_t + \sum_{i=1}^{p} d_i y_{t-i} + \varepsilon_t$$

Here DU_t denotes a dummy variable for a mean shift at each possible structural break (TB), $DU_t = 1$ if *(t>TB)* and zero otherwise. DT_t denotes trend shift, $DT_t = t - TB$ if *(t>TB)* and zero otherwise.

All three models have a unit root with a break under the null hypothesis ($\alpha = 0$) and the alternative is a trend-stationary process with a break ($\alpha < 0$). In Zivot and Andrew (1992), the structural break is unknown and is endogenously determined using different dummy variables for different break dates. The Zivot and Andrews method tests every single point as a potential break date and chooses the date that minimises one-sided t-statistic. After choosing the best fit model and the breakpoint, the estimated results are compared with the critical value of Zivot and Andrew (1992) to decide whether or not the series is stationary.

As specified by Perron (1989), among the three models mentioned above, Models A and C are capable of explaining most economic time series. Most of the subsequent literature, therefore, has employed one of these two models. Moreover, among Models A and C, Sen (2003) shows that, if the true model is C, and Model A is used, there will be a substantial loss in power. Whereas, if Model C is used, regardless of the fact that Model A archives the better fit, a loss in power exists but is small. For that reason, we choose Model C for all one-break unit root test calculations.

3.3.2.2 Unit root test in the presence of two structural breaks

Lee and Strazicich (2003) have pointed out that applying a one-break unit root test, when two breaks should be used, can lead to a loss of power. So, two-break unit root tests should also be considered in this study. We adopt the Lee and Strazicich (2003; LS), which depends on the Lagrange Multiplier (LM) unit root test. Suppose y_t is a series of interest:

$$y_t = \delta' Z_t + e_t,\ e_t = \beta e_{t-1} + \varepsilon_t$$

Here Z_t is a vector for exogenous variables, $\varepsilon_t \sim N(0, \sigma^2)$.

LS proposes two models: Model A has two shifts in level and Model C has shifts in level and trend.

Model A: $Z_t = [1, t, D_{1t}, D_{2t}]'$ where $D_{jt} = 1$ for t≥ $T_{Bj} + 1$, j=1,2 and zero otherwise. T_{Bj} denotes breakpoint.

Model C: $Z_t = [1, t, D_{1t}, D_{2t}, DT_{1t}, DT_{2t}]'$ where $DT_{jt} = t$ for t≥ $T_{Bj} + 1$, j=1,2 and zero otherwise.

Under the LM unit root test with two endogenous breaks, the rejection of the null implies trend stationary.

3.3.3 ARDL methodology: bound test for cointegration

Our study employs the autoregressive distributed lag model (ARDL) proposed by Pesaran *et al.* (2001). The ARDL specification, including unrestricted intercept and unrestricted trend under the general vector autoregressive model (VAR), is:

$$\mathrm{z_t} = \beta + \mathrm{ct} + \sum_{\mathrm{i}=1}^{\mathrm{p}} \varphi_\mathrm{i} \mathrm{z_{t-i}} + \epsilon_\mathrm{t} \qquad \text{with } \mathrm{t} = 1,2,3 \dots \mathrm{T}$$

This is the most general case with both unrestricted intercepts and unrestricted trends. β represents the vector for intercepts, c denotes trend coefficients, z_t is the vector for the dependent variable, y_t, and independent variables, x_t.

Subtracting both left-hand side (LHS) and right-hand side (RHS) of the equation with z_{t-1} and rewriting the model under the equilibrium-correction model (ECM) to have:

$$\Delta z_t = \beta + ct + \pi z_{t-1} + \sum_{i=1}^{p} \tau_i \Delta z_{t-i} + \epsilon_t \qquad \text{with } t = 1,2,3 \ldots T$$

$$\text{with } \pi = I_{k+1} + \sum_{i=1}^{p} \gamma_i \,;\ \tau_i = \sum_{j=i+1}^{p} \gamma_i$$

I is a unit matrix, γ_i is a short-term coefficient matrices. The coefficients π and τ_i depict long- and short-term relationships, respectively.

Partitioning the error term ϵ_t as: $\epsilon_t = (\epsilon_{yt}, \epsilon'_{xt})$, the variance matrix has the form:

$$\Omega = \begin{pmatrix} \varpi_{yy} & \varpi_{yx} \\ \varpi_{xy} & \varpi_{xx} \end{pmatrix}$$

Substituting $z_t = (y_t, x_t')'$ provides a conditional model in the form:

$$\Delta y_t = c_0 + c_1 t + \pi_{y,x} z_{t-1} + \sum_{i=1}^{p} \psi_i \Delta z_{t-i} + \varpi' \Delta x_t + u_t \qquad \text{with } t = 1,2,3 \ldots T$$

$u_t \sim N(0, \varpi_{uu})$, $\varpi_{uu} = \varpi_{yy} - \varpi_{yx} \Omega_{xx}^{-1} \varpi_{xy}$

Therefore, the long-term relationship is tested with the null:

$H_0: \pi = 0$ and $H_1: \pi \neq 0$.

Partition the long-term relationship vector π conformably with two specific variables y_t and x_t ($z_t = (y_t, x_t')'$ we have:

$$\pi = \begin{pmatrix} \pi_{yy} & \pi_{yx} \\ \pi_{yy} & \pi_{xx} \end{pmatrix}$$

To test the long-term relationship between variables in level, we employ the bound test in Pesaran *et al.* (2001). The idea is to test for the coefficients related to variables y_{t-1} and x_{t-1}. The null hypothesis $H_0^{\pi_{yy}}\ :\ \pi_{yy} = 0,\ H_0^{\pi_{yx,x}}\ ; \pi_{yx,x} = 0$ and the alternatives $H_1^{\pi_{yy}} : \pi_{yy} \neq 0\ ;\ H_1^{\pi_{yx,x}}\ \pi_{yx,x} \neq 0$. The joint null hypotheses following Pesaran *et al.* (2001) are:

$$H_0: H_0^{\pi_{yy}} \cap H_0^{\pi_{yx,x}}$$

$$H_1: H_1^{\pi_{yy}} \cup H_1^{\pi_{yx,x}}$$

The bound procedure is as follow: If the F-statistic is larger than the critical value bounds, it is not necessary to know the order of integration of each variable to reject the null. It means that there is a long-term relationship between variables. However, if the F-value lies within the bounds, inference would be inconclusive. In this case, the asymptotic distribution of the F-statistics is non-standard. The lower bound is calculated assuming all variables are stationary *I*(0), and the upper bound assumes that all variables are non-stationary *I*(1), (Pesaran, 2001). Because asymptotic theory is not influenced by the addition of dummy variables (Pesaran, 2001), dummy variables can be used to account for the structural breaks in ARDL estimation.

3.3.4 Granger non-causality test of Toda and Yamamoto

Most of the traditional Granger causality empirical tests require pre-tests: the unit root test and the cointegration test. If economic variables in the VAR system are $I(1)$ with no cointegration, one can estimate a VAR in first-order differences of the variables "so that the conventional asymptotic theory" is satisfied (Toda and Yamamoto, 1995). If the variables are cointegrated, for example two variables $I(1)$ are cointegrated of order CI(1,1), an error-correction model can be specified. However, one may wish to avoid these unit root tests and cointegration test, which "are known to have low power", sensitive to the value of nuisance parameters in finite sample and not really reliable for the usual sample size of economic time series. Therefore, it is desirable to have a kind of Granger causality test, which is robust to the order of integration and cointegration between the variables.

Toda and Yamamoto (1995) proposed a Toda–Yamamoto Granger (TYDL) non-test to estimate the VAR specification in levels for any "possibly integrated or cointegrated VAR" (Toda and Yamamoto, 1995). No cointegration test needs to be examined using this methodology.

A VAR with lag number $(k + d_{max})$ estimated with k is the optimal lag length of the VAR in level using information criteria, and d_{max} is maximum order of integration of the series in the dataset. Here the lag order of the VAR is augmented, depending on the highest order of integration of the variables as well. Toda and Yamamoto (1995) have proven that Wald test statistics in this augmented VAR are asymptotically distributed.

The system VAR in levels has the following form:

$$z_t = \beta + \sum_{i=1}^{k+dmax} \varphi_i z_{t-i} + \epsilon_t \qquad \text{with } t = 1,2,3 \dots T$$

Write out the above equation to have the new one:

$$z_t = \beta + \sum_{i=1}^{k} \varphi_i z_{t-i} + \sum_{i=k+1}^{dmax} \varphi_i z_{t-i} + \epsilon_t \qquad \text{with } t = 1,2,3 \dots T$$

Assuming there is a system of two variables X and Y, we rewrite the above equation with z_t on the RHS is substituted by Y_t and X_t

$$z_t = \beta + \sum_{i=1}^{k} \varphi_i Y_{t-i} + \sum_{i=k+1}^{dmax} \varphi_i Y_{t-i} + \sum_{i=1}^{k} \phi_i X_{t-i} + \sum_{i=k+1}^{dmax} \phi_i X_{t-i} + \epsilon_t$$

The Granger non-causality test following Toda–Yamamoto (1995) is equivalent to the null hypothesis testing:

H_0: $\phi_1 = \phi_2 = \phi_3 = \dots = \phi_k = 0$ and H_1: not H_0

These restrictions on the first k variables are tested using the usual asymptotic theory. The rejection of null hypothesis implies that there is Granger causality from X to Y.

3.4 Descriptive statistics

To measure the interaction between the stock market and macroeconomic variables, a wide set of macro variables is collected on a monthly basis from Datastream. We follow Bekhet and Matar (2013) and Aburgi (2008) in using the following variables: the industrial production index, the money supply, the prime lending rate, and the exchange rate. Global factors, proxied by the MSCI world index, are added to the model following Fifield (2002, 2006) and Aburgi (2008) to account for the global integration of financial markets. As we have mentioned above, this initial variable selection is an avoidable problem (Fama, 1981). The variables not only follow the previous literature, but also fit the theoretical proposition of APT that any macro variables affecting the nominator and denominator of the dividend discount model of stock price can be considered in this relationship. The sample period is from January 2001 to December 2016, owing to data availability.

The notations of the variables: Thailand's stock market index, industrial production index, money supply, prime lending rate, and exchange rate, and the global factors are SPI, IP, M1, R, NER, and MSCI, respectively. They are transformed into the natural logarithm form except the lending rate. This logarithmic transformation is frequently applied in macroeconomic data to reduce skewness. Furthermore, it makes the results interpretable: coefficients on a natural logarithmic version illustrate the proportional difference (Gelman and Hill, 2007). Among the five macroeconomic variables, the money supply series is seasonally adjusted to remove seasonal effect, whereas the collected industrial production is already seasonally adjustment.

Table 3.1: Definition and variables transformation

Variables	Definition	Transformation	Units
SPI	Stock price index	Natural logarithm	Index, 1975 = 100
IP	Industrial production	Natural logarithm	Index, 2000 = 100
M1	Money supply	Natural logarithm	National currency
NER	Official exchange rate	Natural logarithm	National currency per US dollar
R	Prime lending rate	Interest rate charged on the most credit-worthy customers	Percentage per annum
MSCI	MSCI world index	Large and mid-cap equity performance across 23 developed countries	

We report the descriptive statistics and the correlation matrix together with time-series plot of the variables.

Table 3.2: Descriptive statistics of data

	SPI	IP	M1	R	NER	MSCI
Mean	6.675283	4.451220	6.948091	7.038021	3.575204	7.132014
Median	6.637350	4.534565	6.920979	7.125000	3.552289	7.139437
Maximum	7.376421	4.753784	7.494088	8.750000	3.822173	7.491375
Minimum	5.617098	3.907778	6.212715	5.750000	3.375603	6.621496
Skewness	−0.34605	−0.81644	−0.24278	0.23042	0.340835	−0.28695
Kurtosis	2.148640	2.479354	1.892713	2.233533	1.839219	2.175971
Jarque–Bera	9.630560	23.49892	11.69475	6.398804	14.49669	8.067059
P-value	0.008105	0.000008	0.002887	0.040787	0.000711	0.017712

The Jarque–Bera and *p*-value statistics are used to test the normality of the series. The table results show that the normality is rejected for all series. The kurtosis of all variables is less than 3, illustrating the thinner tails than normal distribution of them. The skewness values are negative, meaning that they are skewed to the left.

Figure 3.1: Data plots of the used variables (in logarithmic form)

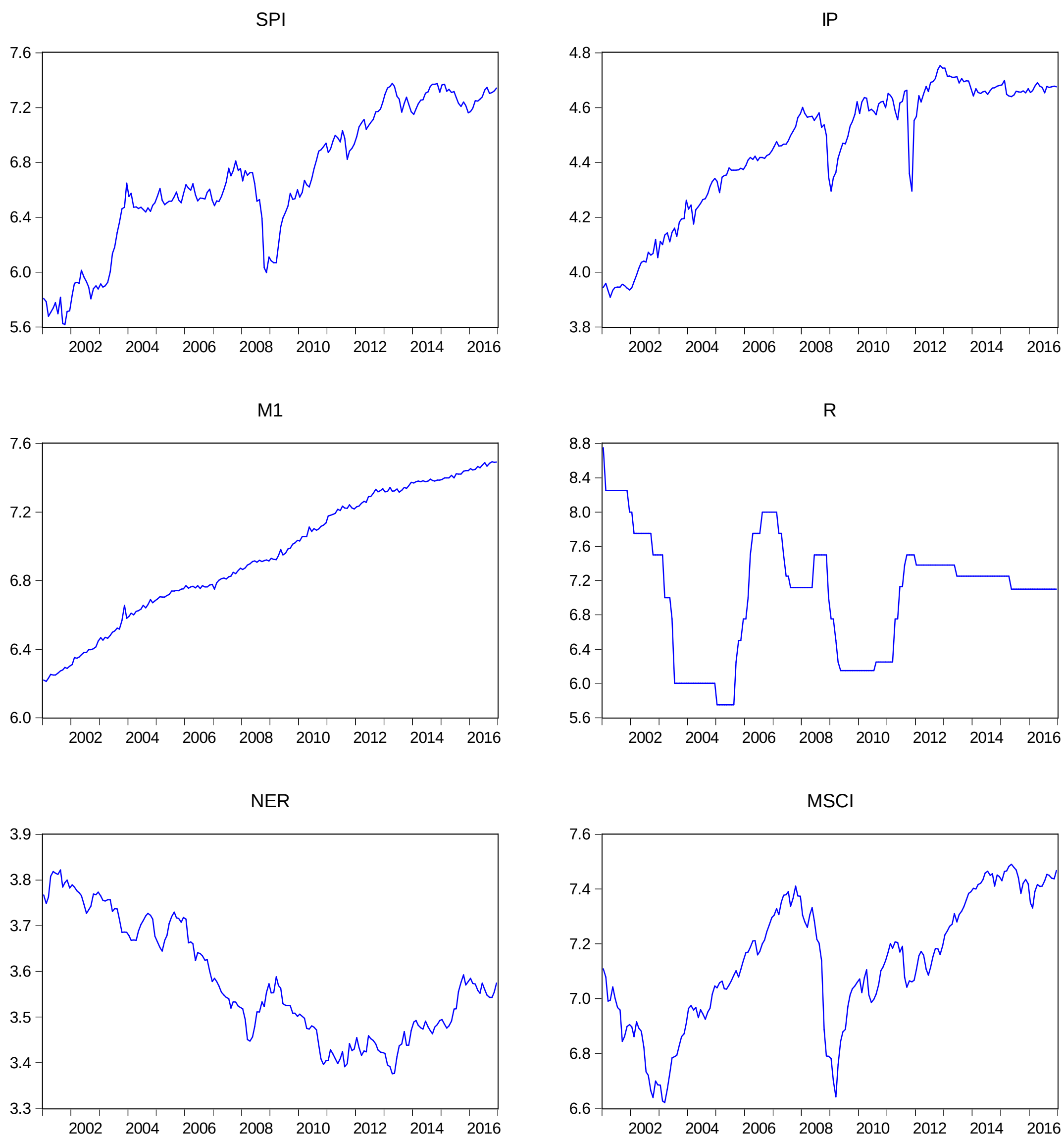


Figure 3.1 illustrates the time-series plots of the variables used in our study: the stock price index, the industrial production, the money supply, the prime lending rate, the exchange rate, and the MSCI world index. Although expanded in recent decades, Thailand's stock price index and the industrial production index shared a large drop during the global financial crisis. There was another sharp fall in the latter variable, industrial production, in the year 2011/2012, which can be explained by the 2011 Thai floods. Severe and widespread flooding during this time disrupted production and reduced output, causing the industrial production index to fall to its lowest level during the research period.

As for the exchange rate, the Thai Baht has appreciated considerably. It seems to be associated with the development of the Thai stock market together with large purchases of Thai equities from non-resident investors. The increase in money supply and decrease in lending rate illustrate the expansionary monetary policy of the country.

Overall, from Figure 3.1, we obtain the inverse trend between the stock price index and lending rate and exchange rate. The stock price index and the other two variables (industrial production and money supply) seem to move in the same direction.

Table 3.3: Correlation matrix between variables

	SPI	IP	M1	R	NER	MSCI
SPI	1	0.908315	0.935642	−0.13657	−0.78291	0.815916
IP	0.908315	1	0.937626	−0.16844	−0.89252	0.728454
M1	0.935642	0.937626	1	−0.10597	−0.84173	0.716055
R	−0.13657	−0.16844	−0.10597	1	0.084245	0.180387
NER	−0.78291	−0.89252	−0.84173	0.084245	1	−0.56923
MSCI	0.815916	0.728454	0.716055	0.180387	−0.56923	1

As for correlation, the results reported in Table 3.3, namely the correlation matrix between variables, produce some plausible outcomes. High and positive correlations between the stock market index (SPI) and the industrial production (IP) or the money supply (M1)) are not problematic in this case. This is because the employment of the ARDL model allows us to deal with non-stationary series, which are usually expected to be highly correlated. The negative correlation between the stock price index (SPI) and the exchange rate (NER) suggests more formal cointegration tests are needed among the series.

3.5 Empirical results

To measure the interaction between the stock market and macroeconomic variables, the ARDL methodology is employed to examine the long-term relationship, whereas the TYDL methodology is utilised to make inferences about the causality relationship.

Estimates are carried out in the following steps: first, a unit root test is performed to understand the nature of the series (stationary or non-stationary); second, ARDL is employed to examine the long-term relationship; and third, a

Granger causality test is used to understand the short-term interaction between them.

3.5.1. Unit root test

One advantage of the ARDL model over the other cointegration techniques is that it does not require the order of integration test as it can be applied irrespective of whether the input series are I(0) or I(1). However, the stationary tests are still needed to validate the properties of the series (ie whether they are I(0) and I(1), not I(2)). We employ two main streams of unit root tests: the traditional unit root test without structural break and the unit root test in the presence of structural breaks.

3.5.1.1 The traditional unit root test without structural breaks

Table 3.4 shows the results employing traditional unit root tests. They are tested on the level and the first difference to confirm that all of them are I(1) and I(0), none is I(2).

Table 3.4: Unit root test at level of variables

The unit root test results including the ADF, the PP, and the KPSS tests. The signs ***, **, and * denote significant levels at 1%, 5%, and 10%, respectively.

Variables	ADF t stat	PP t stat	KPSS t stat	I(0) or I(1)
SPI	−3.23301*	−2.63188	0.10288	Inconclusive
IP	−1.925766	−2.40295	0.3579***	I(1)
M1	−1.378902	−2.4871	0.22821***	I(1)
R	−3.39191**	−1.72106	0.11624	Inconclusive
NER	−0.94053	−1.55984	0.34897***	I(1)
MSCI	−1.42235	−1.36392	0.976019***	I(1)

Table 3.5: Unit root test at first difference of variables

The unit root test results at first difference of variables, including the ADF, the PP, and the KPSS tests. The signs ***, **, and * denote significant levels at 1%, 5%, and 10%, respectively. D denotes the first difference operator.

D(Variables)	ADF t stat	PP t stat	KPSS t stat	Variable: I(2) or not
D(SPI)	−12.2921***	−12.4462***	0.048182	Not I(2)
D(IP)	−12.0003***	−16.6195***	0.371983*	Not I(2)
D(M1)	−8.44759***	−19.5763***	0.429436*	Not I(2)
D(R)	−11.0975***	−11.8686***	0.171946	Not I(2)
D(NER)	−10.9976***	−10.7509***	0.032622	Not I(2)
D(MSCI)	−10.1475***	−10.2456***	0.091334	Not I(2)

The inconclusive results of the three conventional unit root tests suggest that the variables are among I(0) or I(1) series (based on a 95% confidence interval). None of variables is I(2). This suggests the application of the ARDL model for long-term cointegration.

3.5.1.2 Unit root test with a structural break

Owing to the characteristics of the variables analysed in the previous section, we employ the Zivot and Andrews (1992) unit root test with one structural break for all variables except industrial production. As for the industrial production index, the Lee and Strazicich (2003) unit root test, allowing for two structural breaks, is employed.

Table 3.6: Unit root test with one structural break

The Zivot and Andrew (1992) unit root test with one structural break. The signs ***, **, and * denote significant levels at 1%, 5%, and 10%, respectively.

	t-statistics	I(0) or I(1)
SPI	−4.01295	I(1)
M1	−2.86165	I(1)
R	−4.55423	I(1)
NER	−4.71166	I(1)
MSCI	-5.84497***	I(0)

Table 3.7: Unit root test with two structural breaks

The LM unit root test statistics with two structural breaks. Critical values for LM test with two-break Models A (level with shift) and C (level with trend) are tabulated in Lee and Strazicich (2004) and Lee and Strazicich (2003), respectively. The signs ***, **, and * denote significant levels at 1%, 5%, and 10%, respectively.

	LM two structural breaks (Model A: level shift)	LM two structural breaks (Model C: level, trend)
IP	−0.10489**	−0.217798***
	(−2.740)	(−4.755)

The table above shows the results of a unit root test when accounting for the structural break in the series. The outcome of the Zivot and Andrews (1992) for the first four variables SPI, M1, R, and NER suggests that we cannot reject the null hypothesis at 5% significance level. It means that the first four series have a unit root with one break. As for the MSCI index, the *t*-statistics is larger than the critical value, meaning that the MSCI index is a stationary series. When it comes to the variables industrial production IP, the outcome from the LM test in both Model A (two changes in level) and Model C (two changes in level and trend) suggests that the null hypothesis of a unit root is rejected at least at the 95% confidence interval. In other words, the series IP is trend stationary with breaks.

Overall, the three traditional unit root tests (ADF, PP, and KPSS) and the two breakpoint unit root tests (Zivot and Andrews (1992); Lee and Stracizich (2003)) all arrive at inconclusive results of the order of integration. However, they confirm that all variables are I(0) and I(1), none is I(2). This result satisfies the requirement of the ARDL bound test; thus, the ARDL bound test is applied in the next section measuring the long-term relationship between the stock index SPI and other variables.

3.5.2 ARDL bound test for long-term relationships among variables

Our proposed ARDL model to test the long-term relationship between the stock market and macro variables without requiring that all variables must be stationary is:

$$SPI_t = \beta_0 + \beta_{01}t + \beta_1 IP_t + \beta_2 M1_t + \beta_3 R_t + \beta_4 NER_t + \beta_5 MCSI_t + \beta_6 DUM1_t + \beta_7 DUM2C_t$$

$$\begin{aligned}\Delta SPI_t = {} & \beta_0 + \beta_{01}t + \sum_{i=1}^{n1} \beta_1 \Delta SPI_{t-i} + \sum_{i=0}^{n2} \beta_2 \Delta IP_{t-i} + \sum_{i=0}^{n3} \beta_3 \Delta M1_{t-1} + \sum_{i=0}^{n4} \beta_4 \Delta R_{t-1} \\ & + \sum_{i=0}^{n5} \beta_5 \Delta NER_{t-1} + \sum_{i=0}^{n6} \beta_6 \Delta MSCI_{t-1} + \phi_1 SPI_{t-1} + \phi_2 IP_{t-1} + \phi_3 M1_{t-1} \\ & + \phi_4 R_{t-1} + \phi_5 NER_{t-1} + \phi_6 MSCI_{t-1} + \phi_7 DUM1_{t-1} + \phi_8 DUM2_{t-1} + \varepsilon_t\end{aligned}$$

DUM1 and *DUM2* are two dummy variables for the global financial crisis and 2011 Thai floods. *DUM1* takes the value of 1 from January 2008 to December 2009 and is 0 otherwise. *DUM2* takes value of 1 from June 2012 to January 2012 and is 0 otherwise. $n1, n2 \dots n6$ are lag length numbers, determined using the information criteria. $\phi_1, \phi_2, \phi_3, \phi_4, \phi_5, \phi_6$ represent long-term coefficients of the variables.

There are several criteria to select the optimal lag length, such as Akaike Information criterion (AIC), Schwarz Bayesian Criterion (SIC or SBC), Hannan–Quinn Criterion (HQC), and adjusted R-Squared (R2). SIC usually minimises the lag number (Pesaran, 1999), whereas AIC tends to overfit the model (Hurvich and Tsai, 1989). Employing the dataset of nearly 200 observations, this research chooses the AIC criteria rather than underfit the model.

We have the following bound test:

Table 3.8: Bound test for long-term cointegration among the variables

The bound test for long-term cointegration among the variables. The critical values in the bound test are from Table CI, Case V: Unrestricted intercept and unrestricted linear trend (Pesaran, 2001).

F statistics	Significant level	Critical values*		Decision
5.681221	10%	2.75	3.79	Cointegration
	5%	3.12	4.25	
	2.50%	3.49	4.67	
	1%	3.93	5.23	

The calculated F statistics 5.681221 suggests that there exists a long-term relationship between the stock market index and the macro variables. Estimating the long-term relationship, we have the equation:

$$SPI = -0.3698IP + 3.4769M1 + 0.0089R + 0.4071NER + 0.6511MSCI$$

Table 3.9: Estimated long-term coefficients for SPI equation using the ARDL

The long-term estimation results. The signs ***, **, and * denote significant levels at 1%, 5%, and 10%, respectively. The optimal lag length based on AIC is ARDL (4,0,1,7,1,1).

Variable	Coefficient	Std. Error	*t*-Statistic	Prob.
IP	−0.3698	0.24436	−1.5134	0.1321
M1	3.4769***	0.6289	5.5286	0.0000
R	0.0089	0.0321	0.2767	0.7824
NER	0.4071	0.3288	1.2383	0.2174
MSCI	0.6511***	0.1299	5.0089	0.0000

These results are from estimating the long-term relationship between the stock market index and macro variables using the ARDL approach. Among the variables in the cointegration relationship, the money supply M1 and the MSCI index are two macro variables having statistically significant relationships with the stock market index. The money supply M1 has the positive sign, meaning that an increase in the money supply creates higher stock prices in the long term. This positive relationship is empirically supported by Mukherjee and Naka (1995) for Japan, Bulmash and Trivoli (1991) for the US economy, and Wongbangpo and Sharma (2002) for ASEAN countries. An increase in the money supply will raise the public's cash balance through the liquidity effect[6]; therefore, it stimulates investment,

[6] Liquidity effect: introduced by Friedman (1969) to describe how expansionary monetary policy affects three elements of the economy: interest rate, income, and inflation.

consumption, and production level. This consequently leads to the higher price of stocks and other financial assets (Chen, 2012).

The sign of the coefficient on the MSCI variable is statistically significant and positive, meaning that Thailand's stock market moves in the same direction as global stock markets. From the international capital asset pricing model (ICAPM), if financial markets are integrated, a global factor should be used as a priced factor. For that reason, the statistically significant coefficient suggests that Thailand's stock market is integrated with global markets. This finding coincides with Aburgi (2008) and Fifield (2002, 2006).

3.5.3 Granger short- and long-term causality among nominal variables

According to the Granger Representation Theorem, when there is evidence of long-term cointegration between variables, there must be at least a Granger causality among them. The results from previous sections confirm the existence of Granger causality among variables but does not indicate the direction of the causal relationship. This section, therefore, will analyse short- and long-term causality among the variables in the system.

Long-term causality

Using the short-term dynamic part of the ARDL model's output, we have the error-correction model representation as Table 3.10 below.

Table 3.10: The short-term relationship for nominal variable ΔSPI

The short-term estimation results. Δ denotes first different operator.

ECM Regression

Case 5: Unrestricted constant and unrestricted trend

Variable	Coefficient	Std. Error	*t-Statisitc*	Prob.
C	-4.229624	0.715506	-5.911374	0.0000
Trend	-0.003106	0.000519	-5.988937	0.0000
ΔSPI(-1)	-0.141834	0.068760	-2.062742	0.0407
ΔSPI(-2)	-0.002497	0.056209	-0.044421	0.9646
ΔSPI(-3)	0.171747	0.055355	3.102656	0.0023
ΔM1	0.202792	0.210923	0.961449	0.3378
ΔR	-0.034141	0.026336	-1.296375	0.1967
ΔR(-1)	-0.041178	0.026213	-1.570883	0.1182
ΔR(-2)	-0.035420	0.026734	-1.324901	0.1871
ΔR(-3)	-0.042784	0.026383	-1.621688	0.1068
ΔR(-4)	-0.013208	0.027772	-0.475595	0.6350
ΔR(-5)	-0.109059	0.026726	-4.080647	0.0001
ΔR(-6)	0.027934	0.025538	1.093829	0.2757
ΔNER	-0.430692	0.247139	-1.742712	0.0833
ΔMSCI	0.957684	0.082365	11.62725	0.0000
DUM1	-0.032212	0.010418	-3.092080	0.0023
DUM2	0.019791	0.017401	1.137370	0.2571
CointEq(-1)*	-0.206206	0.034786	-5.927850	0.0000
R-squared	0.594011	0.594011	0.594011	0.594011
Adjusted R-squared	0.552683	0.552683	0.552683	0.552683
F-statistic	14.37301	14.37301	14.37301	14.37301

The coefficient of the cointegration term (coefficient related to Cointeq(-1)) is statistically significant and takes the negative value in the range from -1 to 0. First, it confirms the existence of long-term equilibrium. The value depicts the speed of adjustment from the position out of equilibrium in short- to long-term equilibrium. The absolute value of 0.206 means that, on average, any disequilibrium in the last period will be corrected approximately 20.6% in the month following. In other words, it takes approximately five months to bring the disequilibrium to the steady state. This speed of adjustment is greater than that of Bekhet and Matar (2013) and Hassan *et al.* (2012) for the Jordan market, but smaller than almost all other emerging and developed markets (Majid and Yosof, 2009). This finding may have implications for investment strategies; for example, investors could make investments according to the adjustment, approximately five months. They can predict stock prices partly by the macroeconomics information. Second, according to Narayan and Smyth (2006) and Odhiambo (2009), the significance of this cointegration relationship (error-correction term) also indicates the long-term Granger causality: Money supply M1 and MSCI interactively Granger cause the stock market through the error-correction term.

Short-term causality

For short-term Granger causality, the Toda–Yamamoto Granger non-causality test is employed. In a standard Granger causality test, the *F*-statistics on the lagged explanatory variables are used to assess the significance of short-term causality. However, in this case, there is a mixture of both stationary I(0) and non-stationary I(1) series, so the Wald test statistics do not have standard asymptotic Chi-squared distribution under the null. For that reason, the Toda–Yamamoto method, which is robust to any order of integration, is used.

To apply the Toda–Yamamoto (1995) test, the order of integration of each series needs to be determined. The unit root tests in the previous section suggests that all are I(0) and I(1), leading to the $dmax$ number of 1 because $dmax$ stands for the maximum order of integration of the series in the dataset in the methodology. Lag length number (k) of VAR model in level can be identified using information criteria.

Table 3.11: Lag length selection criteria

The lag length selection of level VAR model. *indicates lag order selection using information criterion at 5% level.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	554.5556	NA	1.04e-10	-5.961729	-5.642433	-5.832268
1	2095.800	2928.364	5.66e-18	-22.68666	-21.72878*	-22.29828
2	2175.906	146.8620	3.47e-18	-23.17674	-21.58026	-22.52943*
3	2219.624	77.23570	3.20e-18*	-23.26249*	-21.02742	-22.35627
4	2237.679	30.69239	3.93e-18	-23.06310	-20.18944	-21.89795
5	2275.728	62.14658	3.89e-18	-23.08586	-19.57361	-21.66180
6	2317.040	64.72266	3.73e-18	-23.14489	-18.99405	-21.46190
7	2344.954	41.87047	4.18e-18	-23.05504	-18.26561	-21.11313
8	2372.347	39.26388	4.74e-18	-22.95941	-17.53139	-20.75858
9	2397.303	34.10592	5.57e-18	-22.83670	-16.77008	-20.37694
10	2416.458	24.90133	7.06e-18	-22.64953	-15.94432	-19.93086
11	2465.647	60.66704*	6.49e-18	-22.79608	-15.45228	-19.81848
12	2503.316	43.94766	6.88e-18	-22.81463	-14.83224	-19.57811

The AIC and FPE criteria suggest a lag length of 3, whereas the SC selects the VAR with 1 lag. LR criteria chooses a lag length of 11. The autocorrelation tests on these residuals suggest that the lag number should be 6 to have an overall well-specified VAR model without autocorrelation. With the lag number of 6, there is no serial autocorrelation in the residual as required (Table 3.12)

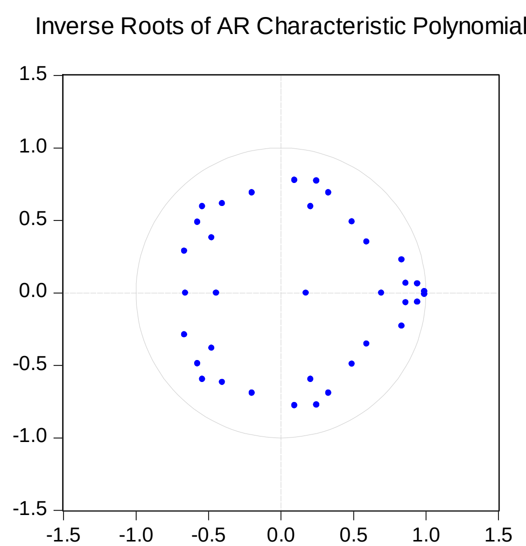
Table 3.12: VAR residuals serial autocorrelation LM test

The serial autocorrelation test in residuals up to 12 lags.

Lags	LM-Stat	Prob
1	45.73073	0.1283
2	31.54729	0.6803
3	43.77585	0.1749
4	41.58062	0.2407
5	37.69176	0.3918
6	51.25171	0.0576
7	42.60893	0.2080
8	32.08977	0.6551
9	24.79812	0.9204
10	33.43051	0.5914
11	31.25441	0.6937
12	50.49922	0.0550

At a lag number of 6, the estimated model is also dynamically stable, because the inverse root lies inside a unit circle as below. It follows the basic principle that a model is dynamically stable if all characteristic roots lie outside the unit circle.

Figure 3.2: The dynamically stable model



With *dmax* equal to 1 and *k* equal to 6, which is calculated above, Toda–Yamamoto (1995) suggests the lag length of 6 for all variables in the system and the extra (7th) lag of each variable to be an exogenous variable in the system. This approach allows the extra lag not to be included in the Wald statistic, giving the Wald test statistic a normal asymptotic Chi-squared distribution. Results of short-term Granger non-causality are illustrated in the six tables below. Each illustrates the non-causality hypothesis testing from the direction of each variable in the system of variables to the dependent variable: stock price index SPI, industrial production IP, money supply M1, prime lending rate R, exchange rate NER, and the MSCI global stock market index.

Table 3.13: Toda–Yamamoto Granger non-causality test with nominal variables

The TYDL Granger causality test for six variables SPI, IP, M1, R, NER, and MSCI. For example, table *Dependent variables SPI* in the top left corner expresses the Granger causality test from the five remaining variables IP, M1, R, NER, and MSCI to SPI.

Dependent variable: M1

Excluded	Chi-sq	df	Prob.
SPI	5.065881	6	0.5354
IP	5.387708	6	0.4951
R	22.89544	6	0.0008
NER	1.649858	6	0.9489
MSCI	2.802638	6	0.8332

Dependent variable: R

Excluded	Chi-sq	df	Prob.
SPI	17.44462	6	0.0078
IP	1.411839	6	0.9651
M1	6.822917	6	0.3375
NER	9.232288	6	0.1609
MSCI	3.251031	6	0.7767

Dependent variable: NER

Excluded	Chi-sq	df	Prob.
SPI	81.64182	6	0.0000
IP	15.60254	6	0.0161
M1	3.252405	6	0.7766
R	33.62529	6	0.0000
MSCI	1.827675	6	0.9348

Dependent variable: MSCI

Excluded	Chi-sq	df	Prob.
SPI	6.547425	6	0.3647
IP	2.039974	6	0.9160
M1	4.056748	6	0.6690
R	6.960991	6	0.3245
NER	2.216568	6	0.8987

When it comes to the causality from macro variables to stock index (using table *Dependent variable: SPI*), the interest rate R is the only variable having a significant p-value in an equation with SPI as a dependent variable. It suggests that the null hypothesis of non-causality from the interest rate to stock market is rejected, which means the interest rate Granger causes the stock market index. This finding coincides with finance theory: interest rates can impact the stock exchange through the effect on the discount rate, on expected cash flow, or through a portfolio rebalancing effect. A rise in the interest rate can directly influence the discounted rate in a standard equity model, consequently changing stock prices. It also influences the financing cost for business, especially those in heavy debt. Production and sales are therefore lowered, creating a reduction in cash flow and stock price. As for the portfolio rebalancing channel, an increase in the interest rate makes investing in fixed-income securities comparatively less attractive. Investors may shift to the equities market, creating stock price changes.

Regarding the reverse Granger causality from the stock market index, SPI, to other macro variables, the remaining five tables with five different dependent variables are examined. Because our research focuses on the relationship between stock prices and macro variables, only Granger causality originating in the stock index will be analysed here. From the tables above, the local stock price is corroborated to Granger cause local exchange rate and interest rate. This latter causality confirms the bi-directional relationship between interest rate and stock market index. Not only being influenced by the interest rate, the stock market index period *(t-1)* also has predictive power on the prime lending rate period *t*. The result coincides with Wongbangpo and Sharma (2002) for Indonesia, Thailand, and Malaysia; Abdullah and Hayworth (1993) and Ratanapakorn and Sharma (2007) for the US stock market. The stock price represents the securities market, whereas the interest rate is a proxy for the money market, which is considered a safe investment. Thus, changes in the stock price's last period can be important in predicting the prime rate.

Interpreting the unidirectional Granger causality from stock market to the remaining variable-exchange rate, portfolio balance theory[7] suggests that the changes in stock price cause changes in determinants of the exchange rate. Stock prices relate to the wealth of the economy; thus, a decrease in stock price results in lower capital inflows and lower money demand of domestic country. Foreign investors in this situation also reduce the demand for both domestic assets and domestic currency. These shifts, therefore, will result in a depreciation of local currency, theoretically explaining the causal relationship between stock price and exchange rate. It is in line with evidence in Hatemi and Roca (2005), Pan *et al.* (2007), and Lin (2012), suggesting that Thailand's government should target economic growth and stock market development to attract capital inflow and prevent a currency crisis.

[7] Portfolio balance theory (McKinnon, 1969) or portfolio balance approach to exchange rate determination. In this model, not only the monetary factor influences the exchange rate, but also the holding of financial assets. The asset menu is expanded to include both domestic and foreign assets, which are assumed imperfect substitutability. In the short run, the level of exchange rate is determined by supply and demand in the asset market.

3.5.4 Diagnostic test

We test the adequacy of the proposed model using the following tests: autocorrelation, normality, heteroskedasticity, and stability test.

Autocorrelation test

Residuals autocorrelation illustrates the situation in which residuals in one period are correlated with the previous periods. We adopt the Breusch–Godfrey serial correlation LM test with the null hypothesis of no serial correlation up to 12 lags in residuals.

Table 3.14: The Breusch–Godfrey LM test for serial correlation

Breusch–Godrey LM test for serial correlation up to lag 12. The hypothesis of the test is: H0: no serial correlation up to lag 12; H1: there is serial correlation up to lag 12.

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 12 lags

F-statistic	0.965901	Prob. F(12,150)	0.4840
Obs*R-squared	13.26993	Prob. Chi-Square(12)	0.3497

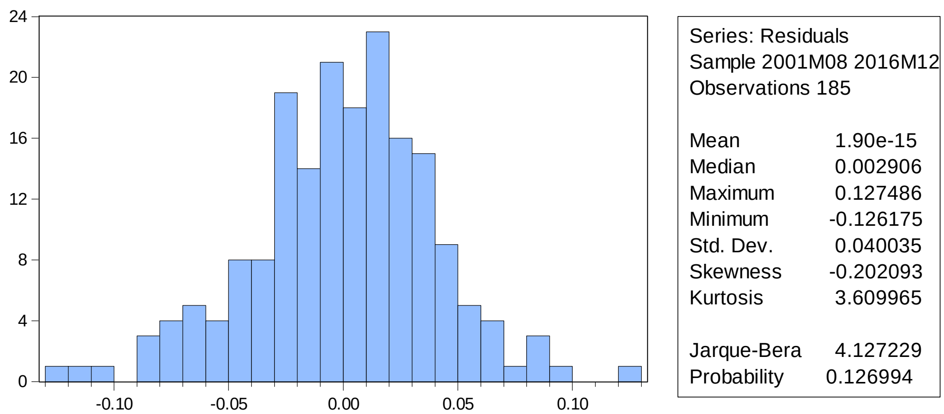
Table 3.15: The correlogram of residuals

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.039	0.039	0.2813	0.596
		2	-0.123	-0.124	3.1314	0.209
		3	-0.026	-0.016	3.2553	0.354
		4	0.005	-0.009	3.2602	0.515
		5	0.046	0.042	3.6680	0.598
		6	-0.089	-0.095	5.1965	0.519
		7	-0.064	-0.046	5.9827	0.542
		8	-0.006	-0.023	5.9891	0.648
		9	-0.032	-0.048	6.1873	0.721
		10	-0.083	-0.092	7.5637	0.671
		11	-0.030	-0.028	7.7395	0.736
		12	0.008	-0.019	7.7508	0.804

The results suggest that there is no problem of autocorrelation in the residuals of the specified model. The p-value is approximately 48%, larger than the 5% critical value, proving that the null hypothesis of no serial correlation cannot be rejected.

Normality test

Figure 3.3: The normality test



The Jarque–Bera null hypothesis is that the residual is normally distributed. With p-value of approximately 0.127, it cannot be rejected that the residual is distributed normally, satisfying one among many diagnostic tests.

Heteroskedasticity

Table 3.16: Heteroskedasticity test: Breusch–Pagan–Godfrey test

Heteroskedasticity Test: Breusch–Pagan–Godfrey

F-statistic	1.466838	Prob. F(22,162)	0.0769
Obs*R-Squared	35.97212	Prob. Chi-Square(22)	0.0922
Scaled explained SS	32.41732	Prob. Chi-Square(22)	0.1797

Heteroskedasticity occurs when the variance of the error is not constant. We use the Breusch–Pagan test to check the residuals for this potential problem. The p-value of the tests shows that the null hypothesis of homoscedasticity cannot be rejected. The residuals of the regression will have the desired value.

Stability test

Figure 3.4: Plot of cumulative sum of recursive residuals (CUSUM)

CUSUM statistics (blue line). The bands (red lines) represent the bounds of the critical region for the test at 5% significance level.

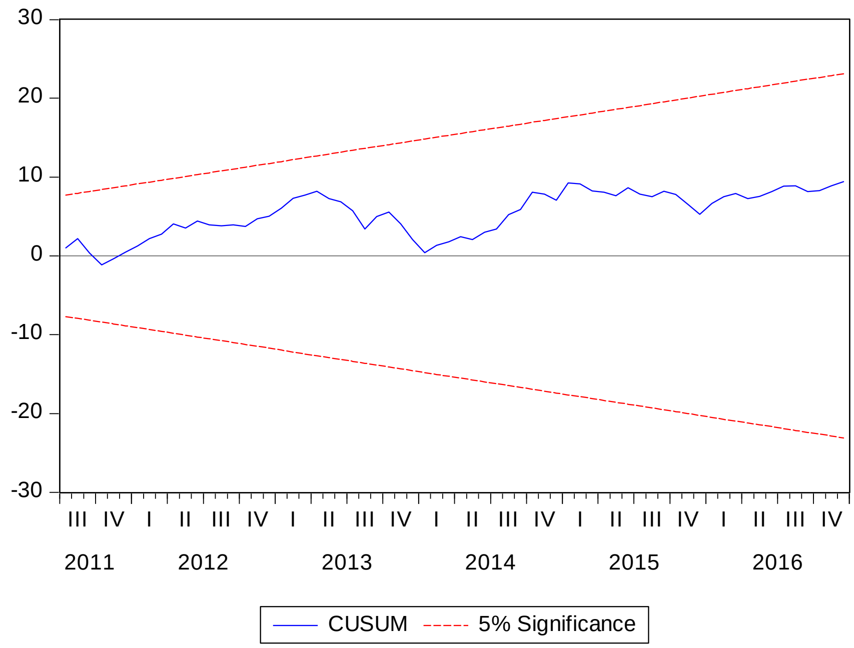
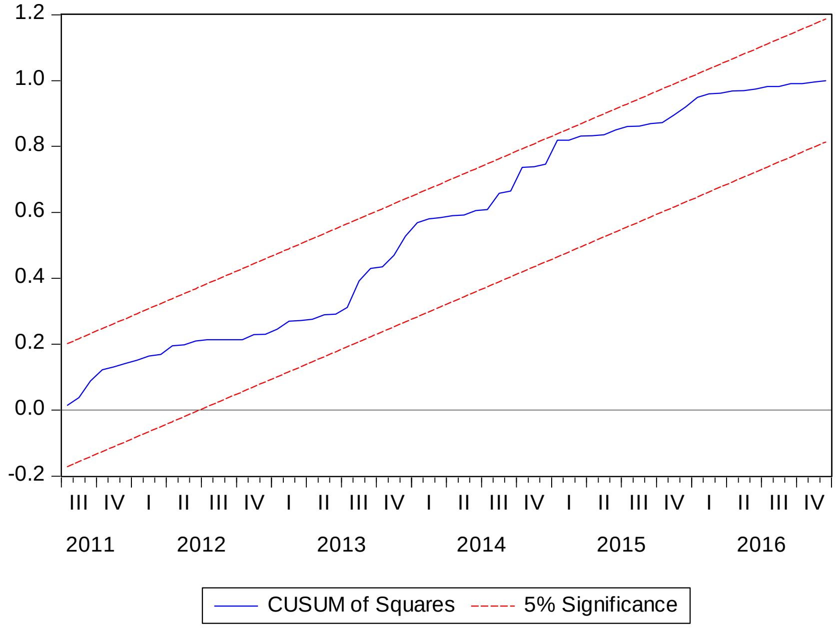


Figure 3.5: Plot of cumulative sum of squares of residuals (CUSUMSQ)

CUSUMSQ statistics (blue line). The bands (red lines) represent the bounds of the critical region for the test at 5% significance level.



To assess the stability of both long- and short-term parameters, the research employs the CUSUM and CUSUMSQ measurements (Borensztein *et al*., 1998; Pesaran and Pesaran, 1997). The plots of CUSUM and CUSUMSQ statistics above are within the 5% significance range. They show that the null hypothesis that all coefficients are stable cannot not be rejected at the 5% level of significance. In other words, they confirm parameter constancy.

Overall, owing to the special characteristics of the dataset (inconclusive between I(1) and I(0)), the ARDL bound test is employed and corroborates the following relationship between the variables: a positive relationship between the stock market index and the money supply and the MSCI index. These findings coincide with the previous literature (Aburgi, 2008; Fifield, 2002, 2006; Humpe and

Macmillan, 2007) and are also supported by the error-correction model and the diagnostics tests. These long-term relationships suggest the existence of causality and are corroborated as follows: The bi-directional between stock market and interest rate and a unidirectional from stock index to exchange rate reflect the stock-oriented model[8] proposed by McKinnon (1969), Branson (1983), and Frankel (1983).

3.6 Conclusion

Literature reviews have suggested the popularity of the research about the stock market index and macroeconomic variables in both developing and developed nations. However, the sign and magnitude of the long-term interaction as well as the short-term Granger causality vary greatly among countries, regions, and continents. With the rising role of the Thai economy in the world economy and the importance of the stock market in economic development, our research therefore aims to determine these relationships in the Thai market with the hope of contributing to the literature, using the most up-to-date dataset. Two questions have been addressed in this chapter: (i) What is the long-term relationship between stock prices and macroeconomic variables? (ii) Do macroeconomic variables Granger cause stock market and vice versa?

Owing to the special characteristics of the dataset (the mixture of stationary and non-stationary variables determined by the traditional unit root test without breaks and the more complicated ones allowing for break (Zivot and Andrews

[8] The stock-oriented model of exchange rate proposed by Branson (1983) and Frankel (1983) posit that stock-price development should determine the exchange rate.

(1992) and Lee and Strazicich (2003) unit root tests)), the autoregressive distributed lag model (ARDL) methodology has been employed for the long-term cointegration test. As for short-term Granger causality studies, Toda–Yamamoto (1995) is preferred over the standard test, which is greatly manipulated by the results of cointegration as well as the unit root test. Dummy variables are added to the model to capture the two important events: the global financial crisis and the 2011 Thai floods to avoid the problem associated with a very small sample as analysed before if dividing the sample into small parts.

This study comes to the following conclusions. There are long-term cointegrations between the stock market index and money supply and the global market index. All coefficients have positive signs and signify the forward-looking aspect of the stock market. An increase in money supply M1 leads to an increase in stock prices on the Thai stock exchange, confirming a positive liquidity effect. As for the global factor, MSCI, the positive cointegration suggests the integration of SET with the global economy.

The existence of long-term cointegration between these variables suggests that there must be at least a Granger causality among them. The short-term Granger causalities, therefore, have been examined and corroborated by the bi-directional Granger causality between the stock price and the interest rate. On one hand, the impact of interest rates on stock prices can arise through the impact on the discount rate, expected cash flow, or through rebalancing fixed-income securities with the stock market equities. On the other hand, the stock price can Granger cause the interest rate, explained by the same clarification of the portfolio rebalancing effect.

Regarding the Granger causality from the stock market to the exchange rate, our study shares the same findings as Hatemi and Roca (2005), Pan *et al.* (2007), and Lin (2012) that the stock price leads the exchange rate. A reduction in the stock price results in a reduction in economic wealth, which then influences capital inflow and demand for domestic currency. The exchange rate, therefore, is Granger caused by the stock market, supporting the portfolio balance theory.

To the best of my knowledge, no research has been done in developing countries considering both questions together to understand the long- and short-term interactions between the stock market index and the set of macro variables. Our analysis, therefore, offers necessary and useful guidelines for investors and policy-makers. As far as investors are concerned, they can employ the long-term cointegration and any short-term movements out of equilibrium to determine an investment strategy. The existence of long-term relationships between the variables suggest arbitrage opportunities, which lend credence to the non-profitability of EMH. As for policy-makers, the stock price can be considered a leading indicator of future economies, because it reflects the performance of the economy, corporate performance, and corporate profits. The cointegration and Granger causality among them are important determinants in the creation of the macroeconomic policy for the country. Furthermore, the Granger causality from stock price to exchange rate in both cases suggests that a currency crisis can be dealt with through their manipulation of the stock market.

Chapter 4

RETURN PREDICTABILITY OF THAILAND: THE COMPONENTS OF STOCK RETURN AND THE ROLE OF GLOBAL AND LOCAL FACTORS

4.1 Introduction

What moves stock prices? Which is more important in the variation of stock returns: the discount rate news or the cash flow news? These questions have been examined in several studies, and the frequent finding is that the variation in expected return is related mostly to dividend yield rather than dividend growth. Will this be true for Thailand, a developing country in the Asian region? Our research aims to answer this question by examining the Stock Exchange of Thailand (SET), but extending previous research by adding macro variables and global factors in one model.

A great deal of literature related to this topic has been studied. They all originate from the original work of Campbell (1988, 1991), decomposing stock-return variance into cash flow news (CFs) and discount rate news (DRs). Cash flow news is defined as the price change given the constant cost of capital, whereas discount rate news is defined as the price change without any change in cash flow. Cash flow news and discount rate news are two fundamental components of stock return; however, CFs is more related to fundamentals than DRs, owing to its link to production (Chen and Zhao, 2009). Their relative importance to each other can be used to determine the underlying causes behind movements in the financial market. In Campbell (1991), the discount rate accounts for a larger proportion of return variance, but the influence depends on time and model specifications. Bernanke and Kuttner (2005) follow this decomposition method to understand the reason behind the reaction of the US stock market to monetary policy changes. They conclude that the breakdown between the two elements, discount rate news and cash flow news, depends on the sample choice and strengthens a surprising view that most of the return's reactions are not to changes in the Federal fund rate, but from the two mentioned elements. Overall, a growing list of papers are adopting this method to understand the mechanism of the financial market, at both the aggregate market index and for disaggregated stocks.

Despite a rapidly growing number of studies following this seminal approach, there have been some criticisms related to the calculation of cash flow news and discount rate news. One of them is Chen and Zhao's (2009) evaluation. The authors argue that, apart from the model specification's error, which affects both the correctness of the DR and CF's calculations, the indirect calculation of CFs as the remaining residual of the VAR system may make its computation more incorrect. These problems will become more severe if the specified model has a limited number of variables. These assessments are supported by Rapach, Strauss, and Zhou's (2013) research on industrialised markets. They strengthen the dominant role of US stock returns in non-US stock markets, even after controlling for their national economic conditions (dividend yield and interest rate), and then raise the need to add the US stock return to the model, which is often ignored in the typical literature. Maio and Philip (2015), one of the most recent works on this topic, do criticise that the evaluations of CFs and DRs are still incorrect if the large set of macro variables is not included in the model. The authors focus on the importance of local macro variables, but do not mention anything related to global factors.

In this paper, we follow the basis variance decomposition approach of Campbell (1991) in understanding stock-return reaction in Thailand's stock market. However, we make some adjustments to account for the criticism above. To be more specific, macro variables have been added to the baseline of Campbell's model as a remedy, according to Chen and Zhao's (2009) problem. The US stock market return series has also been added to quantify the integration in the financial market. Because any higher order VAR can be stacked into first-order form, this chapter will employ the first-order VAR following Campbell (1988, 1991), but will include both local financial variables as well as macro and global factors from July 2004 to December 2016. Results of all three specifications on Thailand's stock return (the baseline, the macro added version, and the global added version) agree with the opinion that both discount rate news and cash flow news share importance in return predictability.

In addition, our research documents the reaction of stock returns by estimating coefficients of the first-order VAR system in which return is ordered first. Regression results coincide with the previous literature of Bernanke and Kuttner (2005) and Ludvigson and Ng (2007) that macro variables add little predictive power to the model. US stock returns, the representative of the global factor, are statistically important in explaining total market index when added to the model.

Overall, this paper is the first that works on the Asian market's return predictability. In addition to applying Campbell's (1991) seminal work in another market, this research also takes into account the criticisms mentioned above by incorporating a large number of macro variables and US stock market returns. Two main empirical questions are addressed:

- What is the VAR estimation for forecasting the stock return?
- What is the VAR decomposition for the stock return?

Two conclusions are drawn here. First, as for the return predictability, macro and financial variables add little predictive power to the return predictability at monthly frequency. Second, as for the return variance decomposition, the inclusion of macro variables and global factors, which are represented by US stock returns, does not lead to any significant change in the relative importance between cash flow news and discount rate news. Both cash flow news and discount rate news are important components of the stock-return variance.

The organisation of the paper is as follows. The next section (Section 2) surveys previous literature related to this study. Section 3 provides the methodology, and Section 4 contains data collection and data processing. Section 5 computes regressed coefficients and variance decomposition. In Section 6, a robustness check is implemented using residual bootstrapping. Finally, Section 7 concludes our work.

4.2 Literature review

The paper relates to several stock-return predictability studies, all derived from Campbell's (1991) seminal work. They are selectively analysed before the determination of the three specifications, ranging from the basic model to the macro and global-factor-added model. The first model of our empirical work, applying a purely baseline model, follows the basis return predictability literature of Campbell and Shiller (1988), Campbell (1991), and Goetzmann and Jorion (1993), whereas the second and third ones derive from the analysis in Chen and Zhao (2009), Maio and Philip (2015), and Rapach, Strauss, and Zhou (2013).

Campbell (1991) proposed a VAR model to evaluate the relationship between expected return and other variables. A VAR is believed more appropriate to gauge the relationship between dividend yield and stock return than the traditional ordinary least square (OLS) estimation employed in Fama and French (1988). The reason is that the conditions of OLS are not satisfied: The right-hand side (RHS) variable (dividend yield) is not exogenous to the left-hand side (LHS) variable (stock return).

In Campbell (1991), stock return becomes one element of the first-order VAR. The first-order VAR assumption is preferred because any higher order VAR can be arranged into first-order form. Unexpected stock returns, discount rate news, and cash flow news are then calculated from the VAR methodology to assess how much variation in the first variable in the system (unexpected stock return) is the result of each of the two components (CFs and DRs). Campbell's (1991) framework is:

$$r_{t+1} - E_t(r_{t+1}) = (E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t)\sum_{j=1}^{\infty}\rho^j r_{t+1+j}$$

$$= N_{CF,t+1} - N_{DR,t+1} \qquad (4.1)$$

The unexpected return on the LHS is the revision of the stock return. Discount rate news is the revision of the expectations of equity return, whereas cash flow news accounts for the revisions in the discounted value of earnings or cash flows. This equation breaks down the contribution of each element (discount rate news and cash flow news) into the unexpected stock return. Working with monthly US data from 1927 to 1988, Campbell finds that the expected return (discount rate news) has greater explanatory power. Results for sub-periods are similar.

Bernanke and Kuttner (2005) is one of the typical studies that adopts Campbell's (1991) seminal work on variance decomposition to answer the question: What explains the stock market's reaction to Federal Reserve Policy? (Bernanke and Kuttner, 2005). The influence of monetary policy on the stock price is quantified into three components, including expected future dividends, real interest rate, and expected future excess return using a VAR specification. Indeed, expected future return still accounts for the largest proportion in this research. Campbell and Voulteenaho (2004) examine the same kind of question about the attributability of discount rate news and cash flow news, but using firm-level data. They call cash flow beta the bad beta and discount rate beta the good beta, and argue that, at the firm level, CF news plays a more important role in explaining unexpected stock-return variance. Here the cash flow is considered bad beta, because it has permanent effects on asset prices and is thus feared, whereas discount rate news is considered the good one because of its temporary fluctuations.

With the inconsistent findings about the role of cash flow news and discount rate news, we come to the question of how to measure CFs and DRs. Most of the work in this field has adopted Campbell (1991), using a vector autoregressive (VAR) system to estimate the DRs first and then the CFs as a residual. However, according to Chen and Zhao (2009), this "easy-to-implement" approach above has suffered from some problems. The authors argue that the calculation of the discount rate news is hardly accurate because of misspecification problems. The inference of cash flow news from them, thus, must be incorrect too. To illustrate this point, the authors take Treasury bonds as the target asset and do variance decomposition. Cash flow news of this asset is zero; thus, discount rate news is expected to be the more influential factor. However, the real calculation shows that CFs, which is inferred from the DRs, takes over the role of DRs, proving that the incorrect inference about the leading role of CFs may be derived from incorrect DRs calculation in this case.

One of the remedies for this misspecification is the inclusion of macro variables. Maio and Philip (2015) add a group of 124 macro variables and use the principal component technique to shrink the dimension of these variables. The discount rate news calculated this way is less likely to be influenced by specification error. Maio and Philip (2015) explain the reason behind this treatment is that investor and related parties make decisions based on a large amount of information. If we do not cover all of these information sources in our model, measurement error will be a severe problem. Nevertheless, it is not easy to observe *a priori* which macro variables are relevant in the model; thus, they propose the extracting method – principal component analysis – to address this problem. Six common factors representing 124 US macro variables are added to the model during the period 1964 January–2010 September. His results are in line with well-known results in previous studies in which discount rate news is the leading component (Campbell, 1991; Campbell and Vuolteenaho, 2004; Bernanke and Kuttner, 2005). The inclusion of a large macro dataset does not significantly change the decomposition between discount rate news and cash flow news, which were already contained in the VAR with only financial variables.

Apart from the variance decomposition, the first-order VAR estimate in Maio and Philip (2015) is also employed to assess the predictive power of each factor. Coefficients estimated from the VAR suggest the significance of dividend yield and two out of the six extracted components of macro variables in forecasting stock return. The R-Squared ratio is improved in the added model, but is still at a low level. This finding coincides with Ludvigson and Ng (2007) in showing relatively small predictive power of the added macro variables.

It is obvious that most of the literature on this topic focuses on the US stock market. Rapach, Strauss, and Zhou (2013) seek to answer the question at an international level by employing the lead–lag relationship between the US monthly stock return and that of non-US-industrialised countries. Using the OLS regression and two-step GMM estimation of the diffusion model, Rapach and his co-authors conclude that lagged US stock returns have a substantial influence on non-US returns even after controlling for domestic macro variables, whereas the opposite is not true (a non-US stock return has "limited predictive" power on US stock returns).

In short, several papers have focused on the return predictability issue. Most of them focus on the US stock market, and some apply the research to other developed countries. The baseline model, a model including macro variables by principal component and a model with added US stock returns have been employed. They all come to the same conclusion that discount rate news is the most influential reason behind the movements of stock returns. The inclusion of macro variables is believed to create no significant changes in the relative importance between the two elements: discount rate news and cash flow news. However, as far as I know, no paper in this field has tried to answer the question relative to Asian markets as well as incorporating both macro variables and global ones into the same model. Owing to integration of financial markets and the fact that Thailand, our target country, is an exporting country with the US as its largest partner, the inclusion of this global factor together with the other one becomes more necessary than ever. In summary, our research targets this gap and aims to answer two questions: Is it necessary to add macro and global variables in the return predictability's first-order VAR model? How about the role of discount rate news and cash flow news in stock-return decomposition in the case of Thailand? VAR estimation and VAR decomposition are employed in the next section to find the answer.

4.3 Methodology

4.3.1 VAR estimation

Analysing estimated coefficients is one of our targets. We follow Bernanke and Kuttner (2005) and Ludivigson and Ng (2007) in using a first-order VAR system to evaluate regressed coefficients, or in other words, to analyse return predictability.

Our first-order VAR has the form:

$$x_{t+1} = A\, x_t + \epsilon_{t+1} \tag{4.2}$$

x_t is a vector $k\ x$ 1 vector for state variables having the first element as stock return; k x 1 dimension. A is the k x k coefficient matrix, and ϵ_{t+1} is a shock.

With three forms of state variable x_t, we have three specifications, including the basis model, the model adding macro variables, and the model adding both macro and global factors, as well as three sets of regression coefficients. Dividend yield ratio, dp_t , is added to the three models because of its importance specified in almost all stock-return predictability literature, such as Campbell and Shiller (1988), Cochrane (1992), Cochrane (2011), Rapach, Straus, and Zhou (2013), and Maio and Philip (2015).

Our baseline state variables are specified by: $x_t = [dp_{t,}\, dd_t, r_{mt}]$, where the added-macro version is given by $x_t = [dp_{t,}\, f'_{t,}\, dd_t, r_{mt}]$. The variables dp_t , dd_t, and r_{mt} are dividend yield, dividend growth, and market return, respectively. f' is a group of macro variables locally, extracted by principal component analysis following Chen and Zhao (2009) and Maio and Philip (2015). The state variables associated with the added-global-factors model are: $x_t = [dp_{t,} f'_{t,} dd_t, r_{mt}, r_{usat}]$. The variable r_{usat} represents the US stock-return index. We follow Rapach, Strauss, and Zhou (2013) in adding only US stock returns as a global factor, owing to its leading role.

Regression coefficients A illustrate the influence of each factor on the stock return. The literature above has already explained the problems of using normal OLS in estimating A (originated specified in Goetzmann and Jorion (1993)); thus, we follow Maio and Philip (2015) and a great number of papers in using Newey–West t-statistics to correct for heteroscedasticity and autocorrelation of the residual. The Newey–West methodology is an extension of "White's heteroscedasticity–consistent standard error," but is corrected for autocorrelation. The corrected standard error is known as the heteroscedasticity and autocorrelation consistent (HAC) standard error or Newey–West standard error. This estimate has been included in almost all econometrics software, so we do not present the mathematics behind the HAC procedure.

4.3.2 VAR model with variance decomposition

Following the variance decomposition literature in Campbell (1991), any unexpected return can be divided into two parts: cash flow news and discount rate news (expected return news). The derivation comes from the definition of total return: total return measures both price movement and dividend income.

$$R_{t+1} = \frac{P_{t+1} + D_{t+1}}{P_t} \tag{4.3}$$

where $R_{t+1}, P_{t+1}, D_{t+1}$ are total stock return, stock price, and dividend paid at time t+1. P_t is the price at time t.

Following logarithmic and other transformations, the Campbell–Shiller return decomposition has the formula (see Appendix 4.3):

$$r_{t+1} - E_t r_{t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j \, r_{t+1+j}$$

$$= N_{CF,t+1} - N_{DR,t+1} \qquad (4.4)$$

In the above equation, the LHS expresses the unexpected return element, and the RHS comprises both the difference between forecast value and real value of cash flow news ($N_{CF,t+1}$) and discount rate news ($N_{DR,t+1}$).

We follow Campbell and Shiller in doing variance decomposition, taking the variance of both sides; therefore, the RHS includes the covariance term. Substituting the return in the equation above r by r_m, we have:

$$Var[r_{m,t+1} - E_t(r_{m,t+1)})$$

$$= Var\left(N_{CF,t+1}\right) + Var\left(N_{DR,t+1}\right) - 2Cov\left(N_{CF,t+1}, N_{DR,t+1}\right) \qquad (4.5)$$

Dividing both sides by the variance, we have the famous formula:

$$1 = \frac{Var\left(N_{CF,t+1}\right)}{\text{Var}\left[r_{m,t+1} - E_t(r_{m,t+1)})\right]} + \frac{Var\left(N_{DR,t+1}\right)}{\text{Var}\left[r_{m,t+1} - E_t(r_{m,t+1)})\right]} - \frac{2Cov\left(N_{CF,t+1}, N_{DR,t+1}\right)}{\text{Var}\left[r_{m,t+1} - E_t(r_{m,t+1)})\right]} \qquad (4.6)$$

The identity above illustrates how much variance in unexpected stock return is attributed to cash flow news and discount rate news and the covariance between them. To calculate these ratios, CF news and DR news need to be estimated. We follow the literature by applying the first-order VAR system to describe the behaviour of the economy and the stock market, as well as to calculate discount rate news and cash flow news.

Calculating discount rate news and cash flow news

The estimate of $N_{CF,t+1}$ and $N_{DR,t+1}$ relies on the first-order VAR system as mentioned in the literature section regarding Campbell (1991), Vuolteenaho (2002), Bernanke and Kuttner (2005), Rapach, Strauss, and Zhou (2013), and Maio and Philip (2015).

Denoting h_{t+1} as the first element (stock return) of the x_{t+1}, h_{t+1} will choose the formula below, in which $e1$ has the first element is one, whereas the other is zero:

$$h_{t+1} = e1' x_{t+1} \tag{4.7}$$

Multi-period forecasts of future return the following first-order VAR (4.2) using the (4.7) expression, we have the form:

$$E_t h_{t+1+j} = e1' \, A^{j+1} x_{t+1} \tag{4.8}$$

Direct calculation of the discount rate news is:

$$N_{DR,t+1} = \ (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j \, r_{t+1+j} = (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j \, h_{t+1+j} \tag{4.9}$$

$$= e1' \, \textstyle\sum_{j=1}^{\infty} \rho^j \, A^j \, \epsilon_{t+1} = e1' \rho \, A(I - \rho A)^{-1} \epsilon_{t+1}$$

$$= \varphi' \epsilon_{t+1}$$

where $\varphi' = e1'\rho\, A(I - \rho A)^{-1}$

There are two ways to calculate $N_{CF,t+1}$. The first is to calculate it indirectly as the residual component of unexpected stock return:

$$N_{CF,t+1} = (r_{t+1} - E_t r_{t+1}) + N_{DR,t+1}$$

$$N_{CF,t+1} = (e1' + e1'\rho\, A(I - \rho A)^{-1})\, \epsilon_{t+1} = (e1' + \varphi')\, \epsilon_{t+1}$$

Another way is to calculate cash flow news first and then calculate the discount rate news:

$$N_{CF,t+1} = (E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j\, \Delta d_{t+1+j} = e2'(I - \rho A)^{-1}\varepsilon_{t+1} = \tau\, \varepsilon_{t+1}$$

$$N_{DR,t+1} = [e2'(I - \rho A)^{-1} - e1']\varepsilon_{t+1} = (\tau - e1)'\, \varepsilon_{t+1}$$

where $e2'$ takes the value of 1 in the position corresponding to the position of log of dividend growth, and $\tau = e2'(I - \rho A)^{-1}$ is a function of VAR coefficients, which translate the VAR shocks into cash flow news.

Although the indirect measurement of cash flow news has been criticised by Chen and Zhao (2009), our methodology employs it in the calculation. We follow suggestions in Chen and Zhao (2009), as well as Campbell *et al.* (2010) and Maio and Philip (2015), in arguing that, with the proper specification of the VAR model, the two approaches are comparable.

4.3.3 Principal component analysis

As mentioned in the literature, adding a great number of macro variables can be a good remedy for model uncertainty. Investors make decisions based on a large set of information, making it necessary to add them to the model. This will reduce the problems of model specification errors and incorrect calculation of cash flow and discount rate news.

Principal component analysis, therefore, is a technique used to summarise a large macro information series into smaller ones. It is developed by Cornor and Korajczyk (1986) and widely applied in research, such as Stock and Watson (2002) and Ludvigson and Ng (2007). The output results – artificial variables – are called principal components and cover most of the variance in the dataset. They are arranged in decreasing order of eigenvalues; the first component has the highest value and accounts for the largest part of variance in our dataset. Below is the short methodology of principal component analysis.

Suppose we have a panel of macro data y_{it} across N sections and T periods. Writing the macroeconomic data under the factor structure, we have:

$$y_{it} = \lambda_i F_t + \varepsilon_{it} \tag{4.10}$$

y_{it} represents background information set at period t for the section i^{th}, F_t denotes latent common factors $r\ x\ 1$ matrix in which r is the number of factors ($r \ll N$). λ_i is factor loadings, and ε_{it} denotes the residual matrix, which is independently and identically distributed (i.i.d).

The estimation of factor F_t $(T\ x\ r)$ matrix is the combination between $\sqrt{T}$ and r largest eigenvalues of yy' matrix with T rows and T columns. The factors are then normalised so that $F_t{}'F_t = I_r$, where I_r is the identity matrix of r dimensions. Then the loadings of the factor matrix can be obtained using the formula: $\hat{\lambda} = y'\hat{F}/T$.

To determine how many factors should be enough to convey the background information, the loss function suggested by Bai and Ng (2002) can be used. Another way is depicting the scree plot[9] in which the cut-off number is usually the hinge of the graph. To be more specific, the scree plot graphs the eigenvalues in descending order. It expresses visually which components explain most of the variation in the macro set. The number of factors can be chosen by retaining those factors in the steep curve before the starting point of flat line trend.

To provide the economic meaning of each factor, which is necessary for interpretation, the group of single regressions between each factor against each macro variable is estimated.

$$\widehat{F_{jt}} = \theta_{ij} y_{it} + u_{i,jt} \tag{4.11}$$

j is the number of factors, i is the number of background information. For example, $j = 2$, $i = 15$, $\theta_{1,15}$ reflects the proportion of variation in F_1 explained by the series ordered 15th in the group. Among i regressions for each j, values of R-Squared are compared. The equation having the highest value of R-Squared can be used to infer that the j^{th} factor can be a representative of i. The economic meaning of the factor, therefore, can be used to infer its impact on the return predictability.

4.4 Data

This section includes details of data collection for both financial variables and a large set of macroeconomic variables. As for macro variables, principal component

[9] A scree plot is the visual form of the Scree test (Cattell, 1966). It is based on the assumption that relevant information is larger than the random noise.

analysis has been implemented to extract the desired variables. Data description has been reported here too.

4.4.1 Macro variables

Thailand's macroeconomic variables have been collected from Datastream for the period May 2004–December 2016. Appendix 4.2 lists names of all of the variables used at a monthly frequency. They include the following information: name of series, description, mnemonic, and transformation code. These codes are specified from Number 1 to Number 6, denoting which steps are necessary to have stationary variables. Number 1 denotes using the original data. Number 2 denotes taking first difference. Number 3 denotes taking second differences. Number 4 specifies the logarithm. Number 5 is for the log differences, and Number 6 mentions the second difference of log. These transformed variables are then standardised to have 0 mean and unit variance.

The macroeconomic data comprises seven main categories: output (Series 1–3), employment (Series 4–5), housing and sales (Series 6–9), money and credit (Series 10–12), interest rate (Series 13–15), foreign exchange (Series 16), and price index (Series 17–21). Employing the scree plot to determine the number of principal components, we have this diagram:

Figure 4.1: The scree plot

The scree plot with the eigenvalues on the vertical line and the number of factors on the horizontal line.

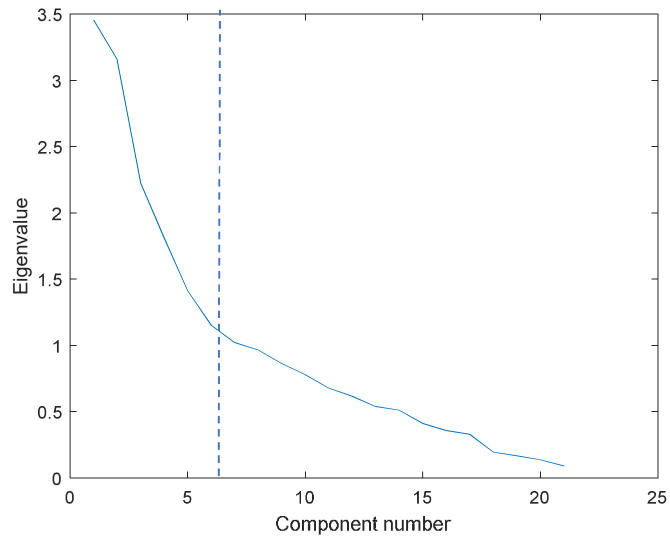
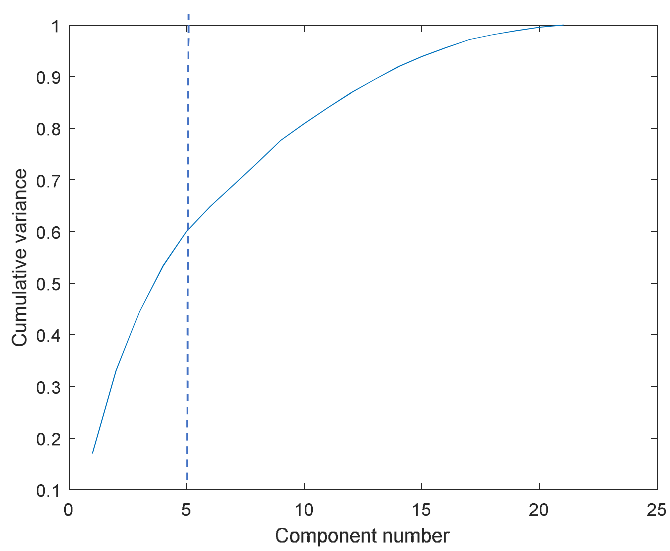


Figure 4.2: Cumulative variance

The cumulative variance on the vertical line and the number of factors on the horizontal line.

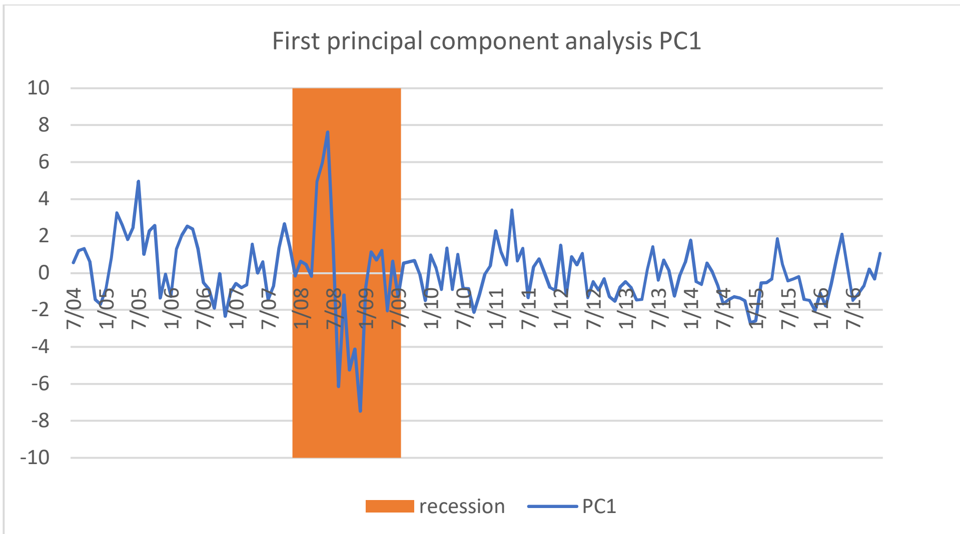


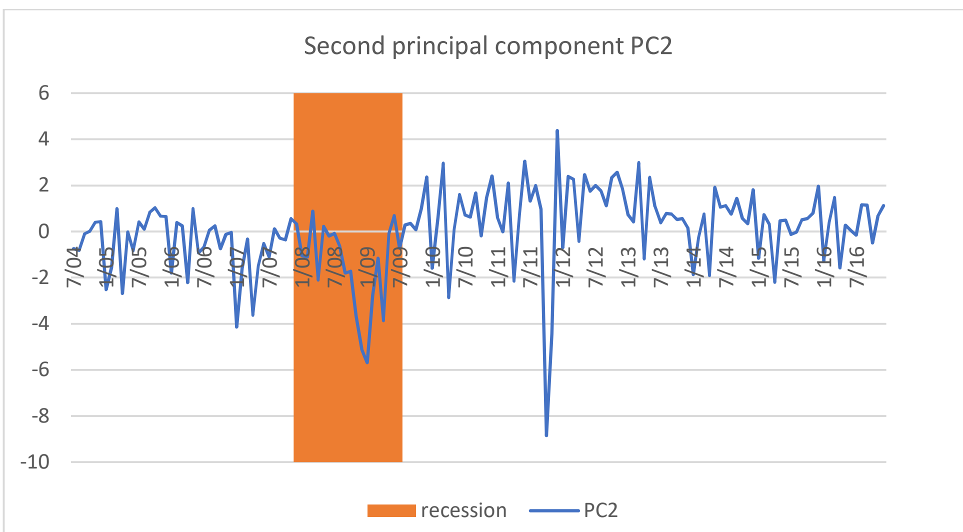
The scree plot is used to illustrate component numbers according to the order of highest to lowest eigenvalues. It is a downward curve having the eigenvalues on the *y*-axis and several factors on the *x*-axis. It can be seen clearly from the graph that the point on the curve having an *x* value of 5 marks the cut-off point. Therefore, the number of principal components that has been chosen is 5. They account for most of the variance of the sample, approximately 60% of the variance of the sample. From that point onwards, adding more factors (moving down along the curve) will improve the total variance, but these latter factors explain little of the variation in our dataset. With the purpose of reducing the number of macro factors, we aim at determining the smallest number of factors explaining most of the variability of the dataset, thus confirming the numbers of the five factors.

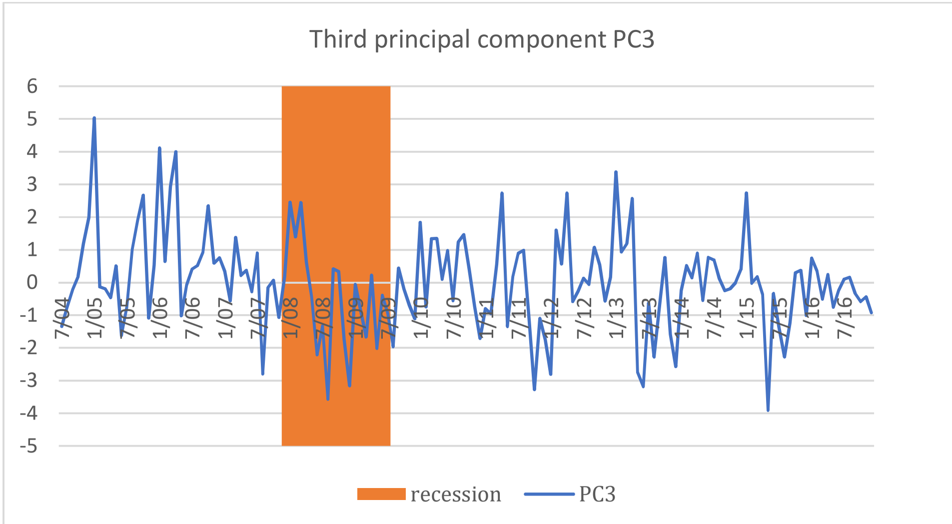
Because five factors are necessary to gauge the variance of all macro variables through the use of the scree plot above, we extract five principal components namely PC1, PC2, PC3, PC4, and PC5 (Figure 4.3). These principal components are constructed from the dataset to summarise their best possible characteristic.

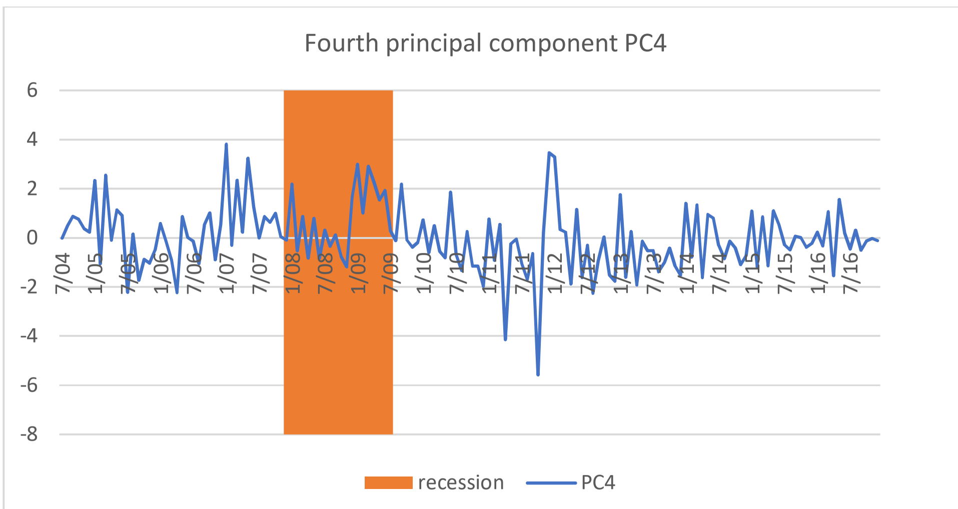
Figure 4.3*:* Time series of macro factors

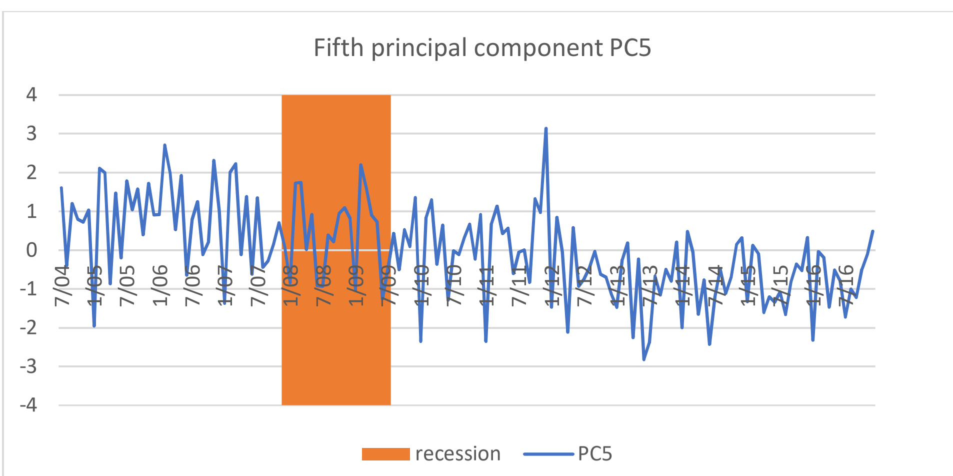
The figures here depict the time series for five macro factors PC1, PC2, PC3, PC4, and PC5 from May 2004 to December 2016. The horizontal axis illustrates the period, and the vertical line is the principal axis on which the data are projected. The orange block illustrates the recession time according to NBER.






Third principal component PC3
6
5
4
3
2
1
0
-1
-2
-3
-4
-5
7/04
1/05
7/05
1/06
7/06
1/07
7/07
1/08
7/08
1/09
7/09
1/10
7/10
1/11
7/11
1/12
7/12
1/13
7/13
1/14
7/14
1/15
7/15
1/16
7/16
recession
PC3


Fourth principal component PC4
6
4
2
0
-2
-4
-6
-8
7/04
1/05
7/05
1/06
7/06
1/07
7/07
1/08
7/08
1/09
7/09
1/10
7/10
1/11
7/11
1/12
7/12
1/13
7/13
1/14
7/14
1/15
7/15
1/16
7/16
recession
PC4


Fifth principal component PC5
4
3
2
1
0
-1
-2
-3
-4
7/04
1/05
7/05
1/06
7/06
1/07
7/07
1/08
7/08
1/09
7/09
1/10
7/10
1/11
7/11
1/12
7/12
1/13
7/13
1/14
7/14
1/15
7/15
1/16
7/16
recession
PC5

To understand which information the factor represents, each of these factors is regressed on each macro dataset. Having five factors and 21 macroeconomic variables, we have 105 regressions with saved values of R-Squared. R-squared are calculated from a simple regression of 21 macro series individually against each of the proposed factors. The following figures illustrate R-Squared information are in graphs below.

Figure 4.4*:* R-squared between the factor PC1 and individual macro series

The values of R-Squared for regressions of PC1 on each macroeconomic variable. The vertical line illustrates values of R-Squared, and the horizontal line depicts the macroeconomic variables, which are ordered according to Appendix 4.2.

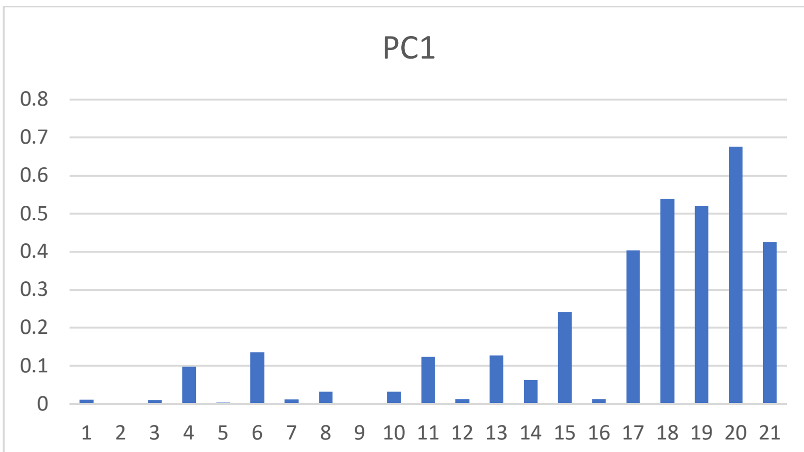


Figure 4.5*:* Values of R-Squared between the factor PC2 and macro series

The values of R-Squared for regressions of PC2 on each macroeconomic variable. The vertical line illustrates values of R-Squared, and the horizontal line depicts the macroeconomic variables, which are ordered according to Appendix 4.2.

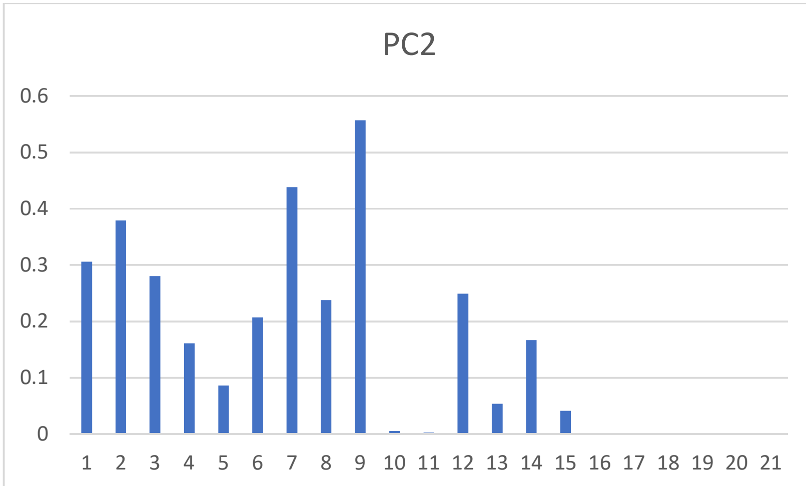


Figure 4.6*:* Values of R-Squared between the factor PC3 and macro series

The values of R-Squared for regressions of PC3 on each macroeconomic variable. The vertical line illustrates values of R-Squared, and the horizontal line depicts the macroeconomic variables, which are ordered according to Appendix 4.2.

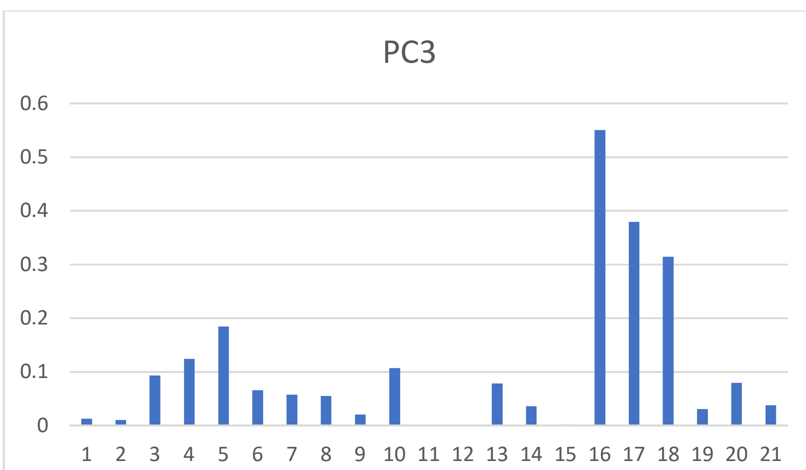


Figure 4.7*:* Values of R-Squared between the factor PC4 and macro series

The values of R-Squared for regressions of PC4 on each macroeconomic variable. The vertical line illustrates values of R-Squared, and the horizontal line depicts the macroeconomic variables, which are ordered according to Appendix 4.2.

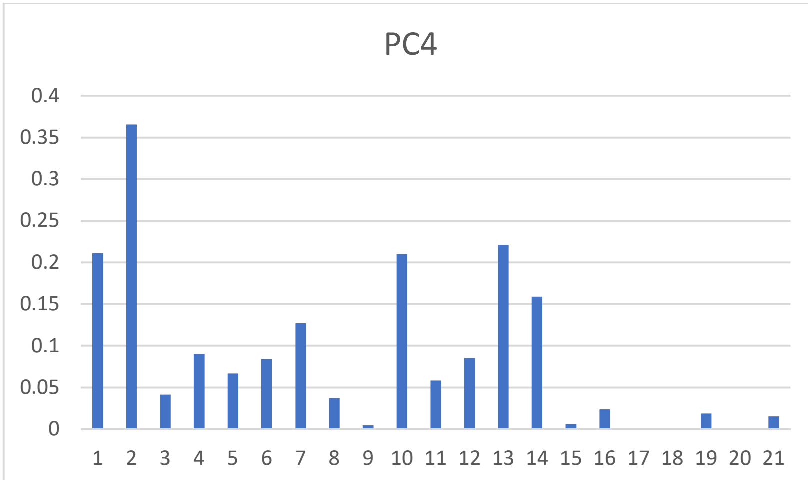
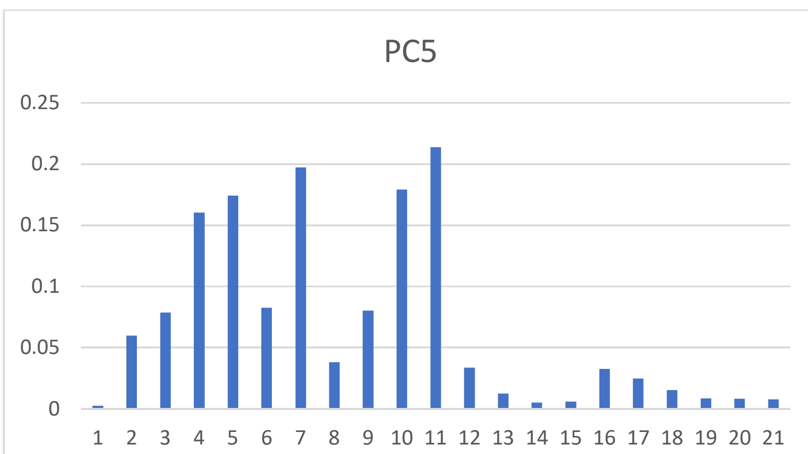


Figure 4.8*:* Values of R-Squared between the factor PC5 and macro series

The values of R-Squared for regressions of PC5 on each macroeconomic variable. The vertical line illustrates values of R-Squared, and the horizontal line depicts the macroeconomic variables, which are ordered according to Appendix 4.2.



The highest R-Squared in the first principal (Figure 4.4 R-squared between the factor PC1 and individual macro series) belongs to the group of price index, illustrating that the first component represents the price index group. The second component represents housing and sales, output. The third is the exchange rate, and the fourth puts more load on output. The last factor is for employment, money, and credit data.

4.4.2 Financial variables

The financial series including dividend yield, dividend growth, and total return for the broad index are available at SET. Total return is the return including accumulated dividends. Dividend yield and dividend growth are based on the 12-month rolling dividends. All three ratios are employed at monthly frequency, and one unit is added to them before the log transformation to handle negative value except for the dividend yield series. The log transformation is applied to the three ratios following Maio and Philip (2015).

Table 4.1 shows descriptive statistics of financial variables in a baseline model. The following value of mean, standard deviation, min, max, and first-order autocorrelation are measured.

Table 4.1: Descriptive statistics for financial variables

	mean	std	min	max	Rho
lndp	−3.34118	0.194624	−3.65738	−2.62417	0.946032
lndd	0.006221	0.032	−0.05053	0.219559	0.358705
lnr	0.039463	0.058297	−0.34135	0.170149	0.18866

rho accounts for first-order autocorrelation of each variable. It has the largest value and approximate to 1 for $lndp$ variable; thus, dividend yield is quite persistent. The coefficient related to Thailand's dividend growth data ($lndd$) is lower, 0.359, than other studies (approximately 0.9 in Maio and Philip (2015)) and gives some ideas about the characteristics of dividend payment in SET.

Table 4.2: Calculates correlation between the three variables

	lndp	lndd	lnr
lndp	1	−0.03597	−0.08813
lndd	−0.03597	1	0.104952
lnr	−0.08813	0.104952	1

Table 4.2 shows that all three variables are not significantly correlated with the other ones. The absolute of correlation terms is below 0.2. The log of return is negatively correlated with the dividend yield term, while positively correlated with the dividend growth. Dividend yield and dividend growth are negatively correlated.

4.5 Empirical analysis

This section comprises three parts: The first part considers the basic model including only financial variables; the second part includes the group of macro variables; and the third part adds the global factor. For each specification, regression coefficients using Newey–West *t*-statistics and variance decomposition are calculated.

4.5.1 Basic model

$x_{t+1} = \alpha + A\, x_t + \epsilon_{t+1}$ with $x_t = [dp_{t,}\, dd_t, r_{mt}]$

Because the focus of the study is on return predictability, we examine only the return equation in our system of three equations.

Estimated coefficients for the return equation

Table 4.3: Regression equation of return

	Coeff	Std Newey	*t*-Newey
constant	0.242497	0.103886	2.334255
Lndp	0.063146	0.029744	2.122975
Lndd	−0.03313	0.139179	−0.23804
Lnr	0.20836	0.099163	2.101198
$\overline{R}^2$	0.08		

In the equation, both dividend yield and lagged stock return are proven to significantly and positively forecast the stock return according to Newey–West *t*-statistics. One-period-lagged market return accounts for approximately 20% the next period's return. The forecasting power of this variable is approximately 3 times the forecasting power of the dividend yield (ca. 6%). As for dividend growth, the coefficient related to this variable is negative, showing that dividend growth and the next period's return move in opposite directions. However, the dividend growth cannot forecast the stock market return as indicated by very low *t*-Newey statistics. These results above are different from what has been found in the literature. Researchers normally find that the monthly basis stock returns do not have significant predictive power. One explanation may be the difference between the markets. Our research looks at a developing market, whereas almost all research has been applied to highly developed markets, such as Japan, the UK, and the US.

Variance decomposition for return equation

Table 4.4: Variance decomposition for return equation in the baseline model

	VAR (DR)	VAR (CF)	−2Cov
Baseline model	0.4873	0.5097	0.003

In our baseline model, the variance in stock return can be accounted for by both the discount rate news and the cash flow news. Cash flow news takes a slightly larger proportion in explaining the fluctuation of return, specifically 51% compared with 48% of the discount rates. The covariance term between these two components is responsible for a minor variation, just 0.3%.

4.5.2 Adding macro factors

$x_{t+1} = \alpha + A\, x_t + \epsilon_{t+1}$ with $x_t = [dp_{t,}\, dd_t, r_{mt}, pc1, pc2, pc3, pc4, pc5]$

Estimated coefficients

Regression coefficients of the return equation:

Table 4.5: Regression coefficients of the return equation with added macroeconomic variables

	Coeff	Std Newey	*t*-Newey
constant	0.278476	0.106566	2.61317
Lndp	0.074153	0.030776	2.409464
Lndd	0.005624	0.136723	0.041138
Lnr	0.221412	0.100703	2.198653
PC1	0.000139	0.003707	0.037372
PC2	0.002844	0.002653	1.072063
PC3	−0.00102	0.002841	−0.35763
PC4	0.006852	0.003216	2.130896
PC5	−0.00536	0.003192	−1.67845
$\overline{R}^2$	0.12		

When adding macro variables to the model, the importance of dividend yield and stock return improves slightly (ca. 6–7.5% for the dividend yield and 20–22% for the stock return). Dividend growth has no connection with the future return as indicated by a coefficient 0.0056 and low *t*-statistics −0.04. An added variable, PC4, statistically influences our future return. PC4 represents data on output, including the industrial production index, manufacturing production index, and capacity utilisation integrated index. This estimated coefficient is small, approximately one out of ten of dividend yields. R-Squared increases from 8% in the baseline model to approximately 12%. All results are somewhat persistent with Maio and Philip

(2015) and Ludvigson and Ng's (2007) conclusions that macro factors play a small role in return predictability.

Variance decomposition for the return equation

Table 4.6: Variance decomposition for the return equation with added macroeconomic variables

	VAR (DR)	VAR (CF)	−2Cov
Baseline model	0.518	0.504	−.022

When it comes to variance decomposition, the added macro variables version generally gives similar results to the original model. Both discount rate news and cash flow news play an important role in return predictability. These two components are still nearly orthogonal, represented by an absolute value of 2% of total variance.

4.5.3 Adding US return to the model

$x_{t+1} = \alpha + A\, x_t + \epsilon_{t+1}$ with $x_t = [dp_{t,}\, dd_t, r_{mt,}, r_{usa}\, , PC1, PC2, PC3, PC4, PC5]$

According to Rapach, Strauss, and Zhou (2013), US stock returns play a leading role in international returns. Their impacts are much more influential even than a countries' own characteristics, such as interest rates and dividend yields. Its impacts are fully diffused to other countries' return with a lag; thus, our model includes lagged US stock returns together with the aforementioned variables.

Considering Thailand as a small country and so following Rapach, Strauss, and Zhou (2013), a shock to return in small countries "does not affect U.S returns". However, as explained above, US stock returns do affect local returns, so it is necessary to decompose the local return into two parts, related and unrelated to US returns, to avoid multicollinearity in the predictive equation.

Regressing local stock return on global stock return using this equation gives:

$$r_{m,t+1} = \alpha + \beta r_{usa,t} + \epsilon_{r,t+1}$$

Extracting the residual term from this equation $\epsilon_{r,t+1}$, we have a series of new returns, which are regarded as orthogonalized local returns. Calculating the lag of this local return and using it as the new local return input, we have new model of return forecast:

$$r_{m,t+1} = \alpha + \beta_1 dp_t + \beta_2 \, dd_t + \beta_3 \epsilon_{r,t} + \beta_4 \, r_{usa,t} + \beta_{11} \, PC_1 + \beta_{12} \, PC_2 + +\beta_{13} \, PC_3 + \beta_{14} \, PC_4 + \beta_{15} \, PC_5 + \epsilon_t$$

$\epsilon_{r,t}$ as the residual of the diffusion equation above will be used as the local return factor in the equation above.

Estimated coefficients for the return equation

Table 4.7: Regression coefficients of the return equation with added macroeconomic variables and global factors

	Coeff	Std Newey	*t*-Newey
Constant	0.321851	0.095751	3.361326
Lndp	0.084871	0.028017	3.029235
Lndd	−0.00308	0.131358	−0.02347
Lnr1	0.152346	0.090086	1.691111
Lnusa	0.266137	0.139055	1.913899
PC1	0.00029	0.003674	0.078942
PC2	0.002927	0.002479	1.180832
PC3	−0.00023	0.002804	−0.08233
PC4	0.00669	0.00311	2.151234
PC5	−0.00587	0.003187	−1.84181
$\overline{R}^2$	0.14		

The predictive score of this model has been improved slightly, to approximately 14%. Local variables, including dividend yield and the fourth principal component of macro variables, somehow maintain the same influential level. Global stock returns substitute the role of domestic returns when they are added to the model, suggesting “lesser extent local” information compared with dominant global information.

Variance decomposition for the return equation

Table 4.8: Variance decomposition for the return equation with added macroeconomic variables and global factors

	VAR (DR)	VAR (CF)	−2Cov
Baseline model	0.512	0.529	−0.041

It can be seen from the table that cash flow news slightly improves its role in variance decomposition when adding the global factor. The cash flow news accounts for a slightly larger proportion than the previous specification, 52% compared with 50%. In contrast, the discount rate news remains approximately constant. Overall, the results do not deviate much from the previous specifications; however, adding more factors give us the more precise evaluation on N_{CF} and N_{DR}.

All of the three models' calculations above reach similar conclusions in both aspects: coefficient value and variance decomposition. As for the regression model, dividend yield keeps its important role in stock-return movement in all three models. The largest coefficient belongs to the last version including both local macro and global factors. Dividend growth does not contribute to the stock-return variation in each specification. The lagged return series, the one that has the largest impact among the variables in the first and second specifications, decreases its influence in the added-global-factor model. This impact is statistically significant at 90% instead of 95% in the two previous cases.

Regarding the variance decomposition part, cash flow news and discount rate news are about equally important in the first model. However, cash flow news is a slightly more influential in the last version, which corrects for specification problems mentioned in the literature. It can be said that the inclusion of local macro variables and global financial returns do bring a slight improvement to the variance decomposition part.

In Thailand's case, these findings are somehow different than common knowledge. Campbell (1991), Campbell and Ammer (1993), Campbell and Vuolteenaho (2004), Bernanke and Kuttner (2005), and Maio and Philip (2015) all find that discount rate news plays a determining role. One possible explanation is that our research is in a developing country in the Asian region, not the highly developed markets in previous studies. A further explanation may come from Rangvid, Straus, and Zhou (2014) that discount rate news becomes less influential in countries pursuing a less dividend smoothing policy and those having relatively small companies. The Thailand stock market index includes the stocks of relatively small companies; thus, cash flow news, which is typically related to the fundamentals of the companies, could have a greater-than-normal impact on the stock-return variance.

4.5.4 Robustness check

We assess the robustness of our variance decomposition by bootstrapping the residuals following Runkle (1987). Specifically, Runkle (1987) proposed this residual bootstrapping method with the basic idea that residual series reflect the true disturbances of our dataset, no matter what the order is. Any combination of random order of the residuals and regressed coefficients can generate an artificial dataset. Suppose we do 1000 times bootstrapping; we will have 1000 generating samples and 1000 variance decomposition results. These results will then be used to evaluate the accuracy of the estimates.

The bootstrap procedure is presented in Appendix 4.1. We do bootstrapping 1000 times for each specification including: the baseline model, the added macro variables model, and the model having both local macro variables and US stock returns.

The sample mean and standard deviation of results in each version are below:

The baseline version

Table 4.9: Bootstrap results of variance decomposition in the baseline model

	DR news	CF news	Cov
Org results	0.4873	0.5097	0.003
Bootstrap results	0.4872	0.5103	0.0025
Std	0.0331	0.0227	0.0393
T-stat	0.0955	0.8358	0.4023

In each specification, the first line (Org results) is the variance decomposition calculated in the previous part; the second, third, and last lines are mean, standard deviation, and standard error calculated from the group of 1000 simulated datasets. *T*-statistics calculated from these data show that there is no difference between the conclusion in the previous section and the bootstrap conclusions.

The added macro variables version

Table 4.10: Bootstrap results of variance decomposition with added macroeconomic variables

	DR news	CF news	Cov
Org Results	0.518	0.504	−0.022
Bootstrap results	0.5200	0.505	−0.0258
Std	0.0405	0.0278	0.0493
T-stat	1.561	1.137	1.924

Version with both macro variables and US stock returns

Table 4.11: Bootstrap results of variance decomposition with added macroeconomic variables and global factors

	DR news	CF news	Cov
Org Results	0.512	0.529	−0.041
Bootstrap results	0.519	0.5439	−0.0629
Std	0.1209	0.2819	0.3969
T-stat	1.830	1.671	1.744

Doing bootstrap 1000 times for the second and the third versions, we have the sample mean and standard deviation in the table. *T*-statistics calculated from these two tables show that there is no difference between our specified variance proportions and the simulations.

Overall, all of the bootstrap results confirm the robustness of the variance decomposition that cash flow news accounts for a slightly greater proportion of stock-return volatility.

4.6 Conclusion

Although the topic of return decomposition has been widely researched in recent years, most studies focus on the US market or highly industrialised ones. Our research focuses on Thailand, one of the leading countries in Southeast Asia. It aims to answer the question: What is more important: discount rate news (expected return) or cash flow news (dividend growth) in the variance of stock returns? Does the inclusion of macro variables and global factors create any changes in the relative importance of the two components?

We follow previous studies of Campbell and Shiller (1988), Campbell (1991), Cochrane (2008), but adding some extensions to account for possible misspecification as stated by Chen and Zhao (2009) and Maio and Philip (2015). These two studies specify that bias estimation of cash flow news can occur when using the original first-order VAR with only financial information. Cash flow news is calculated as the residual of the return decomposition; thus, any incorrect specified model can lead to biased results. Adding more macro variables from the principal component analysis to the model is considered necessary. Furthermore, the opinion of Rapach *et al.* (2013) about the significant role of US stock market returns on other countries is also considered. Overall, three models have been employed: the baseline model with financial information alone; the expanded model, including both financial variables and macro variables; and the last model, including financial and macro variables and global stock returns represented by the US market. The first-order VAR specification has been imposed on the three models here.

The results of the three models come to the same conclusion: that the roles of discount rate news and cash flow news are about equal in determining the variability of stock returns. Each accounts for approximately 50% of Thailand's stock-return variance during period July 2004–December 2016. Robustness tests, using a bootstrap technique, also confirm these numbers. It seems that including macro variables in the second model or adding US stock returns, the world's leading indicator, do not change the attributions statistically. In other words, adding macro variables or US stock returns to Thailand's case does not cause any significant change in the relative importance between expected return and cash flow news.

Apart from variance decomposition, the research also measures the impact of each determinant on the aggregate return predictability of the SET index. Dividend yield is positive and statistically significant in all three models, coinciding with the literature. Dividend growth, in contrast, does not enhance the predictability of stock returns. The presence of global stock returns (US returns) enhances the model's forecasting ability, while decreasing the lagged local stock return's role (Thailand lagged return), compared with the case with no global US returns. This is the result of the separation of common factors (between global and local stock returns) from the local returns in the world of financial integration.

Overall, it is hoped that this chapter's findings can be informative in the following aspects. To academics, this research provides another aspect of return predictability for developing countries in Asia. It is the first research that applies both macro and global factors owing to the characteristics of our target countries: an exporting country with high trade activity with the US and globally. To market participators including investors, funds, and brokers, these results may be helpful in determining investment strategy. Last but not least, it may be helpful for policy-makers and some specific authorities in understanding the integration level. Further studies can be considered, such as stock-return predictability at the bank level or sectoral stock-return predictability.

Chapter 5

CONCLUSION

This thesis studies the behaviour of the stock market index of Southeast Asian countries in three aspects. First, I identify the region's political instability and its impact on ASEAN stock market volatility. The stock market volatility is compared with two periods: before and after the government reform to determine whether the reform helps stabilise or destabilise the market. Second, the long-term relationship between the stock price index and macroeconomic variables is examined to understand the long-term movement of the stock market. Granger causality is also tested to understand the short-term movement of stock prices and macro variables. In the last empirical chapter, stock-return volatility is decomposed into the discount rate news and cash flow news to understand which component creates the larger proportion of variance of stock-return.

In the first empirical study, we contribute to the literature by examining the influence of major political events in Southeast Asian countries, namely the influence of political reforms on the stability of the stock market. We follow Gulen and Mayhew (2000) and Chau *et al.* (2014) in adopting the GARCH framework of Engle (1982) and Bollerslev (1986), but apply it to a new kind of event: government reform. We explain the rationality of GARCH-type models of conditional volatility to deal with the special characteristics of a daily financial dataset. Among the several GARCH-family models, we propose GARCH (1,1), which is used mostly as a benchmark for conditional volatility models. We also account for the other two asymmetric forms, EGARCH (1,1) and GJR-GARCH (1,1), to capture the leverage effects. Using information criteria, we find that among the three specified models, GARCH (1,1) and GJR-GARCH (1,1) are reasonable for our dataset.

To answer the main research questions, we add dummy variables under the multiplicative form to the volatility model assuming that all components of the volatility respond at the same rate to the political reform. The statistically negative sign of the dummy variables in Vietnam, Thailand, and Indonesia suggests that the new government stabilises the stock market. To confirm the robustness of the results, we employ two additional models: a univariate GARCH model with additive dummy variables and a multivariate GARCH model, which allow for the spillover effect of volatility from the global to the emerging countries. We also test the robustness of the results using different event dates. For all specifications, we find that political reforms have volatility, reducing the effect in the three Southeast Asian countries (Thailand, Indonesia, and Vietnam). It suggests that new governments help stabilise the stock market. This finding seems to be consistent with the fact that the new regimes are considered business friendly, offering optimism and transparency to business.

This chapter's findings contribute to the literature by explaining the impact of political events on stock market volatility. It illustrates the long-term volatility-reducing effect of the government reforms in ASEAN countries. Investors engaging in hedging strategies can employ this conclusion to construct investment strategies. As for policy-makers, the results provide information to evaluate the impact of political events on the stock market.

The second empirical study examines another aspect of stock market behaviour: the interaction between stock prices and macro variables in Thailand. Applying both the traditional unit root tests and more complicated tests accounting for the structural breaks, we find that our Thailand dataset is a mixture of stationary and non-stationary series. This result, therefore, confirms the validity of the ARDL model for long-term cointegration and the TYDL for Granger causality once there exists a cointegrating relationship.

Having the ARDL bound test on the set of variables, we find that there exists cointegration between the stock price and macro variables. This long-term relationship suggests that changes in stock price may arise as a forward-looking response to macroeconomic variables. It can be useful for the investment strategies of stock traders or for regulatory purposes. Furthermore, among the five macroeconomic variables (IP, M1, R, NER, and MSCI), two of them (M1 and MSCI) are positively cointegrated with the stock price. The positive sign of cointegration between the stock price index SPI and money supply M1 signify a positive liquidity effect. An increase in money supply, which affects the economy, will boost investment, consumption, and industrial production (Friedman, 1969). As for the MSCI index, the positive sign of this variable signifies the integration of Thailand's stock market in world markets.

Apart from the long-term relationship, the ARDL cointegration test allows us to assess the speed of adjustment from a position out of equilibrium in the short run to long-term equilibrium. In Thailand, it takes nearly half a year to bring disequilibrium back to the steady state. Investors, therefore, could profit when making investments according to this adjustment. As for short-term causality, the interest rate Granger causes the stock price index through the dividend discounted model, the financing cost and the portfolio rebalancing channel. The reverse Granger causality from the stock market index to the interest rate is also corroborated, confirming the bi-directional relationship between them. As for the exchange rate, the unidirectional Granger causality from the stock price to the exchange rate not only supports the portfolio balance theory (McKinnon, 1969; Branson, 1983; Frankel, 1983), but also provides a tool for preventing a currency crisis. The government can manipulate the stock market to deal with a currency crisis.

The third empirical study provides another look at the volatility of the stock-return: variance decomposition. We apply the baseline variance decomposition model of Campbell (1991) together with its modified versions, which allow the role of a large set of macro variables and global factors. The macro variables in our study are extracted from the large dataset from Datastream using principal component analysis to convey most of the dataset's variability.

We find that discount rate news and cash flow news are equally important to Thailand's stock-return volatility, instead of the usual finding in the literature of the dominant role of the discount rate. Robustness tests for the three specifications also confirm this result. A possible explanation may arise from the short-length dataset and because Thailand's stock exchange comprises companies that are relatively small and pursue less dividend smoothing policy than the US does.

In addition to variance decomposition, we also measure the impact of macroeconomic and financial variables on stock returns in Thailand. All three specifications suggest that the stock price does not respond much to the macroeconomic and financial variables in the short run. Although it seems puzzling at first, it suggests that the stock market takes a long-term view of the value of the stock. Thus, the short-term movement in the macro variables, which do not change much, will not be considered. Major policy shifts seem to matter much more than the macro variables, consistent with the first study's findings.

In addition to solving the research questions in each empirical chapter of this thesis, the findings of this thesis also provide insights necessary to elucidate some previous studies. The study of the impact of government reform in Southeast Asia on stock market volatility provides another perspective to the work of Acemoglu (2005) about types of institutions and their importance for growth. The political reforms in our studies bring on the new regime, confirming Acemoglu's (2005) conclusion that different types of institutions appear to have different impacts on economic growth and financial markets.

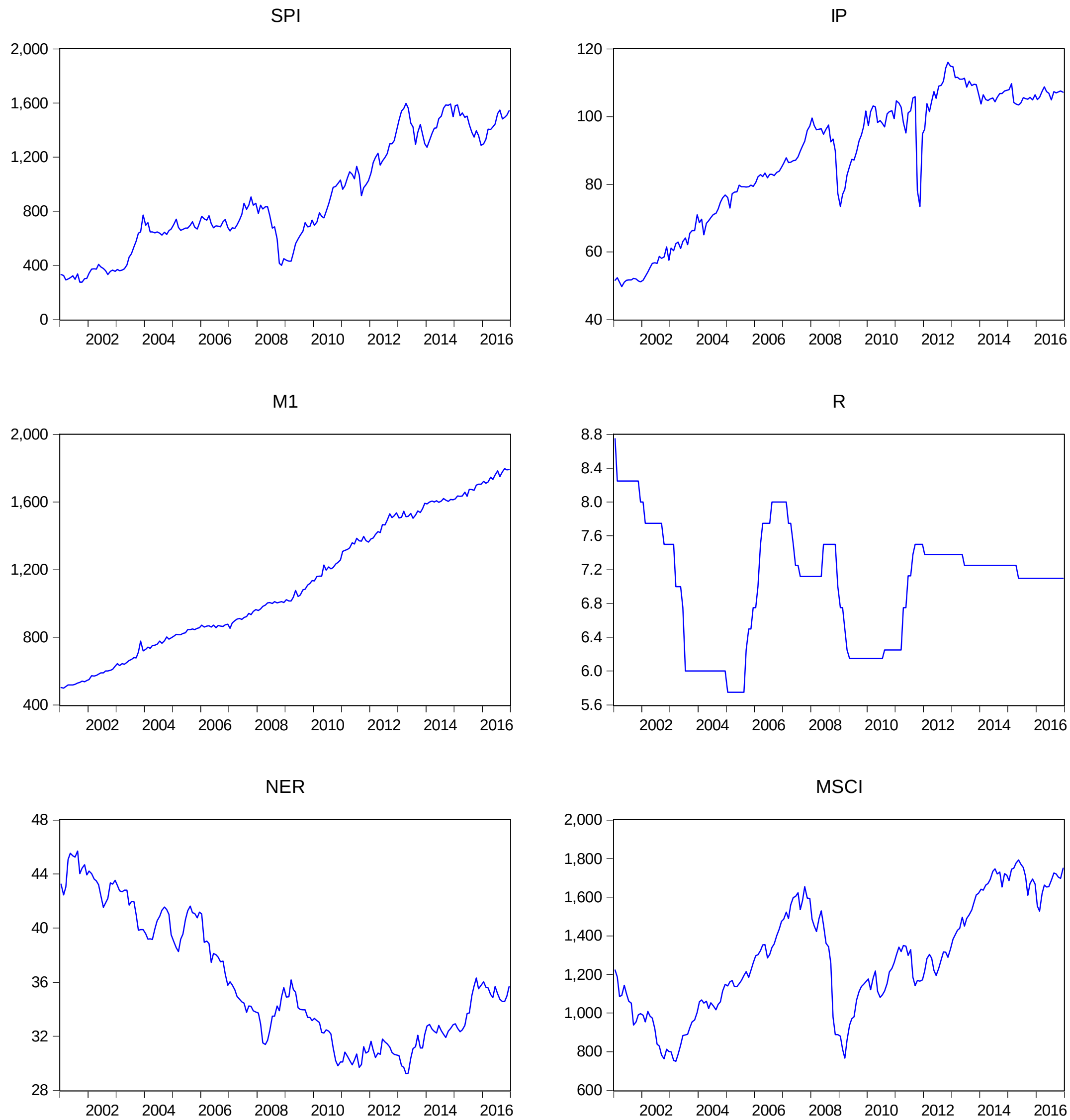
As with other studies, our studies have some limitations, which leads to the consideration of alternative views. First of all, our three studies suffer from the problems caused by the short sample period, owing to the availability of macroeconomic information in ASEAN markets and because the stock markets in ASEAN countries were established quite late. Second, in the univariate model of the first chapter, we assume that each component of the conditional volatility model responds at the same rate to the news through the multiplicative dummy variables. Although the findings of this model have been reinforced by the other model specifications (multivariate model or additive dummies), it is still necessary to have different dummies for different components. Another related topic that might emerge is measuring the ASEAN political uncertainty index and its relationship with volatility in the stock market, or how institutions affect the volatility of financial and non-financial institutions. Last but not least, further sectoral-level analysis about the impact of political reform on the stock market can be considered, to explain why some stocks react to political reform more than others.

APPENDICES

Appendix 3.1 Descriptive statistics of raw data

	SPI	IP	M1	PRIME	ER	MSCI
Mean	888.1185	88.03878	1113.25	7.038021	35.98658	1283.865
Median	763.07	93.6225	1025.2	7.125	34.89309	1260.719
Maximum	1597.86	115.841	1864.2	8.75	45.7034	1792.515
Minimum	275.09	50.32	505.1	5.75	29.2419	751.0681
Skewness	0.311999	-0.53879	0.179273	−0.23042	0.475454	0.062368
Kurtosis	1.831962	2.024203	1.703288	2.233533	1.939428	1.93613
Jarque–Bera	14.0295	16.90683	14.48014	6.398804	16.23232	9.179037
P-value	0.000899	0.000213	0.000717	0.040787	0.000299	0.010158

Appendix 3.2 Graphic representations of raw data



Appendix 4.1: Bootstrap simulation

The variance decompositions of the discount rate news and cash flow news are not coefficients of time-series regression. They are the proportion of variance of the two elements over the total variance of return. To obtain *t*-statistics of these ratios, we follow Runkle's (1987) approach in calculating bootstrapped *t*-statistics. Here the procedure of the baseline model is presented, and that of all substitute models can be applied similarly.

Baseline model: $x_{t+1} = \alpha + A\, x_t + \epsilon_{t+1}$

1. Estimate the basis equation and collect the regressed coefficients and residuals. The size of the coefficient's matrix is the number of observations times the number of state variables, and the residual's one is a single matrix with the same length.
2. Randomly select the residuals for each observation from the specified residuals set above.
3. Form a new dataset from the residuals in Step 2 and the regressed coefficients in Step 1.
4. Carry out Steps 2 and 3 Z times, where Z is the number of bootstraps. For each bootstrap, we calculate the variance decomposition and save the results.

Finally, we have Z sets of results; each set gives the different proportions of discount rate news and cash flow news. Our *t*-statistics are then calculated, each ratio's *t*-stats reflect the deviation of the aforementioned proportion in baseline model compared with the series of results in Z replications.

Appendix 4.2: List of macro variables

The Thai macro variables used in our research are listed in the table below. They are collected from Datastream on a monthly basis. Information related to them includes: name, mnemonic, short description, and the transformation codes. Transformation codes are from 1 to 6; more specifically: 1 stands for using levels, 2 stands for using first differences, 3 stands for using second difference, 4 denotes logarithm, 5 denotes the first difference of logged value, and 6 stands for second-log differences. Finally, according to Stock and Watson (2002b), these transformed data are standardised to have a mean of zero and unit variance.

No.	Name	Mnemonic	Description	T code
1	TH INDUSTRIAL PRODUCTION INDEX (STANDARDIZED) VOLA	THCIND..G		5
2	TH MANUFACTURING PRODUCTION INDEX VOLN	THIPMAN.H		5
3	TH CAPACITY UTILIZATION INTEGRATED INDEX SADJ	THCAPUTLQ		4
4	TH EMPLOYMENT VOLN	THEMPTOTP		4
5	TH UNEMPLOYMENT – RATE OF UNEMPLOYMENT NADJ	THUN%TOTR		5
6	TH NEW HOUSES REGISTERED IN BANGKOK AND NEARBY PROVINCES VOLN	THHOUSE.P		4
7	TH RETAIL SALES INDEX NADJ	THRETTOTF		5
8	TH CONSUMER CONFIDENCE INDEX NADJ	THCNFCONR		5
9	TH BUSINESS SENTIMENTS – ACTUAL NADJ	THCNFBUSR		4
10	TH MONEY SUPPLY: M1 (NARROW MONEY) CURN	THM1....A		6
11	TH MONEY SUPPLY: M3 (BROAD MONEY) CURN	THM3....A		5
12	TH COMMERCIAL BANKS CREDITS – INDIVIDUALS CURN	THCRDCONA		5
13	TH PRIME RATE (MOR) NADJ	THBANKR.		2
14	TH DISCOUNT RATE (EP) NADJ	THDISCRT		2
15	TH GOVT BOND YIELD – 10 YEAR NADJ	THGBOND.		2
16	TH THAI BAHT – REAL EFFECTIVE EXCHANGE RATE INDEX NADJ	THXTW..RF		5
17	TH EXPORT PRICE INDEX NADJ	THEXPPRCF		5
18	TH IMPORT PRICE INDEX NADJ	THIMPPRCF		5
19	TH PPI: PRODS.CLASSIFICATION – ALL PRODUCTS (SEE THPROP00F) NADJ	THPROPRCF		5
20	TH CPI NADJ	THCONPRCF		5
21	TH CPI – EXCL RAW FOOD & ENERGY NADJ	THCPCOREF		5

Appendix 4.3: Formula for the derivation of stock-return variance decomposition

The derivation comes from the definition of total return: total return measures both price movements and dividends incomes.

$$R_{t+1} = \frac{P_{t+1} + D_{t+1}}{P_t}$$

$$R_{t+1} = \frac{1 + \frac{P_{t+1}}{D_{t+1}}}{\frac{P_t}{D_t}} \frac{D_{t+1}}{D_t}$$

Inversing the ratio in the denominator, we have the new equation:

$$R_{t+1} = \left(1 + \frac{P_{t+1}}{D_{t+1}}\right)\left(\frac{D_t}{P_t}\right)\left(\frac{D_{t+1}}{D_t}\right)$$

where $R_{t+1}, P_{t+1}, D_{t+1}$ are total stock return, stock price, and dividend paid at time t+1. P_t is the price at time *t*. Dividing both numerator and denominator by D_{t+1}. Taking log on both sides and denoting $r_{t+1} = \log(R_{t+1})$; $d_{t+1} = \log(D_{t+1})$; $dp_{t+1} = \log\left(\frac{D_{t+1}}{P_{t+1}}\right)$; $dp_t = \log\left(\frac{D_t}{P_t}\right)$, we have the new equation:

$$\log(R_{t+1}) = \log\left(1 + \left(\frac{D_{t+1}}{P_{t+1}}\right)^{-1}\right) + \log\left(\frac{D_t}{P_t}\right) + \log\left(\frac{D_{t+1}}{D_t}\right)$$

$$r_{t+1} = \log(1 + e^{-dp_{t+1}}) + dp_t + \Delta d_{t+1}$$

$$- dp_t = -r_{t+1} + \Delta d_{t+1} + \log(1 + e^{-dp_{t+1}})$$

Because $dp_t = \log\left(\frac{D_t}{P_t}\right)$ thus $- dp_t = -\log\left(\frac{D_t}{P_t}\right) = pd_t$

Our equation becomes:

$$pd_t = -r_{t+1} + \Delta d_{t+1} + \log(1 + e^{pd_{t+1}})$$

Taylor expansion of the last term about the point $P/D = e^{pd}$

$$\log(1 + e^{pd_{t+1}}) \approx \log(P/D + 1) + \frac{P/D}{P/D + 1}(p_{t+1} - d_{t+1} - pd)$$

For each dataset, calculating the ratio $\rho = \frac{PD}{PD+1}$ and substituting into the equation, we have:

$$r_{t+1} \approx \rho(p_{t+1} - d_{t+1}) - (p_t - d_t) + \Delta d_{t+1}$$

Moving the element $(p_t - d_t)$ to the LHS, the new equation becomes:

$$r_{t+1} \approx -\rho(d_{t+1} - p_{t+1}) + \Delta d_{t+1} + (d_t - p_t)$$

$$p_t - d_t \approx \Delta d_{t+1} - r_{t+1} + \rho(p_{t+1} - d_{t+1})$$

Iterating the last equation forwards to have:

$$p_t - d_t \approx \sum_{j=1}^{\infty} \rho^{j-1}(\Delta d_{t+j} - r_{t+j})$$

The meaning of this approximate identity is that the price dividend ratio today is approximately equal to the sum of discounted value of all news about future dividend and future returns. We follow Campbell–Shiller return decomposition by taking $E_{t+1} - E_t$ on both sides:

$$(E_{t+1} - E_t)(p_t - d_t) \approx (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^{j-1}(\Delta d_{t+j} - r_{t+j})$$

$$[E_{t+1}(p_t) - E_t(p_t)] - [E_{t+1}(d_t) - E_t(d_t)] = (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^{j-1}(\Delta d_{t+j} - r_{t+j})$$

Because at the time point $t + 1$, the forecast value for the previous period t is the real value or $E_{t+1}(p_t) = E_t(p_t)$; $E_{t+1}(d_t) = E_t(d_t)$, thus the above equation can be written in the following form:

$$0 = (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^{j-1} (\Delta d_{t+j} - r_{t+j})$$

$$(E_{t+1} - E_t) r_{t+1} = (E_{t+1} - E_t) \Delta d_{t+1} + \sum_{j=2}^{\infty} \rho^{j-1} (\Delta d_{t+j} - r_{t+j})$$

$$r_{t+1} - E_t r_{t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j}$$

$$= N_{CF,t+1} - N_{DR,t+1}$$

References

Abugri, Benjamin A. "Empirical relationship between macroeconomic volatility and stock returns: Evidence from Latin American markets." *International Review of Financial Analysis* 17.2 (2008): 396–410.

Acemoglu, Daron, Tarek A. Hassan, and Ahmed Tahoun. *The power of the street: Evidence from Egypt's Arab Spring*. No. w20665. National Bureau of Economic Research, 2014.

Aggarwal, Reena, and Pietra Rivoli. "Seasonal and day-of-the-week effects in four emerging stock markets." *Financial Review* 24.4 (1989): 541–550.

Alexander, Carol. "Volatility and correlation: measurement, models and applications." *Risk Management and Analysis* 1 (1998): 125–171.

Alexander, Carol. *Market models: A guide to financial data analysis*. John Wiley & Sons, 2001.

Allivine, Fred D., and D. D. O'Neil. "Stock market returns and the presidential election cycle." *Financial Analysts Journal* 36.5 (1980): 49–56.

Amihud, Yakov, and Avi Wohl. "Political news and stock prices: The case of Saddam Hussein contracts." *Journal of Banking & Finance* 28.5 (2004): 1185–1200.

Ang, James B., and Warwick J. McKibbin. "Financial liberalization, financial sector development and growth: evidence from Malaysia." *Journal of Development Economics* 84.1 (2007): 215–233.

Arin, K. Peren, Davide Ciferri, and Nicola Spagnolo. "The price of terror: The effects of terrorism on stock market returns and volatility." *Economics Letters* 101.3 (2008): 164–167.

Asteriou, Dimitrios, and Stephen G. Hall. "Applied Econometrics: a modern approach, revised edition." *Hampshire: Palgrave Macmillan* (2007).

Baba, Y., et al. *Multivariate simultaneous generalized arch, Department of Economics, University of California at San Diego*. Working Paper, 1990.

Bai and Ng. Determining the number of factors in approximate factor models, *Econometrica 70, 191–221, 2002.*

Barone, Emilio. "The Italian stock market: efficiency and calendar anomalies." *Journal of Banking & Finance* 14.2–3 (1990): 483–510.

Basher, Syed Abul, and Perry Sadorsky. "Hedging emerging market stock prices with oil, gold, VIX, and bonds: A comparison between DCC, ADCC and GO-GARCH." *Energy Economics* 54 (2016): 235–247.

Bautista, Carlos C. "Stock market volatility in the Philippines." *Applied Economics Letters* 10.5 (2003): 315–318.

Bekhet, Hussain Ali, and Ali Matar. "Co-integration and causality analysis between stock market prices and their determinates in Jordan." *Economic Modelling* 35 (2013): 508–514.

Bernanke and Kuttner. What explains the stock market's reaction to Federal Reserve policy? *Journal of Finance* 60: 1221–1257, 2005.

Białkowski, Jędrzej, Katrin Gottschalk, and Tomasz Piotr Wisniewski. "Stock market volatility around national elections." *Journal of Banking & Finance* 32.9 (2008): 1941–1953.

Bilson, Christopher M., Timothy J. Brailsford, and Vincent J. Hooper. "Selecting macroeconomic variables as explanatory factors of emerging stock market returns." *Pacific-Basin Finance Journal* 9.4 (2001): 401–426.

Bittlingmayer, George. "Output, stock volatility, and political uncertainty in a natural experiment: Germany, 1880–1940." *The Journal of Finance* 53.6 (1998): 2243–2257.

Bollerslev, Tim. "Generalized autoregressive conditional heteroskedasticity." *Journal of Econometrics* 31.3 (1986): 307–327.

Booth, James R., and Lena Chua Booth. "Is presidential cycle in security returns merely a reflection of business conditions?." *Review of Financial Economics* 12.2 (2003): 131–159.

Borensztein, Eduardo, Jose De Gregorio, and Jong-Wha Lee. "How does foreign direct investment affect economic growth?." *Journal of International Economics* 45.1 (1998): 115–135.

Boutchkova, Maria, et al. "Precarious politics and return volatility." *The Review of Financial Studies* 25.4 (2012): 1111–1154.

Boyd, John H., and Edward C. Prescott. "Financial intermediary-coalitions." *Journal of Economic Theory* 38.2 (1986): 211–232.

Branson, William H. "A model of exchange-rate determination with policy reaction: evidence from monthly data." (1983).

Brooks, Chris. *Introductory econometrics for finance*. Cambridge University Press, 2014.

Chandavarkar, Anand. "Of finance and development: neglected and unsettled questions." *World Development* 20.1 (1992): 133–142.

Brooks, Robert D., Sinclair Davidson, and Robert W. Faff. "An examination of the effects of major political change on stock market volatility: the South African experience." *Journal of International Financial Markets, Institutions and Money* 7.3 (1997): 255–275.

Brown, Stephen J., and Jerold B. Warner. "Using daily stock returns: The case of event studies." *Journal of Financial Economics* 14.1 (1985): 3–31.

Bulmash, Samuel B., and George William Trivoli. "Time–lagged interactions between stocks prices and selected economic variables." *The Journal of Portfolio Management* 17.4 (1991): 61–67.

Campbell, John Y., and Robert J. Shiller. "The dividend-price ratio and expectations of future dividends and discount factors." *The Review of Financial Studies* 1.3 (1988): 195–228.

Campbell. A variance decomposition for stock return. *Economic Journal* 101, 157–179, 1991.

Campbell and Ammer. What moves the stock and bond markets? A variance decomposition for long term asset returns. *Journal of Finance 48, 3–26, 1993.*

Campbell, John Y., and Tuomo Vuolteenaho. "Bad beta, good beta." *The American Economic Review* 94.5 (2004): 1249–1275.

Carosso, Vincent P. *Investment banking in America: A history*. Vol. 25. Harvard Univ Pr, 1970.

Chau, Frankie, Rataporn Deesomsak, and Jun Wang. "Political uncertainty and stock market volatility in the Middle East and North African (MENA) countries." *Journal of International Financial Markets, Institutions and Money* 28 (2014): 1–19.

Chen, Nai-Fu, Richard Roll, and Stephen A. Ross. "Economic forces and the stock market." *Journal of Business* (1986): 383–403.

Chen, Ming-Hsiang. "Macro and non-macro explanatory factors of Chinese hotel stock returns." *International Journal of Hospitality Management* 26.4 (2007): 991–1004.

Chen and Zhao. Return decomposition. *Review of Financial Studies* 22, 5213–5249, 2009.

Chen, Joseph S., ed. *Advances in hospitality and leisure*. Vol. 8. Emerald Group Publishing, 2012.

Cheng, Su-Yin. "Substitution or complementary effects between banking and stock markets: Evidence from financial openness in Taiwan." *Journal of International Financial Markets, Institutions and Money* 22.3 (2012): 508–520.

Chesney, Marc, Ganna Reshetar, and Mustafa Karaman. "The impact of terrorism on financial markets: An empirical study." *Journal of Banking & Finance* 35.2 (2011): 253–267.

Choudhry, Taufiq. "Day of the week effect in emerging Asian stock markets: evidence from the GARCH model." *Applied Financial Economics* 10.3 (2000): 235–242.

Cochrane, John H. "Explaining the variance of price–dividend ratios." *The Review of Financial Studies* 5.2 (1992): 243–280.

Cochrane. The dog that did not bark: A defense of return predictability. *Review of Financial Studies* 21, 1533–1575, 2008.

Cochrane, John H. "Presidential address: Discount rates." *The Journal of Finance* 66.4 (2011): 1047–1108.

Connor, Gregory, and Robert A. Korajczyk. "Performance measurement with the arbitrage pricing theory: A new framework for analysis." *Journal of Financial Economics* 15.3 (1986): 373–394.

De Long, J. Bradford, and Marco Becht. *"Excess volatility" and the German stock market, 1876–1990*. Vol. 82. European University Institute, 1992.

Devereux, Michael, *et al*., eds. *The Dynamics of Asian Financial Integration: Facts and Analytics*. Taylor & Francis, 2011.

Dhakal, Dharmendra, Magda Kandil, and Subhash C. Sharma. "Causality between the money supply and share prices: a VAR investigation." *Quarterly Journal of Business and Economics* (1993): 52–74.

Diamandis, Panayiotis F., and Anastassios A. Drakos. "Financial liberalization, exchange rates and stock prices: Exogenous shocks in four Latin America countries." *Journal of Policy Modeling* 33.3 (2011): 381–394.

Diamond, Douglas W. "Financial intermediation and delegated monitoring." *The Review of Economic Studies* 51.3 (1984): 393–414.

Doan, Thomas A. "RATS handbook for ARCH/GARCH and volatility models." *Draft version. Estima, Evanston, IL* (2013).

Ding, Zhuanxin, Clive WJ Granger, and Robert F. Engle. "A long memory property of stock market returns and a new model." *Journal of Empirical Finance* 1.1 (1993): 83–106.

Engle, Robert F. "Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation." *Econometrica: Journal of the Econometric Society* (1982): 987–1007.

Engle, Robert F., and Clive WJ Granger. "Co-integration and error correction: representation, estimation, and testing." *Econometrica: Journal of the Econometric Society* (1987): 251–276.

Engle, Robert F., Victor K. Ng, and Michael Rothschild. "Asset pricing with a factor-ARCH covariance structure: Empirical estimates for treasury bills." *Journal of Econometrics* 45.1-2 (1990): 213–237.

Engle, Robert F., and Victor K. Ng. "Measuring and testing the impact of news on volatility." *The Journal of Finance* 48.5 (1993): 1749–1778.

Fama, Eugene F. "Stock returns, real activity, inflation, and money." *The American Economic Review* 71.4 (1981): 545–565.

Fama and French. Dividend yields and expected stock returns. *Journal of Financial Economics 22, 3–25, 1988.*

Fama, Eugene F. "Stock returns, expected returns, and real activity." *The Journal of Finance* 45.4 (1990): 1089–1108.

Ferson, Wayne E., and Campbell R. Harvey. "The variation of economic risk premiums." *Journal of Political Economy* 99.2 (1991): 385–415.

Fifield, S. G. M., D. M. Power, and C. D. Sinclair. "Macroeconomic factors and share returns: an analysis using emerging market data." *International Journal of Finance & Economics* 7.1 (2002): 51–62.

Fifield, S. G. M., and D. M. Power. "The Role of Economic and Fundamental Factors in Emerging Markets Share Returns: A Comparison of Asian and Non-Asian Countries." *Journal of Accounting and Finance* 5.1 (2006): 1–18.

Frankel, Jeffrey A. *Monetary and portfolio-balance models of exchange rate determination*. University of California, Berkeley, Department of Economics, 1987.

French, Kenneth R. "Stock returns and the weekend effect." *Journal of Financial economics* 8.1 (1980): 55–69.

Füss, Roland, and Michael M. Bechtel. "Partisan politics and stock market performance: The effect of expected government partisanship on stock returns in the 2002 German federal election." *Public Choice* 135.3 (2008): 131–150.

Gelman, Andrew, and Jennifer Hill. *Data analysis using regression and multilevelhierarchical models*. Vol. 1. New York, NY, USA: Cambridge University Press, 2007.

Glosten, Lawrence R., Ravi Jagannathan, and David E. Runkle. "On the relation between the expected value and the volatility of the nominal excess return on stocks." *The Journal of Finance* 48.5 (1993): 1779–1801.

Goetzmann and Jorion. Testing the predictive power of dividend yields. *Journal of Finance 48,* 663–679.

Granger, Clive WJ, Bwo-Nung Huangb, and Chin-Wei Yang. "A bivariate causality between stock prices and exchange rates: evidence from recent Asianflu☆." *The Quarterly Review of Economics and Finance* 40.3 (2000): 337–354.

Greenwood, Jeremy, and Boyan Jovanovic. "Financial development, growth, and the distribution of income." *Journal of Political Economy* 98.5, Part 1 (1990): 1076–1107.

Gujarati, Damodar N., and D. Porter. "Basic Econometrics McGraw-Hill International Edition." (2009).

Gulen, Huseyin, and Stewart Mayhew. *The dynamics of international stock index returns*. Working paper, University of Georgia, 1999.

Gulen, Huseyin, and Stewart Mayhew. "Stock index futures trading and volatility in international equity markets." (2000).

Habibullah, Muzafar Shah, and Ahmed Zubaidi Baharumshah. "Money, output and stock prices in Malaysia: an application of the cointegration tests." *International Economic Journal* 10.2 (1996): 121–130.

Hacker, R. Scott, and Abdulnasser Hatemi-J. "Tests for causality between integrated variables using asymptotic and bootstrap distributions: theory and application." *Applied Economics* 38.13 (2006): 1489–1500.

Hansen, Peter R., and Asger Lunde. "A forecast comparison of volatility models: does anything beat a GARCH (1, 1)?." *Journal of Applied Econometrics* 20.7 (2005): 873–889.

Hatemi-J, Abdulnasser, and Eduardo Roca*. "Exchange rates and stock prices interaction during good and bad times: evidence from the ASEAN4 countries." *Applied Financial Economics* 15.8 (2005): 539–546.

Hassan, Gazi Mainul, and Hisham M. Al Refai. "Can macroeconomic factors explain equity returns in the long run? The case of Jordan." *Applied Financial Economics* 22.13 (2012): 1029–1041.

Hendry, David F. "Econometric modelling with cointegrated variables: an overview." *Oxford Bulletin of Economics and Statistics* 48.3 (1986): 201–212.

Hodrick. Dividend yields and expected stock returns: Alternative procedures for inference and measurement. *Review of Financial Studies* 5, 337–386, 1992.

Humpe, A., and P. Macmillan. "Can macroeconomic variables explain long term stock movements? A Comparison of the US and Japan." *Center for Dynamic Microeconomic Analysis Working Paper Series* (2007).

Hurvich, Clifford M., and Chih-Ling Tsai. "Regression and time series model selection in small samples." *Biometrika* 76.2 (1989): 297–307.

Ibrahim, Mansor. "Macroeconomic variables and stock prices in Malaysia: An empirical analysis." *Asian Economic Journal* 13.2 (1999): 219–231.

Ibrahim, Mansor H., and Hassanuddeen Aziz. "Macroeconomic variables and the Malaysian equity market: A view through rolling subsamples." *Journal of Economic Studies* 30.1 (2003): 6–27.

Jammazi, Rania, et al. "Main driving factors of the interest rate-stock market Granger causality." *International Review of Financial Analysis* (2017).

Jensen, Michael C., and William H. Meckling. "Theory of the firm: Managerial behavior, agency costs and ownership structure." *Journal of Financial Economics* 3.4 (1976): 305–360.

Johansen, Søren, and Katarina Juselius. "Maximum likelihood estimation and inference on cointegration—with applications to the demand for money." *Oxford Bulletin of Economics and Statistics* 52.2 (1990): 169–210.

Karolyi, G. Andrew. "A multivariate GARCH model of international transmissions of stock returns and volatility: The case of the United States and Canada." *Journal of Business & Economic Statistics* 13.1 (1995): 11–25.

Karolyi, George Andrew. "The consequences of terrorism for financial markets: what do we know?." (2006).

Kar, Muhsin, Şaban Nazlıoğlu, and Hüseyin Ağır. "Financial development and economic growth nexus in the MENA countries: Bootstrap panel granger causality analysis." *Economic Modelling* 28.1 (2011): 685–693.

Keim, Donald B., and Robert F. Stambaugh. "A further investigation of the weekend effect in stock returns." *The Journal of Finance* 39.3 (1984): 819–835.

Kumar Narayan, Paresh, and Russell Smyth. "Higher education, real income and real investment in China: evidence from Granger causality tests." *Education Economics* 14.1 (2006): 107–125.

Kwon, Chung S., and Tai S. Shin. "Cointegration and causality between macroeconomic variables and stock market returns." *Global Finance Journal*10.1 (1999): 71–81.

Lee, Junsoo, and Mark C. Strazicich. "Minimum Lagrange multiplier unit root test with two structural breaks." *The Review of Economics and Statistics* 85.4 (2003): 1082–1089.

Levine, Ross. "Financial development and economic growth: views and agenda." *Journal of Economic Literature* 35.2 (1997): 688–726.

Levine, Ross, and Sara Zervos. "Stock markets, banks, and economic growth." *American Economic Review* (1998): 537–558.

Lin, Chien-Hsiu. "The comovement between exchange rates and stock prices in the Asian emerging markets." *International Review of Economics & Finance* 22.1 (2012): 161–172.

Lintner, John. "The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets." *The Review of Economics and Statistics* (1965): 13–37.

Lo, Andrew W., and A. Craig MacKinlay. "Stock market prices do not follow random walks: Evidence from a simple specification test." *The Review of Financial Studies* 1.1 (1988): 41–66.

Lobo, Bento J. "Jump risk in the US stock market: Evidence using political information." *Review of Financial Economics* 8.2 (1999): 149–163.

Lucas, Robert E. "On the mechanics of economic development." *Journal of Monetary Economics* 22.1 (1988): 3–42.

Ludvigson, Sydney C., and Serena Ng. "The empirical risk–return relation: A factor analysis approach." *Journal of Financial Economics* 83.1 (2007): 171–222.

Lumsdaine, Robin L., and David H. Papell. "Multiple trend breaks and the unit-root hypothesis." *The Review of Economics and Statistics* 79.2 (1997): 212–218.

Maio, Paulo, and Dennis Philip. "Macro variables and the components of stock returns." *Journal of Empirical Finance* 33 (2015): 287–308.

Majid, M., and Rosylin Mohd Yusof. "Long-run relationship between Islamic stock returns and macroeconomic variables: An application of the autoregressive distributed lag model." *Humanomics* 25.2 (2009): 127–141.

Maysami, Ramin Cooper, and H. H. Sim. "An empirical investigation of the dynamic relations between macroeconomic factors and the stock markets of Malaysia and Thailand." *Jurnal Pengurusan* 20 (2001).

Maysami, R. C., and H. H. Sim. "Macroeconomic forces and stock returns: a general-to-specific ECM analysis of the Japanese and South Korean markets." *International Quarterly Journal of Finance* 1.1 (2001): 83–99.

Maysami, Ramin Cooper, and Hsien Hui Sim. "Macroeconomics variables and their relationship with stock returns: error correction evidence from Hong Kong and Singapore." *The Asian Economic Review* 44.1 (2002): 69–85.

Maysami, Ramin Cooper, Lee Chuin Howe, and Mohamad Atkin Rahmat. "Relationship between macroeconomic variables and stock market indices: Cointegration evidence from stock exchange of Singapore's All-S sector indices." *Jurnal Pengurusan (UKM Journal of Management)* 24 (2005).

McKinnon, Ronald I. *Portfolio balance and international payments adjustments*. Stanford University, Research Center in Economic Growth, 1966.

Mei, Jianping, and Limin Guo. "Political uncertainty, financial crisis and market volatility." *European Financial Management* 10.4 (2004): 639–657.

Merton, Robert C., and Zvi Bodie. "A conceptual framework for analyzing the financial system." *The Global Financial System: A Functional Perspective* (1995): 3–31.

Mossin, Jan. "Equilibrium in a capital asset market." *Econometrica: Journal of the Econometric Society* (1966): 768–783.

Mukherjee, Tarun K., and Atsuyuki Naka. "Dynamic relations between macroeconomic variables and the Japanese stock market: an application of a vector error correction model." *Journal of Financial Research* 18.2 (1995): 223–237.

Nasseh, Alireza, and Jack Strauss. "Stock prices and domestic and international macroeconomic activity: a cointegration approach." *The Quarterly Review of Economics and Finance* 40.2 (2000): 229–245.

Nelson, Daniel B. "Conditional heteroskedasticity in asset returns: A new approach." *Econometrica: Journal of the Econometric Society* (1991): 347–370.

Newey, Whitney K., and Kenneth D. West. "Hypothesis testing with efficient method of moments estimation." *International Economic Review* (1987): 777–787.

Newey and West. A simple, positive semi-definite, heteroscedasticity and autocorrelation consistent covariance matrix. *Econometrica 55, 703–708.*

Nordhaus, William D. "The political business cycle." *The Review of Economic Studies* 42.2 (1975): 169–190.

Odhiambo, Nicholas M. "Energy consumption and economic growth nexus in Tanzania: An ARDL bounds testing approach." *Energy Policy* 37.2 (2009): 617–622.

Pan, Ming-Shiun, Robert Chi-Wing Fok, and Y. Angela Liu. "Dynamic linkages between exchange rates and stock prices: Evidence from East Asian markets." *International Review of Economics & Finance* 16.4 (2007): 503–520.

Pástor, Ľuboš, and Pietro Veronesi. "Political uncertainty and risk premia." *Journal of Financial Economics* 110.3 (2013): 520–545.

Patrick, Hugh T. "Financial development and economic growth in underdeveloped countries." *Economic Development and Cultural Change* 14.2 (1966): 174–189.

Perron, Pierre, and Timothy J. Vogelsang. "Testing for a unit root in a time series with a changing mean: corrections and extensions." *Journal of Business & Economic Statistics* 10.4 (1992): 467–470.

Pesaran, Mohammad Hashem, and Bahram Pesaran. *Working with Microfit 4.0: interactive econometric analysis;[Windows version]*. Oxford University Press, 1997.

Pesaran, Hashem, and Yongcheol Shin. "An Autoregressive Distributed Lag Modelling Approach to Cointegration, Chapter 11." *Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium*. 1999.

Pesaran, M. Hashem, Yongcheol Shin, and Richard J. Smith. "Bounds testing approaches to the analysis of level relationships." *Journal of Applied Econometrics* 16.3 (2001): 289–326.

Phillips, Peter CB, and Pierre Perron. "Testing for a unit root in time series regression." *Biometrika* 75.2 (1988): 335–346.

Pradhan, Rudra P., Mak B. Arvin, and Atanu Ghoshray. "The dynamics of economic growth, oil prices, stock market depth, and other macroeconomic variables: Evidence from the G-20 countries." *International Review of Financial Analysis* 39 (2015): 84–95.

Rapach, Strauss and Zhou. International stock return predictability: What is the role of United States? *The Journal of Finance* 68, 1633–1662, 2013.

Ratanapakorn, Orawan, and Subhash C. Sharma. "Dynamic analysis between the US stock returns and the macroeconomic variables." *Applied Financial Economics* 17.5 (2007): 369–377.

Rigobon, Roberto, and Brian Sack. "The impact of monetary policy on asset prices." *Journal of Monetary Economics* 51.8 (2004): 1553–1575.

Rigobon, Roberto, and Brian Sack. "The effects of war risk on US financial markets." *Journal of Banking & Finance* 29.7 (2005): 1769–1789.

Ross, S. A. "The arbitrage theory of capital asset pricing, *Journal of Economic Theory*. (1976).

Runkle, David E. "Vector autoregressions and reality." *Journal of Business & Economic Statistics* 5.4 (1987): 437–442.

Rushdi, Mustabshira, Jae H. Kim, and Param Silvapulle. "ARDL bounds tests and robust inference for the long run relationship between real stock returns and inflation in Australia." *Economic Modelling* 29.3 (2012): 535–543.

Schumpeter, Joseph A. "1934." *The theory of economic development* (1911).

Schwert, G. William. "Why does stock market volatility change over time?." *The Journal of Finance* 44.5 (1989): 1115–1153.

Sharpe, William F. "Capital asset prices: A theory of market equilibrium under conditions of risk." *The Journal of Finance* 19.3 (1964): 425–442.

Singh, Ajit. "Financial liberalisation, stockmarkets and economic development." *The Economic Journal* 107.442 (1997): 771–782.

Smales, Lee A. "The role of political uncertainty in Australian financial markets." *Accounting & Finance* 56.2 (2016): 545–575.

Stock, James H., and Mark W. Watson. "Macroeconomic forecasting using diffusion indices." *Journal of Business & Economic Statistics* 20.2 (2002): 147–162.

Stock and Watson. Forecasting using principal components from a large number of predictors. *Journal of the American Statistical Association 97, 1167–1179.*

Tsouma, Ekaterini. "Stock returns and economic activity in mature and emerging markets." *The Quarterly Review of Economics and Finance* 49.2 (2009): 668–685.

Toda, Hiro Y., and Taku Yamamoto. "Statistical inference in vector autoregressions with possibly integrated processes." *Journal of Econometrics* 66.1 (1995): 225–250.

Vuolteenaho, Tuomo. "What Drives Firm-Level Stock Returns?." *The Journal of Finance* 57.1 (2002): 233–264.

Wisniewski, Tomasz Piotr. "Is there a link between politics and stock returns? A literature survey." *International Review of Financial Analysis* 47 (2016): 15–23.

Wolfers, Justin, and Eric Zitzewitz. "Using markets to inform policy: The case of the Iraq war." *Economica* 76.302 (2009): 225–250.

Wong, Kie Ann, Tak Hee Hui, and Choy Yin Chan. "Day-of-the-week effects: evidence from developing stock markets." *Applied Financial Economics* 2.1 (1992): 49–56.

Wongbangpo, Praphan, and Subhash C. Sharma. "Stock market and macroeconomic fundamental dynamic interactions: ASEAN-5 countries." *Journal of Asian Economics* 13.1 (2002): 27–51.

Zakoian, Jean-Michel. "Threshold heteroskedastic models." *Journal of Economic Dynamics and Control* 18.5 (1994): 931–955.

Zivot, Eric, and Donald W. K. Andrews. "Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis." *Journal of Business & Economic Statistics* 20.1 (2002): 25–44.