ตลาดหลักทรัพย์มีปฏิกิริยาอย่างไรต่อการเปลี่ยนแปลงทางการเมือง

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บทคัดย่อ

การศึกษานี้ศึกษาปฏิกิริยาของตลาดหลักทรัพย์ต่อการเปลี่ยนแปลงทางการเมืองในประเทศไทย ตั้งแต่วันที่ 1 ตุลาคม 2556 ถึง 12 เมษายน 2566 โดยอาศัยแบบจำลองเชิงประจักษ์ ได้แก่ แบบจำลอง GJR-GARCH (1,1) เพื่อตรวจสอบความผันผวนของผลตอบแทนตลาดหลักทรัพย์ โดยแบ่งช่วงเวลาสำหรับการศึกษาออกเป็น 5 ช่วงทั้งก่อนและหลังการเปลี่ยนแปลงทางการเมือง ผลการศึกษาพบว่าความไม่แน่นอนทางการเมืองในประเทศไทยส่งผลลบต่อความผันผวนของตลาดหลักทรัพย์ ซึ่งบ่งชี้ว่าความผันผวนของตลาดหลักทรัพย์เกิดจากข่าวร้ายมากกว่าข่าวดีจากสถานการณ์การเปลี่ยนแปลงทางการเมือง โดยมีหลักฐานเชิงประจักษ์คือค่าแกมม่ามีค่าเป็นบวกอย่างมีนัยสำคัญในแบบจำลอง GJR-GARCH ดังนั้นในช่วงดังกล่าว ตลาดหลักทรัพย์จึงเกิดภาวะดัชนีเป็นขาลงส่งผลให้ผลตอบแทนติดลบ

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HOW DOES THE STOCK MARKET REACT TO POLITICAL CHANGE?

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Abstract

This research scrutinizes Thailand's stock market response to shifts in the political landscape between October 1, 2013, and April 12, 2023. Employing the GJR-GARCH (1,1) model, the empirical analysis investigates stock market return volatility across five distinct subperiods preceding and following political changes. The results found that political instability in Thailand harmed the stock market volatility, suggesting that the stock market's volatility was caused by bad news more than good news captured by a significant positive gamma in the GJR-GARCH models. Therefore, during that period, the stock market experienced a downward trend in the index, resulting in negative returns.

Keywords: Stock Market Volatility, GJR-GARCH Model, Political Uncertainty

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Introduction

The ambit of investors' engagement in the stock market is constrained by the boundaries of their national economy, resulting in a limited capacity to mitigate investment risks through diversification. Consequently, these investors remain susceptible to various risks, particularly systemic ones. In contrast to idiosyncratic risk, which can be curtailed by spreading investments across a diverse array of securities, as posited by Markowitz (1952), recent empirical inquiries underline the potency of economic variables—such as exchange rates, interest rates, and inflation in catalyzing volatility in investment returns within the realm of securities (Ghani, Guo, Ma, & Li, 2022; Olweny & Omondi, 2011). Furthermore, the recent COVID-19 pandemic has introduced an additional source of market volatility, as evidenced by scholarly exploration (Apergis, Mustafa, & Malik, 2022; Bouri, Naeem, Nor, Mbarki, & Saeed, 2022). This constellation of factors coalesces to engender systemic risks inherent in domestic securities investments. Political stability emerges as a critical driver of systematic risks in this context.

Central to investment determinations is the mutable arena of political dynamics, influencing investor sentiments through alternating currents of positivity and negativity. This phenomenon finds empirical substantiation in the research of Białkowski, Gottschalk and Wisniewski (2008), who investigate the repercussions of national elections on stock market volatility across 27 OECD countries. Their findings expose a twofold escalation in index return volatility in the lead-up and aftermath of elections as investors react to unforeseen electoral outcomes. Analogously, Lean and Yeap (2016) elucidate the asymmetric impact of political elections on Malaysian stock returns and volatility, revealing heightened pre-election volatility juxtaposed against post-election moderation, albeit the latter effect dissipates gradually over a month. Moreover, the work of Chau, Deesomsak and Wang (2014) delves into the impact of political unrest and uprisings on stock market volatility in the MENA region, discerning augmented volatility in Islamic indices during times of political turmoil, while uprisings exert limited or negligible influence on conventional market volatility.

The annals of Thailand's political evolution over nine decades bespeak a complex narrative characterized by frequent political transformations, often resulting from governance lapses and the exigency of coercive power transfers. This recurrent sequence, typified by 13 coup d'état episodes, witnessed its most recent instantiation on May 22, 2014, orchestrated under the leadership of Army Commander-in-Chief General Prayut Chan-o-cha. This particular juncture was catalyzed by public dissent against the “extreme” amnesty bill advanced by the Yingluck Shinawatra government, culminating in the most significant street rally in Thai political history and demanding the resignation of Prime Minister Yingluck. This heralded a period of political turbulence, further compounded by the Constitutional Court's verdict deeming the dismissal of National Security Council Secretary Thawil Pliensri illegitimate, compelling the retirement of Prime Minister and Minister of Defense Ms Yingluck Shinawatra. Subsequently, General Prayut Chan-o-cha assumed the mantle of Prime Minister, a tenure that spanned eight years until the parliament's dissolution. This sequence also heralded the imposition of a new cabinet after a coup, signifying a paradigm shift in political governance.

As we navigate the trajectory of this study, a discernible thematic tapestry unfolds: the oscillations of Thailand's political canvas reverberate conspicuously within the volatility of its stock market. Empirical validation buttresses this linkage, underscoring the overriding influence of negative news a pattern buttressed by the significant positive gamma parameter encapsulated within the GJR-GARCH models. This confluence ultimately manifests in a tangible downtrend in the stock market index, culminating in adverse returns.

Given this intricate interplay between political events and market sentiment, probing the implications assumes paramount significance, particularly within the context of Thailand's mutable political dynamics. The study embarks upon a comprehensive temporal journey, commencing six months before the 13th coup d'état revolution and culminating with the proclamation of parliament dissolution on May 20, 2023. Delving into the correlation between stock market return volatility and political uncertainty bears crucial ramifications for risk-averse investors. Notably, previous research, epitomized by Baxter and Jermann (1997), elucidates investors' marked preference for domestic assets, engendering a heightened resonance of country-specific political risks within their investment portfolios. Such findings transcend the realm of investment to extend into the sphere of election prediction, augmenting the empirical foundation for the pragmatic utility of pre-election forecasts.

Therefore, the focal thrust of this study coalesces into two overarching objectives: the scrutiny of the stock market's comportment in the crucible of coup d'état epochs and the exploration of its reactions within the prelude and aftermath of general political elections.

Researcg Objectives

1. The scrutiny of the stock market's comportment in the crucible of coup d'état epochs

2. The exploration of its reactions within the prelude and aftermath of general political elections.

Literature Review

Investors navigating the realm of stock market investments are confronted with multifarious risks, classified into systematic and unsystematic dimensions (Markowitz, 1952; Sharpe, 1964). Building upon Markowitz's seminal work, Sharpe (1964) advanced the Capital Asset Pricing Model (CAPM) as a means to price individual securities or portfolios, discerning the efficacy of diversification in mitigating unsystematic risk while failing to impede systematic risk. The former is typified by idiosyncratic factors such as managerial inefficiencies, flawed business models, liquidity constraints, and labor disputes, which can be ameliorated through portfolio diversification across varied industries. In contrast, the latter pertains to broader influences enveloping entire markets or sectors, encompassing natural calamities, meteorological events, inflation, shifts in interest rates, and even macroeconomic or sociopolitical upheavals like warfare or terrorism. The capacity of diversification to counteract systematic risk is, however, constrained, leading investors to adopt diversified asset classes like equities, real estate, and fixed-income instruments, thereby attenuating vulnerability to large-scale market perturbations (Tiwari, Trabelsi, Alqahtani, & Raheem, 2020).

Intriguingly, specific attention is warranted towards country-specific risks, encapsulating uncertainties inherent in investing within a particular nation. These uncertainties, originating from diverse sources, including political, economic, exchange rate, and technological factors, can potentially culminate in financial losses for investors, signifying a prominent facet of systemic risk. This nexus is underscored by scholarship (Buckley, Arner, Zetzsche, & Selga, 2019; Danielsson, Macrae, & Uthemann, 2022; Festić, Kavkler, & Repina, 2011; Hillier & Loncan, 2019) that has duly underscored the potency of political uncertainty, especially within the contemporary milieu of technological advancements and globalization. Enhanced political polarization, growing governmental influence on economic activities, and mounting technological disruptions have collectively augmented uncertainty levels (Baker & Bloom, 2013), rendering political instability a salient contributor to systemic risk in stock market investments.

The existing corpus of literature has delved extensively into the interplay between political dynamics and stock market behavior, notably the volatility in market returns, yielding variegated findings. Exemplifying this spectrum, Lin and Wang (2005) probed the substitution effect's impact on the Nikkei 225 stock's behavior using the Asymmetric Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, revealing that the shifting influence of the ruling party lacked essential explanatory power over Nikkei 225 returns and volatility. Conversely, Hartwell (2018) investigated the impact of political volatility on capital markets within EU-candidate countries and neighboring territories, evidenced by the deleterious effect of political volatility on stock market returns. Similarly, Yeh and Lee (2000) observed the asymmetric response of return volatility to favorable and unfavorable news in Mainland China's stock markets, discerning a more profound impact of negative news on future volatility. Koulakiotis, Papapanagos and Papasyriopoulos (2016) illuminated the Greek political elections' impact on the Athens Stock Exchange (ASE), revealing positive abnormal returns encircling the election period.

Against this backdrop, the Thai context, marked by recurrent political shifts encompassing coups and general elections, emerges as a compelling arena to investigate the nexus between these events and stock market volatility. Notably, Figure 1 portrays fluctuations in the SET index in congruence with political events spanning October 2014 to March 2023. Noteworthy trends unveil an upward trajectory preceding the May 22, 2014, coup revolution, followed by a decline post-revolution, reflecting the adverse impact of the coup on the stock market. The subsequent emergence of General Prayut Chan-o-cha's government led to six years of governance, culminating in the March 24, 2019, 26th general election, which engendered a positive market response before and a negative one after the election. Furthermore, the stock market index witnessed acute volatility amid the COVID-19 outbreak, which overshadowed global markets. These patterns foreground the pivotal role of investors' sentiments in influencing market dynamics amidst political transformations, prompting the formulation of hypotheses:

H1: The stock market's reaction to political change differs between periods before and after the coup.

H2: The stock market's reaction to political change differs between periods before and after general elections.

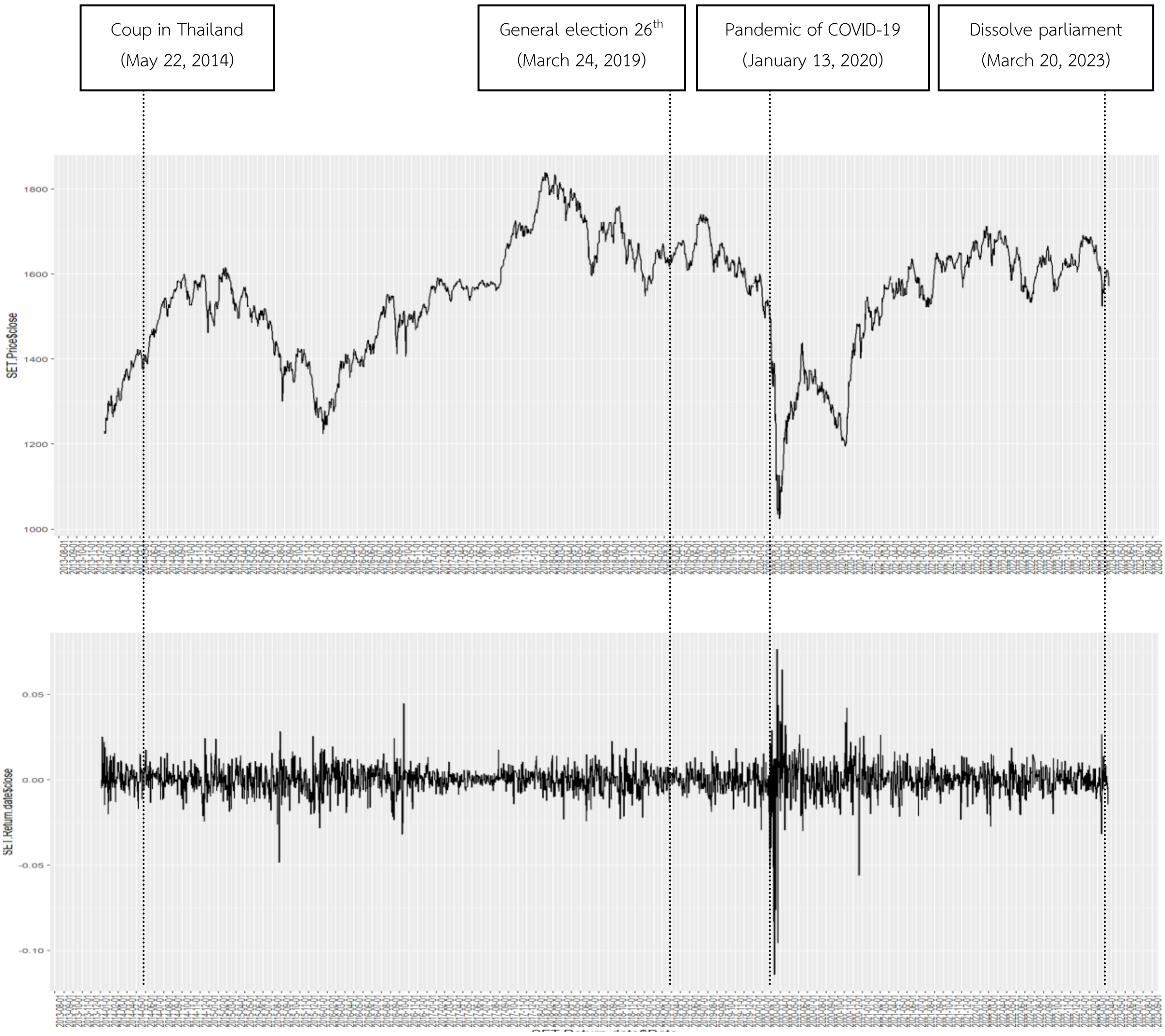

Figure 1 Changes in SET index corresponding with political changes from October 2014 to March 2023

Data

This study uses the daily closing of the stock index (SET Index). The data was collected from the stock market report from October 1, 2013, to April 12, 2023. The data were collected six months before and after the event and excluded data during the COVID-19 pandemic. Thus, the total data used in this study was 742 observations and divided into five periods (period 1(P1), 154 observations; period 2(P2), 145 observations; period 3(P3), 150 observations; period 4(P4), 142 observations; and period 5(P5), 151 observations). The periods used in the study are shown as follows:

P1: start from October 1, 2013, until May 21, 2014 (before the coup event)

P2: start from June 1, 2014, until December 31, 2014 (after the coup event)

P3: start from August 1, 2018, until March 10, 2019 (before the general election 26^{th})

P4: start from April 1, 2019, until October 31, 2019 (after the general election 26^{th})

P5: start from September 1, 2022, until April 12, 2023 (before the general election 27^{th})

Empirical Methodology

The data in this study are transformed into the daily returns series. Daily returns are calculated as the first difference in the natural logarithms of the stock market index,

$$R_t = \ln(I_t / I_{t-1}) \tag{1}$$

Where I_t and I_{t-1} are the values of each index for period t and $t-1$, respectively, in the event of a trading day following a non-trading day, daily returns are calculated based on the last trading day.

An analysis of the stock market's response to political changes is in the form of volatility. Since the data used in this study are time series, suitable tools for analyzing such effects include time series families such as an asymmetric Generalized Autoregressive Conditional Heteroscedastic (GARCH) known as the GJR-GARCH model employed in this study.

Engle and Ng (1993) developed a new diagnostic test emphasizing the asymmetry of volatility response to news and empirically tested Japanese stock market data with several GARCH models. These models include the GARCH model (Bollerslev, 1986), the exponential GARCH model (EGARCH) (Nelson, 1990), the asymmetric GARCH model (AGARCH), and the asymmetric non-linear GARCH model (NGARCH) (Engle & Ng, 1993) and GJR-GARCH Model. Engle and Ng (1993) consider the GJR GARCH model the best parametric one. It can better capture the asymmetric effects of new information on the volatility of returns. Consistent with the Hartwell (2018) study, he shows that GJR-GARCH outperforms other GARCH family models such as EGARCH.

GJR-GARCH(p,q) model by Glosten, Jagannathan and Runkle (1993) as asymmetry in the ARCH process. The conditional variance equation of the GJR-GARCH model is specified as,

$$h_t = \alpha_0 + \sum_{j=1}^{p} \beta_j h_{t-j} + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} \tag{2}$$

Where h_t is the conditional variance of the stock index return series, which is assumed to follow a GJR-GARCH (p,q) (where p is the order of the GARCH terms and q is the order of the ARCH terms) process ; β_j is the parameter to j of GARCH (h_{t-j}); α_i is the parameter of ARCH (ε_{t-i}^2); γ denotes the asymmetric parameter; d_{t-1} denotes a dummy variable when $\varepsilon_{t-1} < 0$, $d_{t-1} = 1$(negative shock) and when $\varepsilon_{t-1} \geq 0$, $d_{t-1} = 0$ (positive shock).

Results

Table 1 shows descriptive statistics of the stock market return. The volatility measured from the standard deviation in the pre-revolution period (rP1) is the highest at 0.010 in other periods, such as the pre-general elections of the 26th (rP3) and 27th (rP5). However, the average return is the highest at 0.038% in the period after the coup event, and volatility decreases. It shows that the stock market response has higher confidence after the coup. Consequently, the market responded to that sentiment declining pre-general election of the 26th period, in line with the lowest market return of -0.03%. The stock market return then increases at -0.02% after the election period of the 26th.

Table 1 Descriptive statistics of stock market return

Variable	Obs.	Mean (%)	Median (%)	Min (%)	Max (%)	SD
rP1	154	0.0092	0.0763	-5.3731	2.5286	1.0103
rP2	145	0.0388	0.0390	-2.4361	2.4419	0.7049
rP3	150	-0.0287	0.0509	-2.2869	2.2707	0.7468
rP4	142	-0.0162	-0.0093	-1.8595	1.6919	0.6034
rP5	151	-0.0171	-0.0437	-3.1763	2.6620	0.6735

Note. The sample of market return is divided into five periods. rP1 is the market return pre-coup event from October 1, 2013, to May 21, 2014. rP2 is the market return after the coup event from June 1, 2014, to December 31, 2014. rP3 is the market return before the general election of the 26th from August 1, 2018, to March 10, 2019. rP4 is the market return after the general election of the 26th from April 1, 2019, to October 31, 2019. rP5 is the market return before the general election of 27th from September 1, 2022, to April 12, 2013.

Volatility around the coup revolution and the 26th election was different, as shown in Table 2. Testing volatility results show that equity returns before and after the coup and the 26th general election event differ, with F-statistics of 2.054 and 1.531, respectively.

Table 2 F-statistics test for the variances of two different periods.

Variable	F statistic	P-value
rP1 and rP2	2.0539	0.0000***
rP3 and rP4	1.5315	0.0109**

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

The most common statistical tests are used to check if a given time series is stationary. The unit root test is one of the most commonly used statistical tests when analyzing the stationarity of a series. Stationary is a significant factor in the time series. For example, the first step in ARIMA, time series forecasting, is determining the number of differences needed to make the series stable since a model cannot predict on non-stationary time series data. This study applies the Augmented Dickey-Fuller (ADF) test to test the unit root test. As a result, every period selected for the study indicates that time series data has no unit root, suggesting stationary, as shown in Table 3. Therefore, we can perform further analysis to find a suitable Auto-Regressive Integrated Moving Average (ARIMA) model used in GJR-GARCH analysis.

Table 3 Augmented Dickey-Fuller (ADF) test for the presence of a unit root

Variable	ADF (test statistics)	P-values
rP1	-5.082	0.000***
rP2	-6.052	0.000***
rP3	-5.084	0.000***
rP4	-4.049	0.000***
rP5	-4.852	0.000***

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

ARIMA models are usually denoted ARIMA (p,d,q), where p is the order of the autoregressive model, d is the degree of difference, and q is the order of the moving average model. ARIMA models use differentiation to convert non-stationary time series into stationary and predict future values from historical data. These models use autocorrelations and moving averages for residual errors in the data to predict future values. In addition, the ARIMA (p,d,q) model used for GJR-GARCH analysis is optimal considering the lowest values of the Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC). The suitable models with the lowest AIC and BIC are shown in Table 4. As a result, the periods rP1, rP3, rP4, and rP5 show that the best ARIMA model is ARIMA(0,0,0) with zero means. In comparison, the period of rP2 indicates ARIMA(1,0,0), which is the best model.

Table 4 ARIMA(p,d,q) model based on the lowest Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) of the stock market return

Variable	Best Model
rP1	ARIMA (0,0,0) with zero mean
rP2	ARIMA (1,0,0) with zero mean
rP3	ARIMA (0,0,0) with zero mean
rP4	ARIMA (0,0,0) with zero mean
rP5	ARIMA (0,0,0) with zero mean

A time series in which the variance increases systematically. For increasing trends, this property of a series is called heteroscedasticity. This implies variation or unequal distribution across the series. If this change in variance over time can be correlated, it can be modelled using an autoregressive process such as ARCH[2]. This study then needs to test the ARCH effect in the time series data. Table 5 shows the Lagrange-Multiplier (LM) test of whether time series data indicates the ARCH effect. The results show that all AMIRA(p,d,q) models in Table 4 have an ARCH effect. Thus, GARCH family models are considered for use in this study.

The GJR-GARCH model is suitable for this study because it can better capture the asymmetric effects of new information on the volatility of returns. The GJR-GARCH model is presented in eq2, and the stock market volatility is driven more by good news or bad news by political changes captured by gamma values (γ).

Table 6 reports the coefficient results derived from GJR-GARCH (1,1) models, including five models, such as P1, P2, P3, P4, and P5, according to the periodic division according to political changes between October 1, 2013, and April 4, 2023, which is the period before the dissolution of parliament. All GJR-GARCH models also report models persistence[3] is measured by $\alpha+\beta+(\gamma/2)$. The results show that all GJR-GARCH models have values less than 1, showing persistent volatility.

[2] An extension of the ARCH model that incorporates a moving average component together with the autoregressive component. The best-known model is Generalized Autoregressive Conditional Heteroscedasticity (GARCH).

[3] The persistence of the conditional variance process is less than one in order to get that the unconditional variance σ^2 exists.

Table 5 The results of the Lagrange-Multiplier (LM) test for the ARCH effect

Variable	Model	Order	LM test (ARCH effect)	P-value
rP1	ARIMA (0,0,0) with zero mean	4	177.0	0.000***
		8	73.8	0.000***
		12	43.8	0.000***
rP2	ARIMA (1,0,0) with zero mean	4	34.35	0.000***
		8	12.92	0.074*
		12	7.79	0.732
rP3	ARIMA (0,0,0) with zero mean	4	71.27	0.000***
		8	31.29	0.000***
		12	18.68	0.067*
rP4	ARIMA (0,0,0) with zero mean	4	32.16	0.000***
		8	14.16	0.048**
		12	6.65	0.826
rP5	ARIMA (0,0,0) with zero mean	4	38.87	0.000***
		8	17.75	0.013**
		12	10.72	0.467

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

The parameter gamma (γ) in the GJR-GARCH model is used to capture the asymmetrical effect of bad news (decrease in stock indices, hence negative R_t) and good news (increase in stock indices, hence positive R_t). The result from Model P1 shows that gamma is 0.137 and insignificant, then it can be concluded that it is the symmetry of returns. The positive and negative returns are not different in the period of the pre-coup event. However, the asymmetrical effect is present in the period after the coup event in Model P2. The gamma has a significant positive with a value of 0.268, and then it can be concluded that the impact of news is asymmetric. Bad news affects volatility more than good news, implying decreases in stock indices. From this result, it can be explained that the coup revolution harmed the stock market.

Also, the gamma has a significant positive with a value of 0.170; the asymmetrical impact is presented in the pre-general election period in Model P3. Thus, it shows negative returns due to bad news affecting volatility more than good news. Subsequently, the asymmetrical impact continues after the 26th general election. The gamma has a significant positive with a value of 0.188, showing that bad news affects volatility more than good news, as shown in Model P4. Recently, the government led by Commander-in-Chief General Prayut Chan-o-cha announced the dissolution of the parliament and held the 27th general election on May 14, 2023. As a result, the stock market's volatility was affected by bad news more than good news, as shown in Model 5. The gamma has a significant positive with a value of 0.394, suggesting that bad news affects volatility more than good news.

Discussion and Conclusion

The scope of investor engagement in the stock market is bounded by national economic limitations, leaving them susceptible to various risks, especially systemic ones. Unlike idiosyncratic risks that diversification can alleviate, recent empirical research emphasizes economic variables like exchange rates, interest rates, and inflation as drivers of volatility in investment returns (Ghani et al., 2022; Olweny & Omondi, 2011). Moreover, the COVID-19 pandemic has introduced additional market volatility sources (Apergis, Mustafa, & Malik, 2022) (This issue was not the focus of this study), resulting in systemic risks inherent in domestic securities investments. Notably, political stability emerges as a critical systemic risk driver.

Political dynamics significantly impact investor sentiments through alternating positivity and negativity. This pattern finds empirical support in research by Białkowski, Gottschalk and Wisniewski (2008), indicating increased index return volatility around national elections across OECD countries. Lean and Yeap (2016) and Chau, Deesomsak and Wang (2014) observe similar asymmetric impacts of political elections in different contexts. Against this backdrop, Thailand's complex political evolution characterized by frequent shifts, including 13 coup d'état instances, provides an intriguing context for studying the nexus between political dynamics and stock market volatility.

Empirical validation reinforces this link between political events and stock market volatility, especially the power of negative news, as supported by the significant positive gamma parameter in GJR-GARCH models. This interaction manifests in a discernible downtrend in the stock market index, resulting in adverse returns.

The study embarks on a comprehensive temporal journey, spanning pre-coup and pre-/post-general election periods. Exploring the correlation between stock market return volatility and political uncertainty holds crucial implications for risk-averse investors. Moreover, like Baxter and Jermann (1997), previous research underscores the preference for domestic assets, magnifying the resonance of country-specific political risks within investment portfolios.

In light of this, the study's primary thrust converges on two key objectives: analyzing the stock market's behavior during coup d'état events and exploring its reactions during the prelude and aftermath of general political elections. By applying the GJR-GARCH model, the study tests the impact of political events on stock market volatility. The model's coefficient results indicate that different periods have varying impacts. Notably, the coup and the 26th general elections are associated with increased volatility driven by negative news, signifying the market's sensitivity to political changes.

Therefore, this research underscores the intricate relationship between political events, investor sentiment, and stock market volatility. The Thai context, characterized by its history of political shifts, offers a unique setting to examine this nexus. By employing sophisticated models, this study provides insights into the impact of political changes on stock market behavior, contributing to the understanding of Thailand's investment landscape and its potential implications for investors, policymakers, and researchers.

Table 6 Results from GJR-GARCH (1,1)

Parameter	P1 (n=154)	P2 (n=145)	P3 (n=150)	P4 (n=142)	P5 (n=151)
Constant in the mean equation	2.23×10^{-4}	5.39×10^{-4}	-3.06×10^{-4}	-6.00×10^{-6}	-6.90×10^{-5}
	(6.69×10^{-4})	(5.62×10^{-4})	(6.70×10^{-4})	(5.86×10^{-4})	(5.53×10^{-4})
Constant in the volatility equation	4.00×10^{-6}***	6.00×10^{-6}***	4.00×10^{-6}***	3.00×10^{-6}***	1.40×10^{-5}***
	(1.00×10^{-7})	(1.00×10^{-6})	(1.00×10^{-7})	(1.00×10^{-7})	(1.00×10^{-6})
AR (1)		-0.058			
		(0.081)			
ARCH (α)	1.00×10^{-7}	1.00×10^{-7}	1.00×10^{-7}	1.00×10^{-7}	1.00×10^{-7}
	(0.021)	(0.008)	(0.012)	(0.004)	(6.84×10^{-4})
GARCH (β)	0.878***	0.713***	0.840***	0.828***	0.449***
	(0.027)	(0.045)	(0.048)	(0.058)	(0.070)
Asymmetry (γ)	0.137	0.268***	0.170*	0.188*	0.394*
	(0.104)	(0.085)	(0.099)	(0.113)	(0.208)
Diagnostics					
Persistence ($\alpha+\beta+\frac{\gamma}{2}$)	0.947	0.847	0.925	0.922	0.646
Log-likelihood	496.504	528.546	525.616	529.640	557.676

Note: The number in parentheses is the robust standard error. ***, **, and * denote significant at the 1%, 5%, and 10% levels, respectively.

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