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The Effect of Thailand's Political Uncertainty on the Volatility of Stock Market Exchange, Banking Industrial Equity and Business Sentiment

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Abstract: This study examine the impact of Thailand political uncertainty on the Thailand Stock Market Index (SET), the banking industrial equity index (BANK) and the Business Sentiment Index (BSI) volatility. Rely on GARCH methodology and use monthly time series data covering January 2011-March 2015, the results reveal significant impacts of political uncertainty to the volatility of SET, BANK and BSI by political events. Both SET and BANK have increased volatility after coup, unrest and violence occurring. It seems that stock market investors or indirect investors are more sensitive to political events with any violence. Another finding from this study confirms that the volatility of BANK has greater than the volatility of SET, it recommend that stock market investors should avoid to invest in banking industrial equity. Surprisingly, the result of the volatility of BSI has increased. As first, Thailand have a new Prime minister by single-party government and second, from military government by coup, it could imply that business persons have less confidence on economic policy dysfunctions, make them more insecurity and costly. Because the parliamentary dictatorship on single-party government and the military government can keep substantial power to influence economic policy and public is unable to verify the corruption and transparency. The outcomes of this research can contribute to helping global and domestic investors to formulate strategies to minimize their risk. Furthermore, policy administrators may bring the result of this research to inform macro and micro policy formulation.

Key words: Political uncertainty, volatility, stock exchange market, banking industrial equity business sentiment, Generalized Autoregressive Conditional Heteroskedasticity (GARCH), policy

INTRODUCTION

The emerging stock market is considered high risk but with high potential returns (Warren and Radcliffe, 2008; Liew and Chou, 2016). The result of a global economic recession such as subprime mortgage and Euro debt crisis bring a negative returns for the world's equities market; however, the returns are expected to improve, particularly for Asian emerging markets which have higher growth potential and are more attractive than the world market in general (Hsu and Utami, 2016). Hence, high potential returns have enhanced the attractiveness of emerging markets and created the best opportunity for global investors to obtain positive returns. With the rapid growth of capital markets, financial services and the best opportunity for global investments in the Asian equity markets-especially the South-East Asian market investment portfolios have grown continuously since the Asian financial crisis began in 1997, mainly because the revival of the Asian financial market has presented new challenges for practitioners, policy makers and researchers in the finance discipline (SET 2008). Additionally, states that more than half of the global economic output has been generated from the world's emerging economies, mainly in the Asian region. The report from the International Monetary Fund (IMF, 2008) inform that integrated national groups such as the Association of Southeast Asian Nations (ASEAN) can rapidly increase financial asset prices across the region in terms of both direct and indirect investments. Bhattacharyay (2009) reports that ASEAN is considered one of the world's fastest-growing and significant economic regions because the ASEAN Free Trade Agreement (AFTA) merged a group of nations into a single market production base. Moreover, Donald (2017) states that Quantitative Easing (QE) generates more asset price movements and assets purchased in Emerging Market Economies (EMEs). QE policy has been used in countries such as Japan and the US andit stimulates economic growth by purchasing global asset (Lee *et al*., 2015). Consequently as a result of rapid economic growth, financial service improvement and QE policy, it can be

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concluded that the Southeast Asian Stock Market has become an attractive market for global investment. For Thailand in particular, the SET report that the growth index performance was larger than Singaporean, Malaysian and Philippine stock markets. Therefore, the stock market of Thailand is an important player in the ASEAN, South-East Asian and Thailand financial markets. However, the SET has not increased in stability as there is still volatility from non-economic shocks as well as global and domestic economic shocks. Previous researchers have long recognized the relationship between equity price, non-economic shocks and economic shocks. For example, earthquakes, bushfires, cyclones and terrorist attacks are non-economic shocks that affect stock market volatility worldwide (Worthington and Valadkhani, 2004; Haughwout and Rabin, 2005; Takao *et al*., 2013) conclude that the stock market is influenced by many factors, including non-economic, economic and political shocks. Thailand's domestic economy and stock market have varied according to political policy. For example, Pongsudhirak (2008) notes that after Commander Sonthi Boonyaratglin's coup in September 2006, Thailand's freedom house rating dropped from free to not free andit appeared that Thailand's economy took a backwards step. The study by Khositkulporn (2013) states the political uncertainty has a direct effect on stock market volatility. Also, Thailand's economic growth rate was lowest among ASEAN countries after the military coups in 2006 and 2014 (Nidhiprabha, 2015).

Literature review

Interaction between political events, economy and financial market: As documented in the introduction, the stock market generally responds to economic and political information. Emerging stock market returns and volatility are associated with event news-particularly political events (Kutan and Perez, 2002; Chan *et al*., 2001) indicate that political news has a significant effect on stock market activity rather than other economic news. They suggest that financial markets strongly respond when political events take place.

Political stability is a key factor that controls the economy, equity volatility and raises businesspeople and foreigner investor's confidence. Arouri *et al*. (2016) report that the cause of economic policy uncertainties are come from politic effecting on a large set of economic variables such as inflation rate, employment rate and economic growth rate and then reduce stock market return. Business people and investor may concern about transition from democracy to autocracy because they don't know if some autocracy government policy such as impose higher tariffs, appropriate goods and refuse to guarantee contracts may apply (Childers, 2015). The changeover from doing business in a democracy to autocracy becomes much more risky, in order to maximize profits, businesspeople may also decide to increase price to offset indirect costs imposed by the autocracy government (Long, 2008). Frot and Santiso (2013) posit that investors prefer political certainty in relation to value stability and future policies in the political environment. Bilson *et al*., (2002) investigate the relation between political risk and stock returns, focusing on emerging markets and developed markets. They argue that political risk significantly explains the return variation in emerging markets while there is none in developed markets. This finding implies that there is a positive relationship between political risk and ex-post returns in emerging markets. It is suggested that international investors diversify their portfolio from developed stock markets to developing stock markets and create an alternative risk measurement for portfolio management. Economic policy uncertainty and political events increase economic variables and stock market volatility, the result from UAS and India stock market show that policy uncertainty reduces significantly stock return and enlarge stock market volatility (Arouri and Roubaud, 2016).

Political event studies for example, Bilson *et al*. (2002), Perotti and Oijen (2001), Khositkulporn (2013) suggest that local political events are important factors for determining stock price volatility and making asset allocation decisions-particularly in developing and emerging countries-because political events create opportunities to receive excess returns andthey generate efficiency gains in the stock market and for portfolio diversification. Economic policy uncertainty can affect economic activity such as expected risk premiums, inflation, interest rate, increase financing and production costs andincrease financial market risk by reducing the value of protections (Pastor and Veronesi, 2012, 2013). Gulen and Ion (2016) state that corporate investment may suspend or change their decision when some economic variables such as employment, consumption and saving changing due to economic policy uncertainty. Goktepe and Satyanath (2013) indicate that the military has substantial power to influence economic policy from behind the scenes after transferring power to democratic leaders. Thus, political events can affect both stock market returns and the real investment sector.

Coup d'etats, violence, conflicts of interest between several groups and corruption: The result of political uncertainty from coup and single party government can cause corruption, conflicts of interest and violence. Brooks and Mosley (2007) state that political risk is higher in developing countries because there is less transparency and less reliable economic data. The consumers may spend less throughout coup due to expectations about future conflict (Childers, 2015). Ma *et al.* (2003) examine political events affecting foreign investment. They choose the Tiananmen Square incident in China as an unexpected political event and find that the incident had a significant effect on the stock return because the most of protesters was killed by military. Brouwer (2003) states that military dictatorship, political instability and cycles of major economic collapse were the cause of financial unreliability in Latin America but these causes cannot be widespread. Chaarani (2015) examines that both unfavorable and favorable political events can cause of the volatility in Beirut Stock Exchange (BSE). His finding show the case of violence as the number of bombing and assassination have greater impact on BSE's volatility, also show that the Lebanese banking sector have large volatility than market, it imply that BSE investor were more sensitive to any violence from political uncertainty. Thailand's Political Events as a democracy with a strong military influence, Thailand faces a high level of political uncertainty.

As a result of anti-government violence, coup d'etats by the military, dissolution, sedition by people and sedition of the government by multi-parties have brought about a slow economy and devaluated the capital market. Nimkhunthod (2007) evaluates 30 political events, including dissolutions, elections, coups and riots, between 1975 and 2006 to investigate the effect of political events on the SET. The author finds that elections had a positive effect on the stock market in the long term. In contrast, coups result in a temporary negative shock but this can boost the equity market over the long term. He suggests that the level of accessibility to information has improved because market participants are more sophisticated. These results suggest that the market can have an over-reaction to bad news and an under-reaction to good news.

Thailand had a stable democracy after Thaksin Shinawatra become a Prime Minister. He and his party have brought Thailand to the world's active emerging market with a high rate of economic growth, bold leadership, clear investment policy and apparent democratic consolidation which appeared to promise a future in which Thailand could be politically stable, effectively governed and highly attractive to investors. Nevertheless, accusations of corruption, misrule for the sake of graft, aggrandizement and alleged abuses of power were critical charges levelled against Shinawatra and his party. On 19 September 2006, the Royal Thai Army overthrew the government and set up a new government with a military stand (Pongsudhirak 2008). According to Pongsudhirak (2008), a coup would be unnecessary because it cannot boost Thailand's competitiveness in the global market and domestic economy. After a new election, the party that works as a proxy of Thaksin always wins. Further, conflicts of interest between several groups such as political parties, the government, the former government, the red shirt group, the yellow shirt group and the military, caused violence, political and economic uncertainty. IMF (2008) asserts that increased political uncertainty in Thailand shook the nation's economy and financial markets. The power shifts between the red shirt group, the yellow shirt group and other political camps between 2006 and 2010 led to political protests and outbreaks of violence. Thus, political uncertainty and conflicts of interest between several groups lead to violence and result in volatility in the equity market and the economy in general.

MATERIALS AND METHODS

Volatility and GARCH Model: The study of stock market volatility has become a significant topic of interest in the finance literature because stock markets around the world have become more integrated and volatile in general. Many studies have used domestic economic factors such as the proxy of monetary and fiscal policies (exchange rate, interest rate and inflation) and economic indicators (industrial production, money supply, real activity and consumer price index) as well as internal factors such as oil prices, world index, US Treasury bill and trade-weighted world exchange rate which have had a collective cumulative effect on returns volatility in the stock market. Further, policy makers often use and rely on financial volatility estimation as an indicator of financial market and economy vulnerability. For example as serts that the Federal Reserve in the US explicitly took into account stock, bond, currency and commodity volatility to establish its monetary policy. In numerous financial studies, the measurement of stock market volatility is used in two volatility models in different approaches. The first is the Stochastic Volatility (SV) Model and the second is the Autoregressive Conditional Heteroskedastic (ARCH) Model. Poon and Granger (2003) state that the volatility in financial markets or times series volatility forecasting models can be explained by standard deviations, the SV Model and the ARCH and GARCH Models. Empirical findings from their study conclude that GARCH is a more parsimonious model than ARCH and GARCH (1, 1) is the most popular model for examining financial time series. Similarly, Hansen and Lunde (2005) find no evidence that

GARCH (1, 1) is outperformed by more sophisticated models in their analysis of the exchange rate. As a result, the likelihood estimation can explain why ARCH Models are more accepted than SV Models in financial research literature. In financial literature, a commonly used measure of volatility is provided by the class of ARCH Models. Hammoudeh and Li (2008) examine stock market sensitivity to worldwide regional and local events using the GARCH Model. Their results show that volatility is very high, even compared with other emerging markets. They also find that most of the volatility emergency changes in the Arab Gulf stock markets as a result of international events. This suggests that the Gulf Cooperation Council (GCC) is more sensitive to international factors than local factors. Todorov (2012) investigates potential time-variability in the effect of US stock market returns on the returns of 21 frontier markets between 1 December 2005 and 15 January 2010. The analysis shows that time-varying spillovers are statistically important for a majority of these markets in regards to the exposure of these markets to US economic shocks. Malik and Ewing (2009) employ GARCH Models to examine the mean and conditional variance between oil prices and five weekly major US stock market sector returns-financials, industrials, consumer services, health care and technology from 1 January 1992- 30 April 2008. The findings show that there was a different and significant transmission of shocks and volatility between the variables, including: oil prices, financials, industrials, consumer services andhealth care and technology were directly affected by their own news and volatility; the volatility of technology returns and industrials returns were indirectly affected by shocks and volatility in oil returns; the volatility of consumer services and the health care sector were directly and indirectly affected by volatility in oil returns and there was no evidence of direct or indirect effects of oil return volatility on the financial sector. Thus, the US financial sector is insulated from oil market shocks. Asteriou and Hall state that recent developments in financial econometrics have led to the use of models and techniques that can support the investor's attitude in the direction of both expected return and risk (uncertainty). For higher volatility, the expected return may be greater compared with others, whereas lower volatility generates lower risk. The ARCH/GARCH family of models is capable of dealing with the volatility (variance) of the series. Further, Ndako (2012) applies the GARCH family to discover market volatility in South Africa, the result shows that there is no estimated break coinciding with the official liberalisation dates. In addition, the analysis shows that after taking structural breaks into account, volatility decreases following financial liberalisation. Moreover, after applying official liberalisation dates, the results indicate that the effect of financial liberalisation on the stock market is statistically important and not positive.

The data and methodological aspects: In order to capture the effect of political uncertainty on variables, the Business Sentiment Index (BSI) was developed by the BOT. The BSI diffusion index is divided into two main parts. The first part is the information used to compute the index andit comprises six components: production, total order books (which replaces the people's purchasing power and exports in the original version), investment, production cost, performance and employment. Each component is applied with equal weight and is then composed into a single monthly index. The second part is information that reflects business confidence. This information comprises inventories, financial conditions, financial market outlook, selling price, exports, production capacity, expected inflation and limits of business. The representative firms (sample) were acquired from databases of the SET and the Ministry of Industry. The sample consisted of approximately 800 large and medium businesses that had registered capital of at least 200 million Thai baht. The BSI variable was selected because this index reflects the overall domestic economy.

Additionally, the BSI has a significant trend of major components of the GDP which consist of consumption, investments and exports. For instance, if business improves, this could be consistent with an increase in domestic demand which reflects consumer purchasing power or it could be reciprocal with external demand which reflects the export sector and other positive factors concerning production costs. Finally, the BSI also affects investment activities and, in turn, employment. The Stock Exchange of Thailand index (SET) and the Banking Industrial Equity Index (BANK) were collected by the SET. The SET index was computed daily based on constituent stocks representing energy, banking, finance, mining, property and industry, among others. The BANK index was computed daily based on banking companies. The data required for the analysis were obtained from secondary sources. The researcher collected monthly time series data covering January 2011-March 2015; the data were collected from different sources as show in data sources table. All sources were databases that were separated into the four sub-periods as follows (Table 1).

Table 1: Data source

Variable	Data type	Data sources
SET index	Stock market data	SET
BANK index	Stock market data	SET
Business sentiment index	Economic data	BOT

Table 2: Military's coup between May 2014 and March 2015

Variables	Sub-sample 1 January 2011-June 2011	Sub-sample 2 July 2011-April 2014	Sub-sample 3 May 2014 and March 2015
Prime Minister	From political party with military support	From political election	From military
Political condition	Full democracy with military back up	Full democracy	Dictatorial with military control
Political events	Instability with protestand violence (bloody)	Instability withprotest, violence and coup (bloody)	Stability withnon-protest, non violence (bloodless)

This study covers the period January 2011 to March 2015 which enables dependent relationships to be compared in a period of relative financial stability which has resulted in Thailand's political certainty. Financial instability results in political uncertainty.

From January 2011 to June 2011, Thailand had an unstable political situation because the government was accused of receiving military support and was not elected by a vote. The government declared a state of emergency in 2011 and the military, police and the government enforced crackdowns on protestors which led to >100 protestors being killed. After crackdowns, the government announced house dissolution and makes an election.

From July 2011 to April 2014 there was a full democracy but unstable political conditions because of the anti-government protest against a proposed political amnesty bill that would allow ousted leader Thaksin Shinawatra to return to Thailand without being punished. The government declared a state of emergency and announced a house dissolution and election. There was a military coup between May 2014 and March 2015 and the military's leader becomes a new government and manage the nation till now (Table 2).

To obtain the answers, the computer program EViews was employed to analyses the compiled data and obtain the research results (Griffiths *et al*., 2012). Before estimating the GARCH Model, the study should determine whether all data are heteroskedastic (non-constant) or homoskedastic (constant) by conducting the Breusch-Pagan Lagrange multiplier test which Breusch and Pagan (1979) developed for heteroskedasticity (non-constant). The LM statistic can be calculated as follows:

$$LM = obs \times R^2$$

Hill *et al*. (2011) and Asteriou (2006a, b) state that the LM test statistic is distributed under a chi-square distribution with degrees of freedom equal to the number of slope coefficients included in the auxiliary regression. An LM statistic that is less than a Chi-square distribution suggests that the null hypothesis of homoskedasticity can be accepted. An LM statistic that is higher than a chi-square distribution shows that the null hypothesis of homoskedasticity can be rejected. There is sufficient evidence of heteroskedasticity. Also, a stationary time series is one that exhibits a near-constant mean, variance and autocorrelation. A requirement of time series econometric methods is that the data set for estimating the parameters should be stationary. Stationary data are suitable for econometric modelling (Maddala, 2001; Maddala and Wu, 1999; Gujarati, 1978). In addition, Philips (1986) states that inferential statistics such as t-statistics and F-tests can provide misleading results if non-stationary time series data are used in the regression analysis. The formal method used to test the stationarity of a series is the unit root test (Dickey *et al*., 1986; Dickey and Fuller, 1979). Some macroeconomic variables appear to be non-stationary; the step in the co-integration study is necessary to check for the stationarity of the variables and determine the order of integration. All variables have to integrate in the same order andthe order of integration of a series must refer to the number of time series which must be differenced in order to make it stationary (Brooks, 2002). This study tested for unit roots in the natural logarithms of the sample variables. The type of unit root can been specified as Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), Kwiatkowski-Phillips-Schmidt-Shin (KPSS) and Ng-Perron (NP). However, the unit root test can choose two of the four tests-ADF and PP-to test for a unit root in the level and first series. The present study has chosen the ADF and PP tests because of their strength and suitability for the study's data. These two methods are described:

$$\Delta y_t = \alpha y_{t-1} + \sum_{j=1}^{p} \beta \Delta y_{t-1} + \varepsilon_t$$

where, $\Delta y_t = y_t - y_{t-1}$. The factor $\Sigma_{j=1}^{p} \beta \Delta y_{t-1}$ represents the lagged terms with the length of the lag structure 'p' number of lagged difference terms. The distribution theory supporting the ADF test was based on the assumption that the error terms were statistically independent and had a constant variance. Dickey and Fuller (1981) establish that the ADF test is asymptotically valid in the presence of a Moving Average (MA) component, provided that adequate lagged difference terms are included in the test regression. Consequently, when using the ADF test, the researcher must ensure that the error terms are uncorrelated and have a constant variance. According to Phillips (1987), Phillips and Perron (1988) developed the PP test. They propose an alternative (non-parametric statistical methods) method to handle the serial correlation in the error terms without adding lagged difference terms. The PP test is based on the null hypothesis that a unit root exists in the autoregressive representation of the time series. The test regression for the PP analysis is the AR (1) process:

$$\Delta y_{t-1} = \alpha_0 + \beta y_{t-1} + \varepsilon_1$$

Where:

y_{t-1} = The explanatory variable
α_0 = The constant term
β = The Autoreg Ressive (AR) coefficient

If $\beta \geq 1$, Δy_{t-1} is a non-stationary series and the variance of Δy_{t-1} increases with time and approaches infinity. If $\beta < 1$, Δy_{t-1} is a stationary series. If $\beta = 1$, the series contains a unit root and is non-stationary. Hence, the hypothesis of stationarity can be tested by comparing β against 1 where H_0: $\beta = 1$ and H_1: $\beta < 1$.

The PP test is a modification of the ADF t-statistics, taking into account the less restrictive nature of the error process. Brooks (2002) indicates that a unit root test investigates whether time series variables are non stationary by using an AR Model. The ADF test and the PP test are the most famous of the unit root tests and are used to examine the stationarity of time series. Brooks (2002) also reports that if the test statistics are higher than the critical values, the variable is non-stationary. MacKinnon (1991) states that the asymptotic distribution of the PP t-statistics is the same as the ADF t-statistics as the critical values are still applicable. Therefore, both the PP and ADF tests can be performed with the inclusion of a constant and a linear trend or only a constant term (Boschi, 2005; Egert and Kocenda, 2007).

The Generalised Autoregressive Conditional Heteros Kedastic (GARCH) Model was applied in this research to test the impact of Thailand political uncertainty on the Thailand Stock market Index (SET), the Banking Industrial Equity Index (BANK) and the business sentiment index (BSI) volatility. According to Bollerslev (1986) and Taylor (1986) established the GARCH Model. They extended the ARCH Model by allowing the past conditional variance to be a linear function of p lagged conditional variances in addition to q past squared errors. Asteriou (2006a, b) states that the simplest form of the GARCH (p, q) Model is the GARCH (1, 1) Model which changes p = 0 and reduces the model to ARCH (q). The variance equation has the from:

$$Ln(R)_t = \alpha + \beta Ln(R)_{t-1} + u_t$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

The GARCH Model is easy to estimate and performs very well because it has only three unknown parameters: ω, α and β. The (1, 1) in the GARCH (1, 1) Model refers to the presence of a first-order AR GARCH term (the first term in parentheses) and a first-order MAARCH term (the second term in parentheses). The GARCH Model is often interpreted in a financial context where an agent or trader predicts a period's variance by forming a weighted average of the long-term average (the constant), the forecasted variance from the GARCH term and information about the volatility observed in the ARCH term. If the asset return is unexpectedly large in either the upwards or the downwards direction, then the trader will increase the estimate of the variance for the next period. This model is also consistent with the volatility clustering often seen in financial return data where large changes in returns are likely to be followed by further large changes.

This model specification usually performs very well and provides a more flexible framework to capture various dynamic structures of conditional variance. This is because the GARCH Model incorporates the time-varying conditional variance and the covariance process. Knight and Satchell (1998) state that the GARCH Model has been modified to allow the distributions of both the conditional variance and the observed variable (unconditionally) to be computed numerically. Consequently, the conditional variance of the time series relies on the squared residuals of the process which is the square of the lagged innovation. However, there are limitations in the ARCH Model as developed by Engle (1982) and presented by Pagan (1996), Pagan and Schwert (1990). Their studies show that the GARCH Model performs well in comparison with other methods regarding volatility in the stock market. In addition, Bollerslev *et al*. (1994) confirm that the GARCH and ARCH Models are widely used in various branches of econometrics-especially in financial time series analysis. Hansen and Lunde (2005) examine whether sophisticated volatility models provide a better description of financial time series than parsimonious models. They address this question by comparing 330 ARCH-type Models to estimate the one-day-ahead conditional variance. The main finding for the exchange rate data shows that the GARCH (1, 1) Model is one of the best-performing models. Thus, this study employs the GARCH (1, 1) Model to examine the volatility dynamics of financial time series.

RESULTS AND DISCUSSION

The descriptive statistics of the SET, banking industrial equity and business sentiment were presented

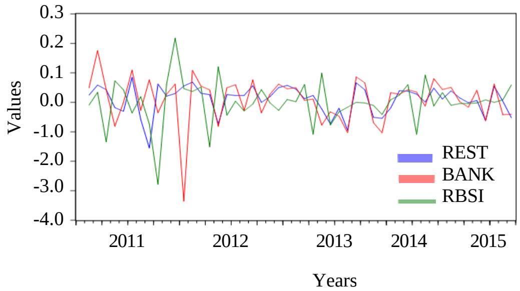

Fig. 1: Plots the time series of monthly returns for the RSET, RBANK and RBSI

Table 3: Descriptive statistics-monthly returns of variables, January 2011March 2015

Variables	RSET	RBANK	RBSI
Mean	0.008920	0.009474	-0.000152
Median	0.023079	0.030079	0.00000000
Maximum	0.084694	0.175682	0.2180020
Minimum	-0.155215	-0.335709	-0.278787
SD	0.048748	0.077852	0.075030
Skewness	-1.113928	-1.68270	-75529997
Kurtosis	4.166361	9.036890	6.559997
Jarque-Bera	13.17446	99.52074	31.15649
Probability	0.001378	0.000000	0.000000
Sum	0.445978	0.473711	-0.007605
Sum sq.dev.	0.116441	0.296985	0.275846
Observations	50.00000	50.00000	50.00000

for the period January 2011 to March 2015. The statistics include the average monthly returns, median, maximum, minimum, standard deviation, skewness, kurtosis, Jacque-Bera statistic and p-value. The RBSI had the highest maximum monthly returns at 0.218002 while the RBANK had the lowest minimum monthly returns at 0.335709. The volatility of returns as measured by the standard deviation increased from 4.8-7.8%. The RBANK had the highest standard deviation while the RSET had the lowest standard deviation. The data indicate that the large standard deviation is illustrated by high risk. As a result, the RBANK exhibited higher risk than variables. All variables exhibited negative skewness, indicating that the sample distributions were approximately symmetric. Additionally, the kurtosis or degree of excess in all variables was >3, indicating that all variables were leptokurtic and had flatter tails and a higher peak than a normal distribution. The Jarque-Bera statistics were all positive and statistically significant. The corresponding p<0.0001 (Table 3 and Fig. 1).

The RSET shows evidence of time-varying volatility in certain periods (volatility clustering). In particular, the RSET alternated between periods of low and high volatility. The volatility clustering of the stock return series fluctuated, showing that small shocks tended to follow small shocks and big shocks tended to follow big shocks. In this case, the highest volatility period was Thailand's political crisis in 2011:Q3. Comparing these

Table 4: Breusch-pagan LM test

Variables	Full-sample	Sub-sample 1	Sub-sample 2	Sub-sample 3
Coefficient				
SET	0.015722**	0.026364*	0.024176**	0.004671***
BANK	-0.261358***	0.032218***	-0.0275735**	0.012446***
BSI	1.00000	1.00000	-0.475135***	-0.002239**
Volatility (σ)				
SET	0.04899	0.048468	0.048353	0.033000
BANK	0.075812	0.070377	0.084448	0.046314
BSI	1.55E-16	6.07E-17	0.04471	0.018844

***, **, *Significant at the 1, 5 and 10% levels, respectively

periods, mid 2013 was another high-volatility period but lower than that of 2011:Q3. The RSET shows that negative returns were larger than positive returns. Next, the monthly series of the RBANK was moderate in 2012-2015 and fluctuated dramatically between 2011:Q4 and 2012:Q1. The RBANK shows that negative returns were larger than positive returns. The monthly returns of RBSI volatility declined from 2011:Q3-2012:Q2. The RBSI shows that negative returns were larger than positive returns. However, all variables were move as a similar direction. The political uncertainty seemed to be highly significant for the RSET compared to other variables. The period of 2011:Q3-2012:Q2 had the highest volatility of all variables because of the parliament dissolution, state of emergency, civil disobedience and military, police and government crackdowns andit became less volatile and violence after full democracy was achieved in 2012.

The next step of the analysis was to conduct the Breusch-Pagan LM test to determine whether all data were heteroskedastic (non-constant). The result of this test guided the researcher on the choice between the ARCH and GARCH Models.

Data were collected from January 2011-March 2015 and converted into monthly index prices. The GARCH Model was chosen to examine volatility in the sample periods. The estimate of the LM test could determine whether the data were heteroskedastic or homoskedastic. The LM statistic was 26.78292, 21.47424 and 5.252872 respectively andhad a probability of χ^2 at 0.0000, 0.0000 and 0.0219, respectively. This suggests that the null hypothesis of homoskedasticity is rejected. The heteroskedasticity was found; thus, it follows that the appropriate model is the GARCH Model (Table 4).

The unit root test is conducted to determine whether all data are stationary. If the variables index return series are non-stationary, the study should model the data with an Error Correction Model (ECM). Conversely, if the stock index return series are stationary, the study should conduct GARCH analysis (Hill *et al*., 2011). To make robust conclusions about the time series properties of the data, this study uses the unit root tests of ADF and PP which were introduced by Dickey and Fuller (1981) and Phillips and Perron (1988), respectively. The result of this test will guide the researcher on the choice between the ECM and GARCH Models.

Table 5: Unit Root test results for monthly series

Variables	ADF test statistics Levels	Prob.	PP test statistics Levels	Prob.
RSET	-6.192879	<0.0000	-6.192879	<0.0000
RBANK	-8.093044	<0.0000	-8.361803	<0.0000
RBSI	-8.355738	<0.0000	-11.64356	<0.0000
1% critical value	-3.571310		-3.571310	
5% critical value	-2.922449		-2.922449	
10% critical value	-2.599224		-2.599224	

Table 6: Summary of GARCH results

Variables	Full-sample	Sub-sample 1	Sub-sample 2	Sub-sample 3
Coefficient				
SET	0.015722**	0.026364*	0.024176**	0.004671***
BANK	-0.261358***	0.032218***	-0.0275735**	0.012446***
BSI	1.00000	1.00000	-0.475135***	-0.002239**
Volatility (σ)				
SET	0.04899	0.048468	0.048353	0.033000
Bank	0.075812	0.070377	0.084448	0.046314
BSI	1.55E-16	6.07E-17	0.04471	0.018844

***, **, * significant at the 1, 5 and 10% levels, respectively

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

Where:

Δy_t = The index for i at time t

$\Delta y_t = y_t - y_{t-1}$, β = Coefficients to be estimated

α = The constant

p = The number of lagged terms

Table 5 reports the unit root tests of all variable index returns at levels. The statistics reported for the ADF and PP tests suggest that all variable index returns follow a stationary process. All of the t-statistics are significant <1% critical value andthe ADF and PP test statistics consistently rejected the null hypothesis of the unit root in all markets analysed. The results show that all variables are stationary in the level form.

Summary statistics of variables

Summary of GARCH results of the full dataset and three subsamples: The results of the GARCH Model (Table 6) show that the RSET and RBANK had high volatility in subsamples 1 and 2 because there was an outbreak of violence towards anti-government groups in both subsamples. These results infer that stock market volatility is sensitive to violence. Subsample 1 was accused of receiving military support and became a government without being elected by a vote. Subsample 2 was a fully democratic government that won an election. Nevertheless, there were accusations of corruption and alleged abuses of power. Anti-government and protest government was general for democratic country but enlarging the violence to any protestors can build up volatility in stock market by decreasing business people and investor's confidence. Our particular findings were similar to studies by Chaarani (2015), IMF (2010), Ma *et al*. (2003), Khositkulporn (2013), Nimkhuntod (2007) and Pongsudhirak (2008). Consequently, the bloody from government crackdown and anti government protestors were the cause of stock market volatility.

The RBSI was volatile in subsample 2 and 3 which implies that investors may not be confident of the government's economy policy as business sentiment is seemingly like investor confidence which requires clear and reliable in political policies. In Thailand, it was difficult to control and verify corruption, transparency and unreliable policies from military and single party government. These findings are similar to those by Arouri *et al*. (2016), Childers (2015), Long (2008), Frot and Santiso (2013), Goktepe and Satyanath (2013), Arouri and Roubaud (2016), Brooks and Mosley (2007). Hence, transparency, unreliable economic policies and corruption were the cause of business sentiment recression.

The study of stock market volatility has grown as a significant topic of interest in the financial literature because market equity around the world has become more integrated and volatile in general. The volatility of Thailand's stock market can be caused by the military remaining as a shadow of the civilian government in Thailand andconflicts of interest between several groups such as political parties, government, former government, red shirt group, yellow shirt group and military, caused political uncertainty in the country. Increased political uncertainty in Thailand is a factor that has shaken the nation's economy and financial markets. The power shifts between the red shirt group, yellow shirt group and other political camps between 2006 and 2011 resulted in political protests and outbreaks of violence. As a result, investor confidence has fallen, consumption has slowed sharply and the SET has faced high volatility, resulting in poor performance. However, political events not only affect the stock market but also investment in the country by business people sentiment. Thus, political events can affect both stock market returns and the real investment sector.

This study applied econometric models to examine as the GARCH Model. Data were collected from January 2011 to March 2015 and converted into monthly index prices. The GARCH Model was chosen to examine volatility in the sample periods. The estimate of the LM test could determine whether the data were heteroskedastic or homoskedastic. In cases where heteroskedasticity was found, the study continued to estimate using the GARCH Model.

Table 7: Summary of finding from GARCH Model

Variables	Full-sample	Sub-sample 1	Sub-sample 2	Sub-sample 3
Coefficient				
SET	0.015722**	0.026364*	0.024176**	0.004671***
BANK	-0.261358***	0.032218***	-0.0275735**	0.012446***
BSI	1.00000	1.00000	-0.475135***	-0.002239**
Volatility (σ)				
SET	0.04899	0.048468	0.048353	0.033000
BANK	0.075812	0.070377	0.084448	0.046314
BSI	1.55E-16	6.07E-17	0.04471	0.018844

Prime minister: from political party with military support, from political election; from military; Political condition: full democracy with military back up, full democracy, dictatorial with military control; Political events: instability with protest and violence, instability with protest, stability with non-protest (bloody), violence and coup (bloody), non-violence (bloodless)

Through this study, the results of the summary statistics show that the RSET, RBANK and RBSI were volatile according to political events. All the results of the GARCH Model also indicate that the RSET and RBANK had high volatility in subsamples 1 and 2 because of an outbreak of violence towards anti-government groups. These results suggest that investors should avoid investing in banking industrial equity because the RBANK had higher volatility than the RSET. Also, it was found that the stock market volatility is sensitive to violence. Additionally, full democracy by people vote in subsample 2 and without any violence across the country by military commanding in subsample 3 (Table 7), the business people have less confident of the government because their economic policies were organized by the military and single party government which hard to verify their activities.

CONCLUSION

Finally, the finding of this research was important but they could be improved for a longer period of time to compare the effect of political events on stock market's volatility economic data. Also, the analysis can be developed in a future research study by applying some macro and micro economic meters.

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