

Article

Inter-Market Mean and Volatility Spillover Dynamics Between Cryptocurrencies and an Emerging Stock Market: Evidence from Thailand and Sectoral Analysis

Yanjia Zhang *, Shih-tse Lo and Dhanoos Sutthiphisal

Martin de Tours School of Management and Economics, Assumption University, Hua Mak Campus, Bangkok 10240, Thailand; shihtselo@msme.au.edu (S.-t.L.); dhanoosstt@au.edu (D.S.)

* Correspondence: p6219659@au.edu

Abstract: The increasing interaction between the equity market and cryptocurrencies has raised concerns about volatility spillovers; however, empirical evidence about sectoral-specific spillover effects in emerging markets is scarce and hard to find. Existing research mainly concentrates on developed markets and aggregate equity indices, leaving a research gap in comprehending how sectoral indices variations impact market interactions in developing financial markets like Thailand. This article investigates the mean and volatility spillover effects between the Thai stock market and leading cryptocurrencies from April 2019 to April 2024. Applying bivariate VAR (1)-BEKK-GARCH (1,1) with an asymmetry model, this study examines the aggregate and sectoral-specific mean and volatility spillovers across major Thai stock market sectors. The findings reveal the significant mean spillover effect from cryptocurrencies to the Thai stock market with sectoral variation, while sectors such as industrials and financials exerted significant linkages, and the agricultural and food sector remains unaffected. Additionally, volatility spillovers were predominantly transmitted from the Thai equity market to cryptocurrency. Moreover, asymmetry effects were observed, with the asymmetry effects mainly transmitted from the Thai equity market to cryptocurrency. These findings provide critical insights for both individual and institutional investors on risk management and portfolio diversification while also helping policymakers with guidance on regulatory measures to mitigate systemic risks in emerging financial markets.

Keywords: risk modeling; applied econometrics; time series analysis; financial markets; cryptocurrencies and stock markets; portfolio management; diversification; emerging markets



Academic Editors: Michael Frömmel, Darko Vukovic and Steven Haberman

Received: 9 December 2024

Revised: 5 April 2025

Accepted: 9 April 2025

Published: 15 April 2025

Citation: Zhang, Yanjia, Shih-tse Lo, and Dhanoos Sutthiphisal. 2025. Inter-Market Mean and Volatility Spillover Dynamics Between Cryptocurrencies and an Emerging Stock Market: Evidence from Thailand and Sectoral Analysis. *Risks* 13: 77. <https://doi.org/10.3390/risks13040077>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Cryptocurrencies, with their increasing interaction with traditional stock markets, have introduced new complexities to the global financial markets. The Thai stock market, an emerging financial market dominated by retail investors ([Stock Exchange of Thailand 2024a](#)), along with the rising adoption of cryptocurrency investment, has raised concerns about volatility and risk transmission among different financial assets. Despite their extreme volatility, cryptocurrencies' high return potential attracts investors seeking portfolio diversification. Prior research revealed that some investors shift to investing in cryptocurrencies during high-uncertainty periods, causing price surges and market fluctuation ([Anamika et al. 2021](#); [Gaies et al. 2021](#)). According to the Modern Portfolio Theory ([Markowitz 1952](#)), return and risk are the two key indicators for portfolio investment decisions. Therefore, it

is crucial for investors to understand the mean and volatility spillover effects between the Thai stock market and cryptocurrency.

The growing importance of cryptocurrencies in Thailand is reflected in the rapid expansion of trading accounts, which are growing faster than the new stock trading accounts (Polkuamdee 2021). The Stock Exchange of Thailand (SET) is one of the largest in Southeast Asia, with a market capitalization of approximately THB 16.91 trillion (USD 503 billion) as of April 2024 (Stock Exchange of Thailand 2025). The Thai cryptocurrency market has grown rapidly, reaching trading volumes of over THB 6600 million (USD 196 million) by October 2021. With the enactment of the Digital Assets Act of 2018, which provided a structured environment for cryptocurrency trading, more and more retail and institutional investors invested in cryptocurrency. However, while cryptocurrencies create new investment opportunities, they also amplify market volatility, sparking concerns about spillover effects on conventional financial markets (Tangwattanasat 2017).

Cryptocurrencies have their unique characteristics. They tend to be more sensitive to behavioral biases. This potentially creates challenges for stock investors who are looking for portfolio diversification. Prior research revealed that irrational behavior persists in the cryptocurrency market (Tjondro et al. 2023). Herding behavior increases during market stress (Yasir et al. 2020). These investor behaviors impact more than just cryptocurrency markets. Additionally, a previous study revealed that financial spillover effects change over time (Choi 2022). Financial spillover effects generally strengthen during financial crises or uncertain times. Scholars have revealed different conclusions about the relationship between stock and cryptocurrency markets. These variations might derive from different sample periods. Cryptocurrency price fluctuations after the COVID-19 pandemic may have altered the spillover effects mechanism between stock and cryptocurrency markets. Furthermore, global shocks such as the COVID-19 pandemic and the Russia–Ukraine conflict impacted the Thai economy and caused the stock market to decrease. The volatility during the COVID-19 pandemic and the Russia–Ukraine conflict was high. Thus, investors should not assume a fixed relationship between cryptocurrencies and stocks.

Additionally, Thailand's stock market attracts substantial foreign investor participation, with international investors accounting for over 50% of the trading volume between 1 January and 9 August 2024 (Stock Exchange of Thailand 2024a). As Southeast Asia's second-largest economy and a strategic player within the ASEAN Economic Community, Thailand holds significant regional financial influence (Thailand Board of Investment 2024a). Consistently successful in attracting Foreign Direct Investment (FDI) through favorable government policies, Thailand remains a key focus for financial research (Thailand Board of Investment 2024b). Furthermore, Thailand's experience with the 1997 financial crisis adds historical depth to the analysis of spillover effects between its stock market and emerging investment tools such as cryptocurrencies.

The Thai stock market has a high participation of retail investors, which makes it more sensitive to sentiment-driven trading (Stock Exchange of Thailand 2024a). Retail investors tend to shift to speculative assets like cryptocurrencies for better profitability during equity market stress. Thus, as an emerging market, the Thai stock market represents a good example for studying spillover effects between cryptocurrencies and equities. In addition, the service sector occupies a large portion of Thailand's economy. Tourism dependencies create financial instability during times of uncertainty, such as the COVID-19 pandemic and the Russia–Ukraine conflict. During the COVID-19 pandemic, industries such as retail, hospitality, and finance may be more influenced by cryptocurrency shocks. Therefore, specific sectoral analysis is valuable since different Thai sectors may demonstrate varying levels of connectedness with cryptocurrencies. A nuanced study on these sectoral mean

and volatility spillover effects provides critical insights to help investors and policymakers make better decisions.

However, existing research regarding mean and volatility spillover effects between the Thai stock market and cryptocurrencies is scarce and hard to find. To our best knowledge, no prior research has been conducted on nuanced spillover and asymmetric effects between the Thai equity sectoral indices and cryptocurrencies. Most existing research concentrates only on the aggregate equity indices and is less concerned with the sectoral variations towards regulations and global shocks. For instance, industries like healthcare and technology tended to be more resilient during the COVID-19 pandemic, while sectors like retail and hospitality tend to be more influenced by external shocks. These variations among different equity sectors require a nuanced sectoral analysis. Similarly, prior research on the relationship between cryptocurrency and equity has focused only on the most prominent cryptocurrency—Bitcoin. Research using the broader cryptocurrency market index and also considering equity sectoral-specific asymmetric effects in emerging markets is rare and hard to find. The present article aims to fill these research gaps by comprehensively investigating spillover and asymmetric effects between the Thai equity sectoral indices and cryptocurrencies. The results of this study will provide crucial insights to help investors and policymakers better understand the mean and volatility transmission mechanisms across different types of financial assets.

This study is inspired by the Modern Portfolio Theory ([Markowitz 1952](#)), which demonstrates that rational investors allocate capital decisions based on return and risk considerations. However, cryptocurrency's significantly higher volatility compared to equity makes it questionable to serve as a hedge asset or increase overall portfolio volatility. Global shocks that influence multiple markets simultaneously generate spillover effects, which result in increased asset connectedness ([Forbes and Rigobon 2002](#)). During the COVID-19 pandemic, financial markets experienced synchronized movement due to international interest rate changes, demand fluctuations, and capital outflows. Investors move capital between different financial asset categories during uncertain times, which triggers spillovers across financial markets ([Uzonwanne 2021](#)). The spillover effect, which represents the transfer of shocks across interconnected assets ([Diebold and Yilmaz 2012](#)), can lead to market instability ([Alkan and Çiçek 2020](#)). This research combines different perspectives to conduct an empirical study of mean and volatility spillover effects in Thailand's financial markets while revealing the significant role of cryptocurrencies in emerging markets.

Therefore, this research aims to investigate the mean and volatility spillover effects between the Thai stock market indices and cryptocurrencies. Using daily data and a bivariate VAR (1)-BEKK-GARCH (1,1) model with asymmetry, we analyze how shocks and volatilities in one market influence the other. Specifically, this study addresses the following research questions: (1) Is there evidence of mean spillover effects between cryptocurrencies (Cryptocurrency Market Index, Bitcoin, and Ethereum) and the Thai stock market (SET Index and its eight sectoral indices)? (2) Is there evidence of volatility spillover effects between cryptocurrencies (Cryptocurrency Market Index, Bitcoin, and Ethereum) and the Thai stock market (SET Index and its eight sectoral indices)?

The rest of this article is structured as follows. Section 2 reviews the related literature on financial spillovers. Section 3 presents the empirical results. Section 4 explains the data and the VAR(1)-BEKK-GARCH(1,1) methodology. Section 5 discusses the findings in relation to existing literature. Finally, Section 6 concludes with policy recommendations, limitations, and directions for future research.

2. Literature Review

During financial crises or uncertain times, financial market volatility generally increases sharply and spillovers across markets (Diebold and Yilmaz 2012). In finance, there are two typical forms of spillover effects: mean and volatility spillover effects. The mean spillover effect refers to an increase in the return of one asset that may lead to the return of the other asset to change simultaneously. The volatility spillover effect refers to the situation where once the fluctuation in returns has started, it persists for some time to decelerate (Alkan and Çiçek 2020).

Aggregate global shocks are a major driver of spillover effects among different financial markets as they have potential influence on multiple economies and financial markets simultaneously. According to Forbes and Rigobon (2002), aggregate or global events such as international capital supply fluctuations, increases in international interest rates, or decreases in international demand can disrupt economic fundamentals in multiple countries. Equity markets in any country affected by such aggregate or global shock will move in the same direction to some extent, so cross-market integration between any affected countries will increase after the aggregate or global shock. The COVID-19 pandemic can be treated as a typical example of aggregate or global shock. During the COVID-19 pandemic, international travel restrictions, increases in international inflation rates, rises in international interest rates, and declines in international demand disrupt economic fundamentals in every country globally. In times of financial uncertainty, investors re-evaluate their portfolio risk exposures, leading to capital flows fluctuating across different financial asset categories. These fluctuating movements of capital increased financial asset correlations.

A compelling financial concept, the flight-to-safety episodes suggest that during extremely financially uncertain times, investors reassess their risk exposures and reallocate their investments from highly volatile financial assets like stocks to relatively safer alternative financial assets (Lehnert 2022). The reallocation of capital among different financial assets reveals investors' efforts to minimize portfolio risks and maintain portfolio profitability during heightened uncertain times. Uzonwanne (2021) revealed that during the bullish and bearish periods of an equity market, investors move their capital between stock and cryptocurrency pairs to minimize portfolio risk and maximize portfolio returns, leading to mean and volatility spillover effects between stock and cryptocurrency pairs. This movement of capital between financial assets aligns with the Modern Portfolio Theory (Markowitz 1952), which suggests that rational investors make portfolio investment decisions based on portfolio risk-return trade-offs.

Before 2020, research revealed spillovers between cryptocurrency and equity markets. For instance, Symitsi and Chalvatzis (2018) found spillover effects in terms of returns between equities and Bitcoin. Specifically, short-term volatility transferred from equity to Bitcoin, whereas Bitcoin exerted long-term volatility transfer to energy equities. Additionally, the study identifies bidirectional and asymmetric shock spillovers between equity and Bitcoin. Vardar and Aydogan (2019) found significant shock and volatility spillover effects from Bitcoin to conventional financial instruments such as the stock market in Turkey. The research revealed significant shock and volatility spillover effects from conventional financial classes to Bitcoin. The shock and volatility transmission mechanism between Bitcoin and conventional financial instruments is bidirectional in Turkey's context.

However, before 2020, some studies revealed limited spillover effects between the stock market and the cryptocurrency. For instance, Corbet et al. (2018) used daily data from 2014 to 2017 and found that cryptocurrencies generally demonstrate isolation from traditional financial markets, which means the spillover effect between the cryptocurrency market and other financial markets is limited. Trabelsi (2018) used daily data from 2021

to 2018 and indicated no substantial spillover effects observed between cryptocurrencies and traditional financial assets. Wang et al. (2019) used daily data from 2013 to 2017 and found that there was no mean and volatility spillover effect between Bitcoin and Chinese stock market.

After 2020, Hsu et al. (2021) found substantial spillover effects between cryptocurrency and traditional financial instruments. Cryptocurrency features change dynamically over time, are affected by economic instability and disturbances, and have asymmetric spillover effects, where negative return shocks have more influence on co-volatility than positive return shocks. Joshi et al. (2022) revealed higher volatility spillover from cryptocurrency to the stock market. Bouri et al. (2022) revealed volatility spillovers between cryptocurrency and equity increased during the COVID-19 pandemic. Elsayed et al. (2022) found substantial return and volatility interactions among markets during the COVID-19 outbreak. Yousaf and Yarovaya (2021) found that the spillover effect between equity and cryptocurrency was increased amidst the COVID-19 pandemic.

Previous studies confirmed the presence of spillover effects between cryptocurrency and stock markets (Aydoğan et al. 2022; Cao and Xie 2022; Elsayed et al. 2022; Malhotra and Gupta 2019), with some studies revealing the time-varying nature of the spillover effects, while others revealed dependent on market conditions (Antonakakis et al. 2019; Hsu et al. 2021; Koutmos 2018; Uddin et al. 2020; Yousaf et al. 2022). Additionally, several studies found evidence of asymmetric spillover effects of positive and negative shocks between stock and cryptocurrency (Bouri et al. 2018; Cao and Xie 2022; Hsu et al. 2021; Kurka 2019). Variations in findings can be attributed to differences in study periods, market conditions, and methodologies. Early research, such as Corbet et al. (2018) and Trabelsi (2018), found weak or no spillovers due to their focus on earlier phases of the cryptocurrency market when integration with traditional finance was minimal. In contrast, studies conducted after 2020 (Hsu et al. 2021; Joshi et al. 2022) reported stronger spillovers as institutional and individual investment increased and financial markets became more interconnected. The COVID-19 pandemic and the Russia–Ukraine conflict have intensified these spillover effects by heightening global financial uncertainty and risk aversion. Bouri et al. (2022) further highlight the presence of asymmetric spillovers, reinforcing that cryptocurrency's role in financial markets continues to evolve.

Although the existing literature has investigated the spillover effects between different financial assets, research on the spillover effect between emerging stock markets, especially the emerging equity sectoral indices, is still very scarce, and relevant literature is hard to find. There are some similarities and limitations in the existing research regarding spillover effects between stocks and cryptocurrency. Firstly, for the equity sample, most of the prior research concentrated on the developed economies' aggregate stock market index, while there was little attention to the mean and volatility spillover effects between emerging equity sectoral indices and cryptocurrency. Secondly, for the sample of cryptocurrency, in previous research regarding the spillover effects between cryptocurrency and stock, most research has mainly focused only on the most prominent cryptocurrency, Bitcoin, ignoring the comprehensive understanding of spillover effect mechanisms between the broader Cryptocurrency Market Index, emerging stock market, and emerging equity sectoral indices. Thirdly, the COVID-19 pandemic, as an aggregate or global shock, affected equity sectoral indices differently. Specifically, prior research revealed that the healthcare, technology, manufacturing, and education sectors were more resilient to the COVID-19 pandemic. However, sectors such as transportation, environment, and mining have been adversely affected by the COVID-19 pandemic (He et al. 2021). The varied responses of different equity sectoral indices to the COVID-19 pandemic highlight the need for research on spillover effects between equity sectoral indices and cryptocurrency. In addition,

prior research revealed the existence of asymmetric effects between traditional financial assets and cryptocurrency, but there is still a lack of comprehensive understanding of the asymmetric effects of positive and negative shocks between emerging equity sectoral indices and cryptocurrency. Thus, in response to these research gaps, this article focuses on the mean and volatility spillover effects and incorporates asymmetric effects into the econometric model between cryptocurrencies and key sectors of the Thai stock market. By integrating the Cryptocurrency Market Index and analyzing the dynamic nature of different equity sectors of an emerging economy, this study provides nuanced empirical evidence for understanding the spillover effect mechanism in emerging markets.

3. Results

3.1. Descriptive Statistics

Tables 1 and 2 demonstrate the relevant descriptive statistics. The mean returns of most stock market sectors in Thailand were approximately zero, except for the consumer products sector, which recorded a slightly negative mean return of -0.001 . In contrast, all three cryptocurrencies exhibited positive mean returns, with Ethereum yielding the highest mean return of 0.003 . These results suggest that, on average, cryptocurrencies outperformed the stock market sectors in terms of mean returns during the observed period. In terms of the standard deviation, for stocks, the standard deviation for all stock returns was around 0.010 ; for cryptocurrencies, the standard deviation of the Cryptocurrency Index, Bitcoin, and Ethereum were all above 0.040 , and the standard deviation of Ethereum was 0.052 , which was the highest among all other assets.

Table 1. Descriptive statistics for returns of Thai stocks.

Assets	SET	SETAgro	SETCon	SETFin	SETIndu	SETProp	SETRes	SETSer	SETTech
Mean	0.000	0.000	−0.001	0.000	0.000	0.000	0.000	0.000	0.000
Std. Dev.	0.011	0.011	0.012	0.014	0.014	0.010	0.014	0.011	0.017
Max	0.077	0.057	0.074	0.085	0.086	0.064	0.118	0.080	0.102
Min	−0.114	−0.123	−0.143	−0.122	−0.148	−0.119	−0.175	−0.108	−0.089
Skewness	−1.914	−2.013	−1.377	−1.185	−1.446	−2.170	−1.954	−0.829	−0.002
Kurtosis	25.217	20.332	21.952	15.515	16.275	27.490	34.337	19.460	6.121
ARCHLM	295.017	244.690	25.364	264.664	252.440	317.265	297.338	233.346	169.492
<i>p</i> -value of ARCHLM	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Jarque–Bera	32,920	21,740	24,770	12,468	13,829	39,191	60,427	19,304	1899
<i>p</i> -value of Jarque–Bera	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ADF	−8.620	−9.185	−9.847	−9.273	−8.208	−9.167	−8.396	−9.812	−9.304
<i>p</i> -value of ADF	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010

Note: SET = Stock market return of Thailand; SETAgro = Return of the Agricultural and Food sector; SETCon = Return of the Consumer Products sector; SETFin = Return of the Financial sector; SETIndu = Return of the Industrials sector; SETProp = Return of the Property and Construction sector; SETRes = Return of the Resources sector; SETSer = Return of the Services sector; SETTech = Return of the Technology sector.

In terms of the maximum return on assets, all cryptocurrencies had a higher maximum return than stocks. To be more specific, Ethereum had the highest maximum return of 0.329 , indicating substantial positive performance during the study period. Bitcoin also had a significant maximum return of 0.198 . The Cryptocurrency Index had a maximum return of 0.177 . The resources sector experienced the highest maximum return at 0.118 among stock sectors. The technology sector had a notable maximum return of 0.102 . The agricultural and food sector had the lowest maximum return among the stock sectors at 0.057 . In terms of the minimum return on assets, the Cryptocurrency Index showed the most dramatic

decline, with a minimum return of -0.485 . Among individual cryptocurrencies, Ethereum experienced a substantial decrease with a minimum return of -0.457 , followed by Bitcoin at -0.392 . The resource sector faced the highest negative return among the stock sectors at -0.175 . The technology sector had the smallest negative minimum return among the stock sectors at -0.089 .

Table 2. Descriptive statistics for returns of cryptocurrencies.

Assets	CI	BTC	ETH
Mean	0.001	0.002	0.003
Std. Dev.	0.049	0.040	0.052
Max	0.177	0.198	0.329
Min	-0.485	-0.392	-0.457
Skewness	-1.577	-0.922	-0.748
Kurtosis	12.410	10.998	10.031
ARCHLM	32.898	36.803	37.909
<i>p</i> -value of ARCHLM	0.000	0.000	0.000
Jarque–Bera	8299	6296	5207
<i>p</i> -value of Jarque–Bera	0.000	0.000	0.000
ADF	-9.615	-9.656	-9.76
<i>p</i> -value of ADF	0.010	0.010	0.010

Note: CI = Return of the Cryptocurrency Index (CCi30); BTC = Return of Bitcoin; ETH = Return of Ethereum.

In terms of skewness of the asset returns, the property and construction sector, and agricultural and food sector had the most negatively skewed returns with values of -2.170 and -2.013 , respectively. This indicates a higher probability of extreme negative returns. The technology sector had a skewness very close to zero (-0.002), suggesting a nearly symmetric distribution of returns. Ethereum and Bitcoin had skewness values of -0.748 and -0.922 , respectively, indicating a slight tendency towards negative returns but a tendency less extreme than many stock sectors. The Cryptocurrency Index had a skewness of -1.577 , indicating a higher probability of extreme negative returns. The services sector had the least negative skewness among the stock sectors at -0.829 , suggesting relatively less asymmetry in its return distribution.

In terms of the kurtosis of the asset returns, the property and construction sector and the agricultural and food sector exhibited the highest kurtosis values at 27.490 and 20.332, respectively. This suggests a distribution with significantly heavier tails. The technology sector had a lower kurtosis value (6.121), suggesting a distribution with lighter tails and a less pronounced peak, indicating a more symmetric distribution of returns. Ethereum and Bitcoin had relatively lower kurtosis values of 10.031 and 10.998, respectively. The Cryptocurrency Index had a kurtosis value of 12.410, indicating a distribution with heavier tails.

Regarding the ARCH-LM test for the returns of assets, the test statistics of all the assets were statistically significant at the 5% level, indicating the presence of autoregressive conditional heteroskedasticity (ARCH) in the asset return, which means that each asset has volatility clustering and needs to be estimated by the ARCH/GARCH model. In terms of the Jarque–Bera test, all the assets' Jarque–Bera statistics were high and statistically significant at the 5% level, rejecting the null hypothesis of the normality of distribution of the asset returns, indicating that all the assets' returns were not normally distributed. The use of ARCH/GARCH-type models is suitable for non-normally distributed data. The results of the ADF test statistics indicate that the null hypothesis was rejected for all assets at the 5% level. This rejection suggested that each asset series was stationary and without a unit root. Consequently, the asset returns' time series are suitable for vector autoregression (VAR) modeling. To specifically study the mean and volatility spillover effect between

bivariate assets of stock and cryptocurrencies simultaneously, this research applies VAR-BEKK-GARCH with asymmetry model, with VAR as the conditional mean equation and BEKK-GARCH with asymmetry as the conditional variance-covariance equation.

3.2. Mean Spillover Effect Between Thai Stocks and Cryptocurrencies

Table 3 provides results of the mean spillover effect between Thai stocks and cryptocurrency pairs. Regarding the mean spillover effect between the return of the SET index and cryptocurrency returns, the p -value of β_{12} for the SET-CI, SET-BTC, and SET-ETH pairs was significant at the 5% level. This suggests that the Cryptocurrency Index, Bitcoin, and Ethereum exerted a significant mean spillover effect on Thailand's stock market returns at a 5% level. Additionally, the estimated coefficient β_{21} for the SET-CI, SET-BTC, and SET-ETH pairs was not significant at the 5% level, indicating SET did not have a mean spillover effect on the Cryptocurrency Index, Bitcoin, or Ethereum at the 5% level (see Table 3, Panel A).

Table 3. Results of bivariate VAR of equity and cryptocurrencies from 19 April 2019 to 11 April 2024.

Panel A: Return of SET index and cryptocurrencies						
	SET-CI		SET-BTC		SET-ETH	
	Estimate	p -value	Estimate	p -value	Estimate	p -value
Mean	Model (SET)		Model (SET)		Model (SET)	
β_{11}	0.044	0.145	0.054	0.056	0.056	0.060
β_{12}	0.014	0.003	0.011	0.044	0.013	0.002
a_{01}	0.000	0.147	0.000	0.179	0.000	0.108
Mean	Model (CI)		Model (BTC)		Model (ETH)	
β_{21}	0.012	0.925	−0.092	0.453	−0.116	0.450
β_{22}	0.009	0.792	0.056	0.118	0.025	0.391
a_{02}	0.002	0.175	0.002	0.053	0.002	0.182
Panel B: Return of agricultural and food sector and cryptocurrencies						
	SETAgro-CI		SETAgro-BTC		SETAgro-ETH	
	Estimate	p -value	Estimate	p -value	Estimate	p -value
Mean	Model (SETAgro)		Model (SETAgro)		Model (SETAgro)	
β_{11}	−0.005	0.860	0.004	0.889	0.013	0.651
β_{12}	0.001	0.907	−0.006	0.308	0.002	0.613
a_{01}	0.000	0.186	0.000	0.201	0.000	0.178
Mean	Model (CI)		Model (BTC)		Model (ETH)	
β_{21}	0.114	0.400	−0.007	0.953	−0.104	0.451
β_{22}	0.009	0.775	0.054	0.163	0.019	0.527
a_{02}	0.001	0.277	0.002	0.114	0.002	0.092
Panel C: Return of consumer products sector and cryptocurrencies						
	SETCon-CI		SETCon-BTC		SETCon-ETH	
	Estimate	p -value	Estimate	p -value	Estimate	p -value
Mean	Model (SETCon)		Model (SETCon)		Model (SETCon)	
β_{11}	0.023	0.492	0.027	0.323	0.033	0.241
β_{12}	0.014	0.009	0.011	0.086	0.012	0.006
a_{01}	−0.001	0.001	−0.001	0.007	−0.001	0.002
Mean	Model (CI)		Model (BTC)		Model (ETH)	
β_{21}	0.020	0.855	−0.138	0.144	−0.127	0.259
β_{22}	0.010	0.749	0.071	0.022	0.013	0.654
a_{02}	0.002	0.176	0.002	0.065	0.002	0.051

Table 3. Cont.

Panel D: Return of financial sector and cryptocurrencies						
	SETFin-CI		SETFin-BTC		SETFin-ETH	
	Estimate	<i>p</i> -value	Estimate	<i>p</i> -value	Estimate	<i>p</i> -value
Mean	Model (SETFin)		Model (SETFin)		Model (SETFin)	
β_{11}	0.058	0.039	0.060	0.048	0.069	0.013
β_{12}	0.015	0.013	0.010	0.175	0.012	0.036
a01	0.000	0.414	0.000	0.177	0.000	0.145
Mean	Model (CI)		Model (BTC)		Model (ETH)	
β_{21}	−0.052	0.392	−0.105	0.173	−0.096	0.352
β_{22}	0.018	0.495	0.062	0.065	0.028	0.358
a02	0.002	0.226	0.002	0.027	0.002	0.138
Panel E: Return of industrials sector and cryptocurrencies						
	SETIndu-CI		SETIndu-BTC		SETIndu-ETH	
	Estimate	<i>p</i> -value	Estimate	<i>p</i> -value	Estimate	<i>p</i> -value
Mean	Model (SETIndu)		Model (SETIndu)		Model (SETIndu)	
β_{11}	0.052	0.038	0.060	0.038	0.049	0.079
β_{12}	0.032	0.000	0.025	0.001	0.023	0.000
a01	−0.001	0.006	−0.001	0.097	−0.001	0.029
Mean	Model (CI)		Model (BTC)		Model (ETH)	
β_{21}	0.079	0.367	−0.041	0.657	−0.066	0.500
β_{22}	0.028	0.429	0.056	0.095	0.017	0.553
a02	0.002	0.152	0.002	0.188	0.002	0.169
Panel F: Return of property and construction sector and cryptocurrencies						
	SETProp-CI		SETProp-BTC		SETProp-ETH	
	Estimate	<i>p</i> -value	Estimate	<i>p</i> -value	Estimate	<i>p</i> -value
Mean	Model (SETProp)		Model (SETProp)		Model (SETProp)	
β_{11}	0.062	0.054	0.069	0.022	0.068	0.021
β_{12}	0.013	0.004	0.011	0.029	0.011	0.008
a01	0.000	0.061	0.000	0.061	0.000	0.039
Mean	Model (CI)		Model (BTC)		Model (ETH)	
β_{21}	0.025	0.869	−0.071	0.546	−0.081	0.597
β_{22}	0.007	0.839	0.051	0.110	0.020	0.497
a02	0.002	0.111	0.002	0.059	0.002	0.122
Panel G: Return of resources sector and cryptocurrencies						
	SETRes-CI		SETRes-BTC		SETRes-ETH	
	Estimate	<i>p</i> -value	Estimate	<i>p</i> -value	Estimate	<i>p</i> -value
Mean	Model (SETRes)		Model (SETRes)		Model (SETRes)	
β_{11}	0.062	0.034	0.066	0.027	0.066	0.027
β_{12}	0.018	0.003	0.016	0.024	0.017	0.003
a01	0.000	0.206	0.000	0.252	0.000	0.149
Mean	Model (CI)		Model (BTC)		Model (ETH)	
β_{21}	0.089	0.413	−0.013	0.899	0.047	0.713
β_{22}	0.012	0.693	0.060	0.107	0.028	0.363
a02	0.002	0.162	0.002	0.081	0.002	0.114

Table 3. Cont.

Panel H: Return of services sector and cryptocurrencies						
	SETSer-CI		SETSer-BTC		SETSer-ETH	
	Estimate	<i>p</i> -value	Estimate	<i>p</i> -value	Estimate	<i>p</i> -value
Mean	Model (SETSer)		Model (SETSer)		Model (SETSer)	
β_{11}	0.032	0.303	0.046	0.119	0.050	0.090
β_{12}	0.008	0.124	0.008	0.202	0.013	0.006
α_{01}	0.000	0.436	0.000	0.190	0.000	0.195
Mean	Model (CI)		Model (BTC)		Model (ETH)	
β_{21}	0.117	0.355	−0.060	0.529	−0.076	0.578
β_{22}	0.030	0.344	0.047	0.152	0.029	0.341
α_{02}	0.001	0.557	0.002	0.074	0.002	0.248

Panel I: Return of technology sector and cryptocurrencies						
	SETTech-CI		SETTech-BTC		SETTech-ETH	
	Estimate	<i>p</i> -value	Estimate	<i>p</i> -value	Estimate	<i>p</i> -value
Mean	Model (SETTech)		Model (SETTech)		Model (SETTech)	
β_{11}	−0.114	0.000	−0.099	0.001	−0.094	0.001
β_{12}	0.026	0.002	0.017	0.042	0.024	0.003
α_{01}	0.001	0.100	0.001	0.117	0.001	0.108
Mean	Model (CI)		Model (BTC)		Model (ETH)	
β_{21}	−0.104	0.161	−0.104	0.141	−0.042	0.555
β_{22}	0.012	0.707	0.066	0.037	−0.002	0.938
α_{02}	0.002	0.145	0.002	0.018	0.003	0.023

Note: SET = Stock market return of Thailand; SETAgro = Return of the Agricultural and Food sector; SETCon = Return of the Consumer Products sector; SETFin = Return of the Financial sector; SETIndu = Return of the Industrials sector; SETProp = Return of the Property and Construction sector; SETRes = Return of the Resources sector; SETSer = Return of the Services sector; SETTech = Return of the Technology sector; CI = Return of the Cryptocurrency Index (CCI30); BTC = Return of Bitcoin; ETH = Return of Ethereum.

In terms of the mean spillover effect between the return of the agricultural and food sector and cryptocurrency returns, the *p* values of both β_{12} and β_{21} for all the SETAgro-CI, SETAgro-BTC, and SETAgro-ETH pairs were not significant at the 5% level, indicating that there was no significant mean spillover effect between the SETAgro-CI, SETAgro-BTC, and SETAgro-ETH pairs at the 5% level (see Table 3, Panel B).

In terms of the mean spillover effect between the return of the consumer products sector and cryptocurrencies, the *p* values of β_{12} for SETCon-CI and SETCon-ETH were significant at the 5% level, indicating that there was a significant mean spillover effect from CI and ETH to SETCon at the 5% level. BTC did not have a significant mean spillover effect on SETCon at the 5% level. The *p* values of β_{21} for all the SETCon-CI, SETCon-BTC, and SETCon-ETH pairs were not significant at the 5% level, indicating that there was no significant mean spillover effect from SETCon on cryptocurrencies at the 5% level (see Table 3, Panel C).

In terms of the mean spillover effect between the return of the financial sector of Thailand and cryptocurrencies, the *p* values of β_{12} for SETFin-CI and SETFin-ETH were significant at the 5% level, indicating that there was a significant mean spillover effect from CI and ETH to SETFin at the 5% level. The *p* values of β_{21} for the SETFin-CI, SETFin-BTC, and SETFin-ETH pairs were not significant at the 5% level, indicating that there was no significant mean spillover effect from SETFin to cryptocurrencies at the 5% level (see Table 3, Panel D).

In terms of the mean spillover effect between the return of the industrials sector of Thailand and cryptocurrencies, the *p* values of β_{12} for all the SETIndu-CI, SETIndu-BTC, and SETIndu-ETH pairs were significant at the 5% level, indicating that there was a significant mean spillover effect from CI, BTC, and ETH to SETIndu at the 5% level. The

p values of β_{21} for all the SETIndu-CI, SETIndu-BTC, and SETIndu-ETH pairs were not significant at the 5% level, indicating that there was no significant mean spillover effect from SETIndu to cryptocurrencies at the 5% level (see Table 3, Panel E).

In terms of the mean spillover effect between the return of the property and construction sector of Thailand and cryptocurrencies, the p values of β_{12} for the SETProp-CI, SETProp-BTC, and SETProp-ETH pairs were significant at the 5% level, indicating that there was a significant mean spillover effect from CI, BTC, and ETH to SETProp at the 5% level. The p values of β_{21} for the SETProp-CI, SETProp-BTC, and SETProp-ETH pairs were not significant at the 5% level, indicating that there was no significant mean spillover effect from SETProp to cryptocurrencies at the 5% level (see Table 3, Panel F).

In terms of the mean spillover effect between the return of the resources sector of Thailand and cryptocurrencies, the p values of β_{12} for all the SETRes-CI, SETRes-BTC, and SETRes-ETH pairs were significant at the 5% level, indicating that there was a significant mean spillover effect from CI, BTC, and ETH to SETRes at the 5% level. The p values of β_{21} for all the SETRes-CI, SETRes-BTC, and SETRes-ETH pairs were not significant at the 5% level, indicating that there was no significant mean spillover effect from SETRes to cryptocurrencies at the 5% level (see Table 3, Panel G).

In terms of the mean spillover effect between the return of the services sector of Thailand and cryptocurrencies, the p values of β_{12} for the SETSer-CI and SETSer-BTC pairs were not significant at the 5% level, indicating that there was no significant mean spillover effect from CI and BTC to SETSer at the 5% level. Only the p -value of β_{12} for SETSer-ETH was significant at the 5% level, indicating a significant mean spillover effect from ETH to SETSer at the 5% level. The p values of β_{21} for all the SETSer-CI, SETSer-BTC, and SETSer-ETH pairs were not significant at the 5% level, indicating that there was no significant mean spillover effect from SETSer to cryptocurrencies at the 5% level (see Table 3, Panel H).

In terms of the mean spillover effect between the return of the technology sector of Thailand and cryptocurrencies, the p values of β_{12} for the SETTech-CI, SETTech-BTC, and SETTech-ETH pairs were significant at the 5% level, indicating that there was a significant mean spillover effect from CI, BTC, and ETH to SETTech at the 5% level. The p -value of β_{21} for all the SETTech-CI, SETTech-BTC, and SETTech-ETH pairs was not significant at the 5% level, indicating that there was no significant mean spillover effect from SETTech to cryptocurrencies at the 5% level (see Table 3, Panel I).

3.3. Volatility Spillover Between Thai Stocks and Cryptocurrencies

Table 4 provides the results of the volatility spillover effect between Thai stocks and cryptocurrency pairs. Regarding the ARCH effect between the return of the stock market of Thailand and cryptocurrencies, the estimated values of a_{12} for SET-CI and SET-BTC pairs were statistically significant at the 5% level, indicating SET had an ARCH effect on Cryptocurrency Index and Bitcoin at the 5% level. The estimated values of a_{21} for all pairs were not statistically significant at the 5% level, indicating that cryptocurrencies had no ARCH effect on the stock market returns of Thailand at the 5% level. The estimated values of g_{12} for SET-ETH were significant at the 5% level, indicating SET has a significant GARCH effect on Ethereum at the 5% level. None of the estimated values of g_{21} were significant at the 5% level, indicating that cryptocurrencies had no significant GARCH effect on SET at the 5% level. In terms of the asymmetric effect between the bivariate assets, the estimated values of d_{12} for SET-CI and SET-ETH were significant at the 5% level, indicating that SET has an asymmetric effect on the Cryptocurrency Index and Ethereum at the 5% level. The estimated value of d_{12} for SET-BTC was not significant at the 5% level, indicating that SET has no asymmetric effect on Bitcoin at the 5% level. The estimated values of d_{21} for

SET-CI, SET-BTC, and SET-ETH were not significant at the 5% level, indicating that the Cryptocurrency Index, Bitcoin, and Ethereum had no asymmetric effect on SET at the 5% level. The Wald tests revealed that volatility spillover from the stock market returns of Thailand (SET) to various cryptocurrencies (CI, BTC, ETH) was statistically significant at the 5% level, while volatility spillover from cryptocurrencies to SET was not significant at the 5% significance level. These results indicate that stock market returns have a more significant effect on the volatility of cryptocurrencies than the reverse situation, suggesting a dominant influence of the stock market over cryptocurrencies during the studied period (see Table 4, Panel A).

Table 4. Results of bivariate BEKK-GARCH of equity and cryptocurrencies from 19 April 2019 to 11 April 2024.

Panel A: Return of set index and cryptocurrencies						
	SET-CI		SET-BTC		SET-ETH	
	Estimate	<i>p</i> -value	Estimate	<i>p</i> -value	Estimate	<i>p</i> -value
c11	0.001	0.000	0.001	0.000	0.001	0.000
c21	−0.002	0.458	0.001	0.815	0.001	0.699
c22	0.010	0.000	0.021	0.000	0.004	0.080
a11	0.157	0.000	0.154	0.000	0.163	0.000
a12	0.404	0.000	0.397	0.001	−0.004	0.972
a21	−0.008	0.121	−0.007	0.324	0.005	0.274
a22	0.299	0.000	0.435	0.000	0.217	0.000
g11	0.945	0.000	0.948	0.000	0.949	0.000
g12	−0.079	0.066	0.060	0.385	−0.084	0.001
g21	0.004	0.088	−0.003	0.700	0.000	0.766
g22	0.922	0.000	0.732	0.000	0.973	0.000
d11	0.331	0.000	0.329	0.000	0.321	0.000
d12	0.623	0.001	0.294	0.201	0.673	0.000
d21	−0.013	0.053	−0.005	0.644	−0.011	0.136
d22	−0.145	0.040	0.033	0.865	−0.038	0.478
H0: a21 = g21 = d21 = 0	7.317	0.062	6.151	0.104	3.643	0.303
H0: a12 = g12 = d12 = 0	26.029	0.000	19.714	0.000	25.016	0.000
Panel B: Return of agricultural and food sector and cryptocurrencies						
	SETAgro-CI		SETAgro-BTC		SETAgro-ETH	
	Estimate	<i>p</i> -value	Estimate	<i>p</i> -value	Estimate	<i>p</i> -value
c11	0.002	0.000	0.002	0.000	0.001	0.000
c21	−0.005	0.166	−0.009	0.010	0.001	0.444
c22	0.022	0.000	0.017	0.000	0.000	1.000
a11	0.099	0.026	0.116	0.015	0.027	0.659
a12	0.697	0.000	0.472	0.000	−0.375	0.008
a21	−0.023	0.003	−0.030	0.002	0.009	0.045
a22	0.387	0.000	0.413	0.000	0.196	0.000
g11	0.942	0.000	0.935	0.000	0.958	0.000
g12	0.120	0.129	0.130	0.066	−0.082	0.000
g21	0.005	0.278	0.014	0.058	−0.002	0.114
g22	0.742	0.000	0.752	0.000	0.977	0.000
d11	0.338	0.000	0.369	0.000	0.347	0.000
d12	0.280	0.344	0.384	0.088	0.638	0.000
d21	−0.002	0.716	−0.025	0.005	−0.010	0.266
d22	0.360	0.000	−0.154	0.093	0.039	0.611
H0: a21 = g21 = d21 = 0	12.471	0.006	27.932	0.000	7.108	0.069
H0: a12 = g12 = d12 = 0	24.476	0.000	26.022	0.000	63.574	0.000

Table 4. Cont.

Panel C: Return of consumer products sector and cryptocurrencies						
	SETCon-CI		SETCon-BTC		SETCon-ETH	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
c11	0.001	0.009	0.001	0.001	0.001	0.007
c21	0.004	0.189	0.001	0.840	0.002	0.572
c22	0.009	0.000	0.014	0.000	0.006	0.000
a11	0.224	0.000	0.226	0.000	0.231	0.000
a12	0.132	0.174	0.060	0.538	0.025	0.769
a21	0.011	0.020	0.005	0.409	0.011	0.024
a22	0.258	0.000	0.311	0.000	0.235	0.000
g11	0.973	0.000	0.974	0.000	0.971	0.000
g12	−0.043	0.084	−0.012	0.708	−0.023	0.234
g21	−0.003	0.092	−0.002	0.639	−0.002	0.182
g22	0.922	0.000	0.855	0.000	0.958	0.000
d11	0.045	0.316	0.031	0.549	−0.061	0.152
d12	0.673	0.000	0.688	0.001	−0.680	0.000
d21	0.003	0.696	0.001	0.846	0.000	0.953
d22	0.196	0.001	0.215	0.007	−0.098	0.017
H0: a21 = g21 = d21 = 0	5.477	0.140	0.805	0.848	5.737	0.125
H0: a12 = g12 = d12 = 0	21.159	0.000	13.733	0.003	53.816	0.000
Panel D: Return of financial sector and cryptocurrencies						
	SETFin-CI		SETFin-BTC		SETFin-ETH	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
c11	0.001	0.104	0.001	0.000	0.001	0.000
c21	0.001	0.951	−0.007	0.227	−0.001	0.533
c22	0.024	0.000	0.019	0.000	0.005	0.014
a11	0.257	0.000	0.195	0.000	0.182	0.000
a12	0.052	0.802	0.405	0.001	0.015	0.858
a21	0.005	0.458	−0.002	0.814	0.011	0.054
a22	0.264	0.000	0.417	0.000	0.235	0.000
g11	0.960	0.000	0.961	0.000	0.964	0.000
g12	0.026	0.721	0.040	0.449	−0.041	0.014
g21	−0.009	0.193	0.000	0.998	−0.001	0.567
g22	0.719	0.000	0.741	0.000	0.968	0.000
d11	0.177	0.003	−0.258	0.000	0.254	0.000
d12	1.061	0.000	−0.050	0.818	0.425	0.001
d21	0.005	0.618	0.005	0.595	−0.006	0.396
d22	0.440	0.000	0.128	0.320	−0.052	0.296
H0: a21 = g21 = d21 = 0	1.886	0.596	0.437	0.933	7.355	0.061
H0: a12 = g12 = d12 = 0	24.437	0.000	16.888	0.001	12.586	0.006
Panel E: Return of industrials sector and cryptocurrencies						
	SETIndu-CI		SETIndu-BTC		SETIndu-ETH	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
c11	0.002	0.000	0.001	0.000	0.001	0.000
c21	−0.006	0.188	0.003	0.589	0.000	0.772
c22	0.021	0.000	0.021	0.000	0.001	0.818
a11	0.236	0.000	0.203	0.000	0.165	0.000
a12	−0.070	0.677	−0.153	0.267	0.027	0.765
a21	−0.006	0.337	−0.007	0.447	0.010	0.012
a22	−0.338	0.000	0.292	0.000	0.199	0.000
g11	0.948	0.000	0.963	0.000	0.967	0.000
g12	0.046	0.497	0.006	0.908	−0.056	0.000
g21	0.001	0.858	−0.001	0.881	−0.001	0.315
g22	0.751	0.000	0.747	0.000	0.979	0.000

Table 4. Cont.

Panel E: Return of industrials sector and cryptocurrencies						
	SETIndu-CI		SETIndu-BTC		SETIndu-ETH	
	Estimate	<i>p</i> -value	Estimate	<i>p</i> -value	Estimate	<i>p</i> -value
d11	0.233	0.000	0.206	0.000	0.243	0.000
d12	0.734	0.000	0.674	0.000	0.486	0.000
d21	0.005	0.571	−0.012	0.357	−0.010	0.052
d22	0.375	0.000	0.263	0.001	−0.040	0.233
H0: a21 = g21 = d21 = 0	2.887	0.409	4.435	0.218	7.277	0.064
H0: a12 = g12 = d12 = 0	12.489	0.006	20.644	0.000	43.110	0.000
Panel F: Return of property and construction sector and cryptocurrencies						
	SETProp-CI		SETProp-BTC		SETProp-ETH	
	Estimate	<i>p</i> -value	Estimate	<i>p</i> -value	Estimate	<i>p</i> -value
c11	0.001	0.000	0.001	0.030	0.001	0.000
c21	0.003	0.461	0.007	0.264	0.001	0.396
c22	0.020	0.000	0.020	0.000	0.005	0.009
a11	0.154	0.000	0.166	0.000	0.157	0.000
a12	0.566	0.002	0.196	0.169	−0.011	0.933
a21	−0.004	0.596	0.009	0.312	0.011	0.004
a22	0.391	0.000	0.432	0.000	0.228	0.000
g11	0.957	0.000	0.953	0.000	0.957	0.000
g12	0.048	0.598	0.044	0.575	−0.066	0.020
g21	−0.006	0.204	−0.017	0.013	−0.002	0.057
g22	0.786	0.000	0.721	0.000	0.970	0.000
d11	0.286	0.000	0.309	0.000	0.282	0.000
d12	0.128	0.665	0.317	0.188	0.537	0.001
d21	0.009	0.100	0.012	0.143	−0.005	0.413
d22	0.269	0.012	0.195	0.031	−0.013	0.817
H0: a21 = g21 = d21 = 0	4.288	0.232	7.778	0.051	8.586	0.035
H0: a12 = g12 = d12 = 0	12.097	0.007	7.407	0.060	12.856	0.005
Panel G: Return of resources sector and cryptocurrencies						
	SETRes-CI		SETRes-BTC		SETRes-ETH	
	Estimate	<i>p</i> -value	Estimate	<i>p</i> -value	Estimate	<i>p</i> -value
c11	0.001	0.000	0.001	0.001	0.001	0.000
c21	−0.002	0.341	−0.002	0.720	0.000	0.873
c22	0.011	0.000	0.018	0.000	0.008	0.000
a11	0.169	0.000	0.183	0.000	0.161	0.000
a12	0.332	0.000	0.323	0.000	0.177	0.029
a21	−0.010	0.065	−0.019	0.014	−0.001	0.928
a22	0.301	0.000	0.351	0.000	0.251	0.000
g11	0.951	0.000	0.951	0.000	0.955	0.000
g12	−0.068	0.011	−0.032	0.472	−0.058	0.013
g21	0.005	0.031	0.011	0.099	0.001	0.725
g22	0.920	0.000	0.816	0.000	0.956	0.000
d11	0.326	0.000	0.292	0.000	0.302	0.000
d12	0.391	0.003	0.145	0.409	0.312	0.022
d21	−0.021	0.008	−0.001	0.923	0.005	0.520
d22	−0.122	0.035	−0.030	0.849	0.044	0.464
H0: a21 = g21 = d21 = 0	14.553	0.002	6.180	0.103	0.863	0.834
H0: a12 = g12 = d12 = 0	42.256	0.000	20.029	0.000	14.075	0.003

Table 4. Cont.

Panel H: Return of services sector and cryptocurrencies						
	SETSer-CI		SETSer-BTC		SETSer-ETH	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
c11	0.002	0.000	0.001	0.000	0.001	0.000
c21	−0.009	0.068	−0.002	0.610	0.002	0.281
c22	0.023	0.000	0.020	0.000	0.003	0.178
a11	0.243	0.000	−0.015	0.812	−0.039	0.311
a12	−0.329	0.103	0.375	0.003	−0.534	0.000
a21	−0.018	0.003	−0.014	0.078	0.012	0.016
a22	0.195	0.003	0.426	0.000	0.187	0.000
g11	0.935	0.000	0.955	0.000	0.961	0.000
g12	0.190	0.081	0.137	0.057	−0.073	0.001
g21	0.003	0.607	−0.002	0.814	−0.003	0.002
g22	0.729	0.000	0.736	0.000	0.972	0.000
d11	0.261	0.000	0.371	0.000	0.338	0.000
d12	0.771	0.002	0.270	0.215	0.348	0.022
d21	0.000	0.999	−0.009	0.350	0.006	0.323
d22	0.495	0.000	0.228	0.012	0.144	0.000
H0: a21 = g21 = d21 = 0	9.314	0.025	8.223	0.042	10.810	0.013
H0: a12 = g12 = d12 = 0	17.722	0.001	16.387	0.001	49.222	0.000
Panel I: Return of technology sector and cryptocurrencies						
	SETTech-CI		SETTech-BTC		SETTech-ETH	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
c11	0.006	0.000	0.005	0.000	0.005	0.000
c21	0.000	0.892	0.006	0.032	−0.005	0.221
c22	0.022	0.000	0.020	0.000	0.027	0.000
a11	0.421	0.000	0.408	0.000	0.389	0.000
a12	0.070	0.570	0.210	0.028	−0.146	0.205
a21	−0.026	0.109	−0.021	0.202	−0.007	0.538
a22	0.217	0.000	0.281	0.000	0.217	0.001
g11	0.815	0.000	0.846	0.000	0.848	0.000
g12	−0.139	0.308	−0.254	0.001	0.128	0.326
g21	0.015	0.358	−0.004	0.813	0.009	0.539
g22	0.772	0.000	0.727	0.000	0.695	0.000
d11	0.144	0.025	0.206	0.002	0.149	0.021
d12	0.676	0.000	0.674	0.000	1.168	0.000
d21	0.022	0.174	0.026	0.136	0.013	0.365
d22	0.459	0.000	0.383	0.000	0.362	0.000
H0: a21 = g21 = d21 = 0	6.669	0.083	5.331	0.149	2.387	0.496
H0: a12 = g12 = d12 = 0	15.982	0.001	21.890	0.000	35.257	0.000

Note: SET = Stock market return of Thailand; SETAgro = Return of the Agricultural and Food sector; SETCon = Return of the Consumer Products sector; SETFin = Return of the Financial sector; SETIndu = Return of the Industrials sector; SETProp = Return of the Property and Construction sector; SETRes = Return of the Resources sector; SETSer = Return of the Services sector; SETTech = Return of the Technology sector; CI = Return of the Cryptocurrency Index (CCi30); BTC = Return of Bitcoin; ETH = Return of Ethereum.

Regarding the ARCH effect between the return of the agricultural and food sector and cryptocurrency returns, the estimated values of both a12 and a21 of SETAgro-CI, SETAgro-BTC, and SETAgro-ETH pairs were statistically significant at the 5% level, indicating that there was bidirectional ARCH effect between SETAgro-CI, SETAgro-BTC, and SETAgro-ETH pairs at the 5% level. The estimated values of both g12 and g21 of SETAgro-CI and SETAgro-BTC were not significant at the 5% level, indicating that there was no significant GARCH effect between SETAgro-CI and SETAgro-BTC pairs at the 5% level. Only the estimated value of g12 for SETAgro-ETH was statistically at the 5% level,

indicating SETAgro has a one-way GARCH effect on ETH at the 5% level. In terms of the asymmetric effect, the estimated value of d_{12} for SETAgro-ETH was significant at the 5% level, indicating SETAgro has an asymmetric effect on ETH at the 5% level. The estimated values of d_{12} for SETAgro-CI and SETAgro-BTC were not significant at the 5% level, indicating that there was no significant asymmetric effect between SETAgro-CI and SETAgro-BTC pairs at the 5% level. The estimated value of d_{21} for SETAgro-BTC was significant at the 5% level, indicating that BTC has an asymmetric effect on SETAgro at the 5% level. The estimated values of d_{21} for SETAgro-CI and SETAgro-ETH were not significant at the 5% level, indicating that CI and ETH have no asymmetric effect on SETAgro at the 5% level. The p -value of the Wald test statistics for the SETAgro-CI and SETAgro-BTC pairs were all statistically significant at 5%, indicating that there was a bidirectional spillover effect between the SETAgro-CI and SETAgro-BTC pairs at the 5% level. In addition, the Wald tests rejected the null hypothesis “SETAgro does not have a unidirectional volatility spillover effect on ETH” at the 5% level but failed to reject the null hypothesis “ETH does not have a unidirectional volatility spillover effect on SETAgro” at the 5% level, indicating that there was a unidirectional volatility spillover effect from SETAgro on ETH at the 5% level (see Table 4, Panel B).

With respect to the ARCH effect between the return of the consumer products sector and cryptocurrencies, the estimated values of a_{12} for all the SETCon-CI, SETCon-BTC, and SETCon-ETH pairs were not statistically significant at the 5% level, indicating that there was no unidirectional ARCH effect of SETCon on cryptocurrencies at the 5% level. The estimated values of a_{21} for the SETCon-CI and SETCon-ETH pairs were statistically significant at the 5% level, indicating that there was a unidirectional ARCH effect from CI and ETH to SETCon at the 5% level, but the estimated value of a_{21} for the SETCon-BTC pair was not statistically significant at the 5% level, indicating that there was no unidirectional ARCH effect from BTC to SETCon at the 5% level. The estimated values of both g_{12} and g_{21} for all SETCon-CI, SETCon-BTC, and SETCon-ETH pairs were not statistically significant at the 5% level, indicating that there was no significant GARCH effect between the SETCon-CI, SETCon-BTC, and SETCon-ETH pairs at the 5% level. In terms of the asymmetric effect, the estimated values of d_{12} for SETCon-CI, SETCon-BTC, and SETCon-ETH were significant at the 5% level, indicating that SETCon has an asymmetric effect on CI, BTC, and ETH at the 5% level. The estimated values of d_{21} for all the SETCon-CI, SETCon-BTC, and SETCon-ETH pairs were not statistically significant at the 5% level, indicating that there was no significant asymmetric effect from cryptocurrencies on SETCon at the 5% level. The Wald tests reject the null hypothesis “SETCon does not have a unidirectional volatility spillover effect on CI, BTC, and ETH” at the 5% level, but fail to reject the null hypothesis “CI, BTC, and ETH do not have a unidirectional volatility spillover effect on SETCon” at the 5% level. These results suggest that the Consumer Products sector returns of Thailand have a pronounced impact on the volatility of specific cryptocurrencies, while the influence from cryptocurrencies to SETCon was not significant at the 5% level (see Table 4, Panel C).

In terms of the ARCH effect between the return of financial sector and Cryptocurrencies, the estimated values of a_{12} for SETFin-CI and SETFin-ETH pairs were not statistically significant at the 5% level, indicating that there was no unidirectional ARCH effect from SETFin to CI and ETH at the 5% level, but the estimated value of a_{12} for SETFin-BTC was statistically significant at the 5% level, indicating that there was a unidirectional ARCH effect from SETFin to BTC at the 5% level. The estimated values of a_{21} for all SETFin-CI, SETFin-BTC, and SETFin-ETH pairs were not statistically significant at the 5% level, indicating that there was no unidirectional ARCH effect from CI, BTC, and ETH to SETFin at the 5% level. The estimated values of both g_{12} and g_{21} of SETFin-CI and SETFin-BTC were not statistically significant at the 5% level, indicating that there was no significant GARCH

effect between SETFin-CI and SETFin-BTC pairs at the 5% level. Only the estimated value of g_{12} for SETFin-ETH was statistically significant at the 5% level, indicating a unidirectional GARCH effect from SETFin to ETH at the 5% level. In terms of the asymmetric effect, the estimated values of d_{12} for SETFin-CI and SETFin-ETH were significant at the 5% level, indicating SETFin has an asymmetric effect on CI and ETH at the 5% level. The estimated value of d_{12} for SETFin-BTC was not significant at the 5% level, indicating no significant asymmetric effect from SETFin to BTC at the 5% level. The estimated values of d_{21} for all SETFin-CI, SETFin-BTC, and SETFin-ETH pairs were not statistically significant at the 5% level, indicating that there was no significant asymmetric effect from cryptocurrencies to SETFin at the 5% level. The Wald tests rejected the null hypothesis “SETFin does not have a unidirectional volatility spillover effect on CI, BTC, and ETH” at the 5% level, but failed to reject the null hypothesis “CI, BTC, and ETH do not have a unidirectional volatility spillover effect on SETFin” at the 5% level. These results suggest that Thailand’s financial sector returns have a pronounced impact on the volatility of cryptocurrencies, while the influence of cryptocurrencies on SETFin was not significant at the 5% level (see Table 4, Panel D).

In terms of the ARCH effect between the return of the Industrials sector and Cryptocurrencies, the estimated values of a_{12} for all SETIndu-CI, SETIndu-BTC, and SETIndu-ETH were not statistically significant at the 5% level, indicating that there was no unidirectional ARCH effect from SETIndu to CI, BTC, and ETH at the 5% level. The estimated values of a_{21} for SETIndu-CI and SETIndu-BTC pairs were not statistically significant at the 5% level, indicating that there was no unidirectional ARCH effect from CI and BTC to SETIndu at the 5% level, but the estimated value of a_{21} for SETIndu-ETH was statistically significant at the 5% level, indicating that there was a unidirectional ARCH effect from ETH to SETIndu at the 5% level. The estimated values of both g_{12} and g_{21} for the SETIndu-CI and SETIndu-BTC pairs were not statistically significant at the 5% level, indicating that there was no significant GARCH effect for the SETIndu-CI and SETIndu-BTC pairs at the 5% level. Only the estimated value of g_{12} for SETIndu-ETH was statistically significant at the 5% level, indicating a unidirectional GARCH effect from SETIndu to ETH at the 5% level. In terms of the asymmetric effect, the estimated values of d_{12} for all the SETIndu-CI, SETIndu-BTC, and SETIndu-ETH pairs were significant at the 5% level, indicating that SETIndu has an asymmetric effect on CI, BTC, and ETH at the 5% level. The estimated values of d_{21} for all the SETIndu-CI, SETIndu-BTC, and SETIndu-ETH pairs were not statistically significant at the 5% level, indicating that there was no significant asymmetric effect of cryptocurrencies on SETIndu at the 5% level. The Wald tests rejected the null hypothesis “SETIndu does not have a unidirectional volatility spillover effect on CI, BTC, and ETH” at the 5% level, but failed to reject the null hypothesis “CI, BTC, and ETH do not have a unidirectional volatility spillover effect on SETIndu” at the 5% level. These results suggest that the industrials sector returns of Thailand have a pronounced impact on the volatility of cryptocurrencies, while the influence of cryptocurrencies on SETIndu was not statistically significant at the 5% level (see Table 4, Panel E).

In terms of the ARCH effect between the return of the property and construction sector and cryptocurrencies, the estimated value of a_{12} for SETProp-CI was statistically significant at the 5% level, indicating that there was a unidirectional ARCH effect from SETProp to CI at the 5% level, but the estimated values of a_{12} for SETProp-BTC and SETProp-ETH were not statistically significant at the 5% level, indicating that there was no unidirectional ARCH effect from SETProp to BTC and ETH at the 5% level. The estimated values of a_{21} for the SETProp-CI and SETProp-BTC pairs were not statistically significant at the 5% level, indicating that there was no unidirectional ARCH effect from CI and BTC to SETProp at the 5% level, but the estimated value of a_{21} for SETProp-ETH was statistically significant at the

5% level, indicating that there was a unidirectional ARCH effect from ETH to SETProp at the 5% level. In terms of the GARCH effect between the pairs, the estimated values of both g_{12} and g_{21} for SETProp-CI were not statistically significant at the 5% level, indicating that there was no significant GARCH effect between SETProp-CI at the 5% level. The estimated value of g_{12} for SETProp-BTC was not statistically significant at the 5% level, indicating that there was no significant GARCH effect from SETProp to BTC at the 5% level; however, the g_{21} for SETProp-BTC was statistically significant at the 5% level, indicating that there was a significant GARCH effect from BTC to SETProp at the 5% level. The estimated value of g_{12} for SETProp-ETH was statistically significant at the 5% level, indicating that there was a significant GARCH effect from SETProp to ETH at the 5% level, but g_{21} for SETProp-ETH was not statistically significant at the 5% level, indicating that there was no significant GARCH effect from ETH to SETProp at the 5% level. In terms of the asymmetric effect, the estimated values of d_{12} for SETProp-CI and SETProp-BTC pairs were not significant at the 5% level, indicating SETProp has no asymmetric effect on CI and BTC at the 5% level. The estimated value of d_{12} for SETProp-ETH was statistically significant at the 5% level, indicating a significant asymmetric effect from SETProp to ETH at the 5% level. The Wald tests rejected the null hypothesis “SETProp does not have a unidirectional volatility spillover effect on CI and ETH” at the 5% level, and rejected the null hypothesis “ETH does not have a unidirectional volatility spillover effect on SETProp” at the 5% level, but failed to reject the null hypothesis “CI and BTC do not have a unidirectional volatility spillover effect on SETProp” at the 5% level, and failed to reject the null hypothesis “SETProp does not have a unidirectional volatility spillover effect on BTC at the 5% level”. These results suggest a bidirectional influence between SETProp and Ethereum, indicating interconnectedness in their return volatilities (see Table 4, Panel F).

In terms of the ARCH effect between the return of the resources sector and cryptocurrencies, the estimated values of a_{12} for all the SETRes-CI, SETRes-BTC, and SETRes-ETH pairs were statistically significant at the 5% level, indicating that there was a unidirectional ARCH effect from SETRes to CI, BTC, and ETH at the 5% level. The estimated values of a_{21} for the SETRes-CI and SETRes-ETH pairs were not statistically significant at the 5% level, indicating that there was no unidirectional ARCH effect from CI and ETH to SETRes at the 5% level, but the estimated value of a_{21} for SETRes-BTC was statistically significant at the 5% level, indicating that there was a unidirectional ARCH effect from BTC to SETRes at the 5% level. The estimated values of both g_{12} and g_{21} for SETRes-CI were statistically significant at the 5% level, indicating a significant bidirectional GARCH effect for SETRes-CI at the 5% level. The estimated value of g_{12} for SETRes-ETH was statistically significant at the 5% level, indicating a significant unidirectional GARCH effect from SETRes to ETH at the 5% level. In terms of the asymmetric effect, the estimated values of both d_{12} and d_{21} for SETRes-CI were significant at the 5% level, indicating that there was a bidirectional asymmetric effect for SETRes-CI at the 5% level. The estimated value of d_{12} for SETRes-ETH was statistically significant at the 5% level, indicating a significant asymmetric effect from SETRes to ETH at the 5% level. The Wald tests rejected the null hypothesis “SETRes does not have a unidirectional volatility spillover effect on CI, BTC, and ETH” at the 5% level, and rejected the null hypothesis “CI does not have a unidirectional volatility spillover effect on SETRes” at the 5% level, but failed to reject the null hypothesis “BTC and ETH do not have a unidirectional volatility spillover effect on SETRes” at the 5% level. These results suggest a notable influence of the resources sector on cryptocurrencies, particularly on the Cryptocurrency Index, Bitcoin, and Ethereum at the 5% significance level (see Table 4, Panel G).

In terms of the ARCH effect between the return of the services sector and cryptocurrencies, the estimated values of a_{12} for the SETSer-BTC and SETSer-ETH pairs were statistically

significant at the 5% level, indicating that there was a unidirectional ARCH effect from SETSer to BTC and ETH at the 5% level, but the estimated value of a_{12} for SETSer-CI was not statistically significant at the 5% level, indicating that there was no unidirectional ARCH effect from SETSer to CI at the 5% level. The estimated values of a_{21} for the SETSer-CI and SETSer-ETH pairs were statistically significant at the 5% level, indicating that there was a unidirectional ARCH effect from CI and ETH to SETSer at the 5% level, but the estimated value of a_{21} for SETSer-BTC was not statistically significant at the 5% level, indicating that there was no unidirectional ARCH effect from BTC to SETSer at the 5% level. The estimated value of g_{12} for SETSer-ETH was statistically significant at the 5% level, indicating a significant unidirectional GARCH effect from SETSer to ETH at the 5% level. The estimated values of g_{12} for SETSer-CI and SETSer-BTC were not statistically significant at the 5% level, indicating no significant unidirectional GARCH effect from SETSer to CI and BTC at the 5% level. In terms of the asymmetric effect, the estimated values of d_{12} for the SETSer-CI and SETSer-ETH pairs were significant at the 5% level, indicating that there was a unidirectional asymmetric effect from SETSer to CI and ETH at the 5% level. The estimated value of d_{12} for SETSer-BTC was not statistically significant at the 5% level, indicating no significant asymmetric effect from SETSer to BTC at the 5% level. The estimated values of d_{21} for SETSer-CI, SETSer-BTC, and SETSer-ETH were not statistically significant at the 5% level, indicating that there was no significant asymmetric effect from CI, BTC, and ETH to SETSer at the 5% level. The Wald tests rejected the null hypothesis “SETSer does not have a unidirectional volatility spillover effect on CI, BTC, and ETH” at the 5% level, and rejected the null hypothesis “CI, BTC, and ETH do not have a unidirectional volatility spillover effect on SETRes” at the 5% level, indicating that there was a significant bidirectional volatility spillover effect between cryptocurrencies and SETRes at the 5% level (see Table 4, Panel H).

In terms of the ARCH effect between the return of the technology sector and cryptocurrencies, the estimated values of a_{12} for the SETTech-CI and SETTech-ETH pairs were not statistically significant at the 5% level, indicating that there was no unidirectional ARCH effect from SETTech to CI and ETH at the 5% level, but there was a unidirectional ARCH effect from SETTech to BTC at the 5% level. The estimated values of g_{12} for the SETTech-CI and SETTech-ETH pairs were not statistically significant at the 5% level, indicating that there was no unidirectional GARCH effect from SETTech to CI and ETH at the 5% level, but there was a unidirectional GARCH effect from SETTech to BTC at the 5% level. In terms of the asymmetric effect, the estimated values of d_{12} for the SETTech-CI, SETTech-BTC, and SETTech-ETH pairs were significant at the 5% level, indicating that there was a unidirectional asymmetric effect from SETTech to CI, BTC, and ETH at the 5% level. The estimated values of d_{21} for all the SETTech-CI, SETTech-BTC, and SETTech-ETH pairs were not significant at the 5% level, indicating that there was no significant asymmetric effect from CI, BTC, or ETH on SETTech at the 5% level. The Wald tests rejected the null hypothesis “SETTech does not have a unidirectional volatility spillover effect on CI, BTC, and ETH” at the 5% level, but failed to reject the null hypothesis “CI, BTC, and ETH do not have a unidirectional volatility spillover effect on SETTech” at the 5% level. These results indicate a unidirectional influence, with the technology sector influencing the volatility of cryptocurrencies at the 5% level. However, there was no significant evidence of volatility spillover from cryptocurrencies to the technology sector at the 5% level (see Table 4, Panel I).

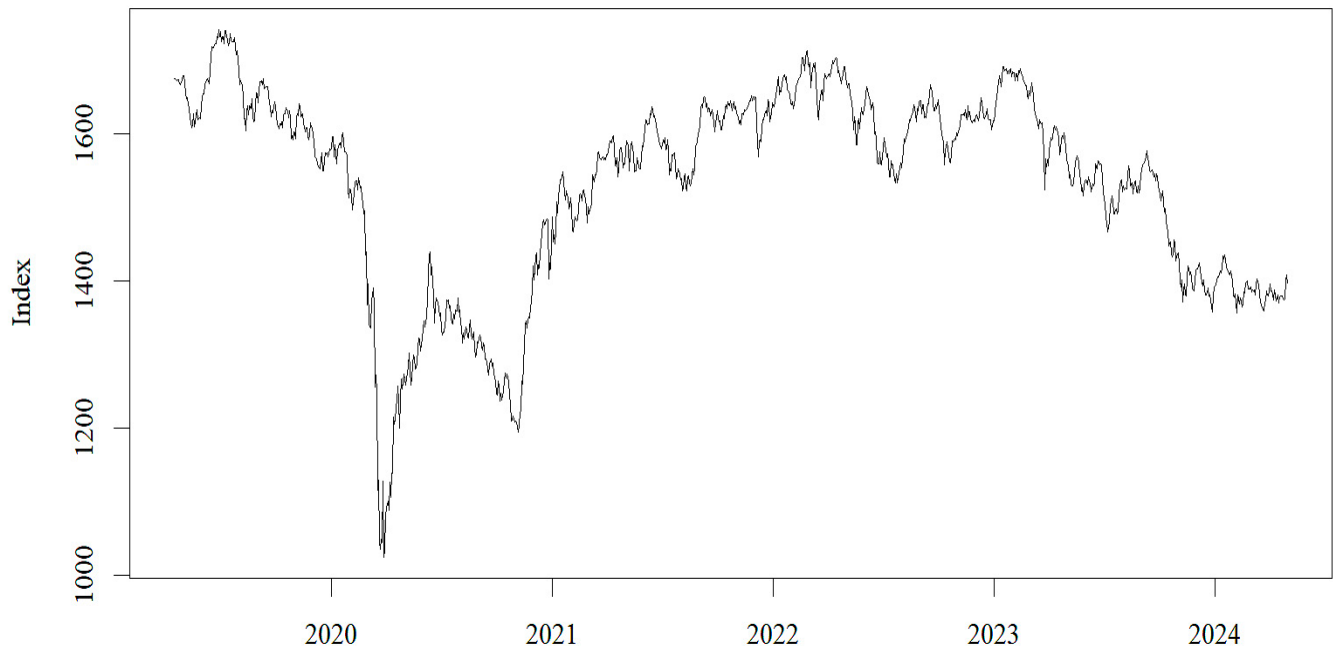
4. Materials and Methods

4.1. Data

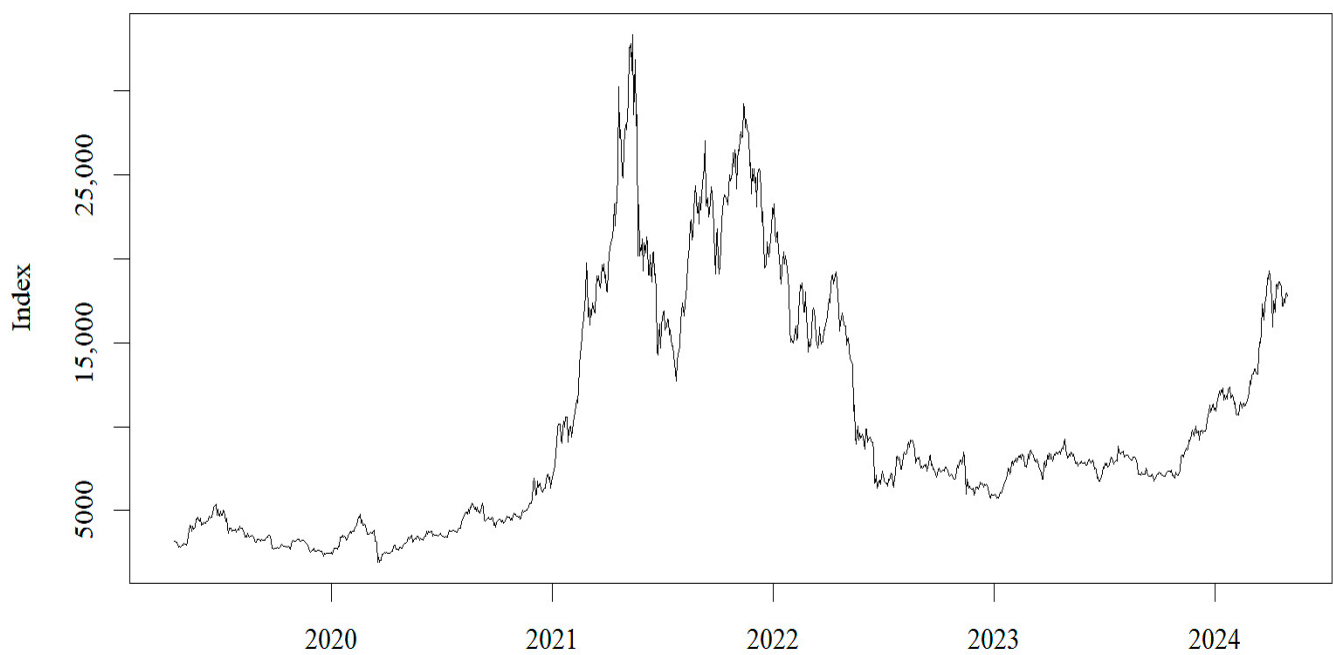
To investigate the mean and volatility spillover effects between cryptocurrencies and the Thai stock market indices, regarding cryptocurrencies, this research considers the Cryptocurrency Market Index, Bitcoin, and Ethereum. For samples of equities, this research selects the Stock Exchange of Thailand (SET) index and the eight key Thai stock sectoral indices. Based on the data availability from the database, each studied asset includes 1211 daily observations, and the study period is from 18 April 2019 to 11 April 2024.

The study period (18 April 2019 to 11 April 2024) was adequately selected because these 5 years comprehensively reflect the key aggregate or global events, such as the COVID-19 pandemic and the Russia–Ukraine conflict. The COVID-19 pandemic is the major aggregate or global shock during the study period. The study period also encompasses other important aggregate or global events like the Russia–Ukraine conflict, which brought further uncertainty and volatility to global financial markets. These aggregate or global shocks affected international financial markets at different stages; thus, the study period can provide nuanced empirical evidence of the spillover effect mechanisms between financial assets. As illustrated in Figure 1, because of the influence of the COVID-19 pandemic on the economic fundamentals and investor sentiments in Thailand, the Stock Exchange of Thailand (SET) index experienced a sharp decrease in early 2020, followed by a gradual recovery and continued fluctuation multiple times. In contrast, the Cryptocurrency Market Index exhibited extremely high volatility over the study period. The Cryptocurrency Market Index before 2021 was relatively lower and less fluctuated; however, after 2021, the Cryptocurrency Market Index experienced a sharp increase and reached an all-time high point and then experienced fluctuation over time. It is important to notice that from 2023 to 2024, while the Stock Exchange of Thailand (SET) index revealed a declining trend, the Cryptocurrency Market Index demonstrated an increasing trend. Overall, the figure highlights the potential of the mean and volatility spillover effects between the Stock Exchange of Thailand (SET) index and the Cryptocurrency Market Index. These observed indices' fluctuation across different crises and recovery phases provides a comprehensive foundation for examining the mean and volatility spillover effects between the Stock Exchange of Thailand (SET) index and the Cryptocurrency Market Index.

Figure 2 illustrates the daily natural logarithm returns for the Thai stock market indices and major cryptocurrencies from 18 April 2019 to 11 April 2024. This study period covers key aggregate or global events such as the COVID-19 pandemic and the Russia–Ukraine conflict, which provides a comprehensive foundation for studying the mean and volatility spillover effects between different financial assets. The study period begins in early 2019, which represents a baseline period prior to the COVID-19 pandemic. Apart from the key global shock of the COVID-19 pandemic, this study also covers another key event, the Russia–Ukraine conflict, which further contributes to international financial market fluctuations. As the figure shows, regarding the daily natural logarithm returns for the Thai stock market indices, all the returns for the Thai stock market indices exhibited a volatility clustering pattern over the study period. All the returns for the Thai stock market indices experienced extreme fluctuation at the beginning of 2020, after the COVID-19 pandemic. The returns for the technology sector show multiple sharp fluctuations over the study period, highlighting that it is sensitive to global shocks such as COVID-19 and the Russia–Ukraine conflict. Regarding the returns series of the cryptocurrencies, all the return series of the Cryptocurrency Index (CCi30), Bitcoin, and Ethereum experienced extreme fluctuations over the study period.



(a) Index of Stock Exchange of Thailand



(b) Index of Cryptocurrency Market: CCI30

Figure 1. Index of the Stock Exchange of Thailand and Cryptocurrency Market (CCI30).

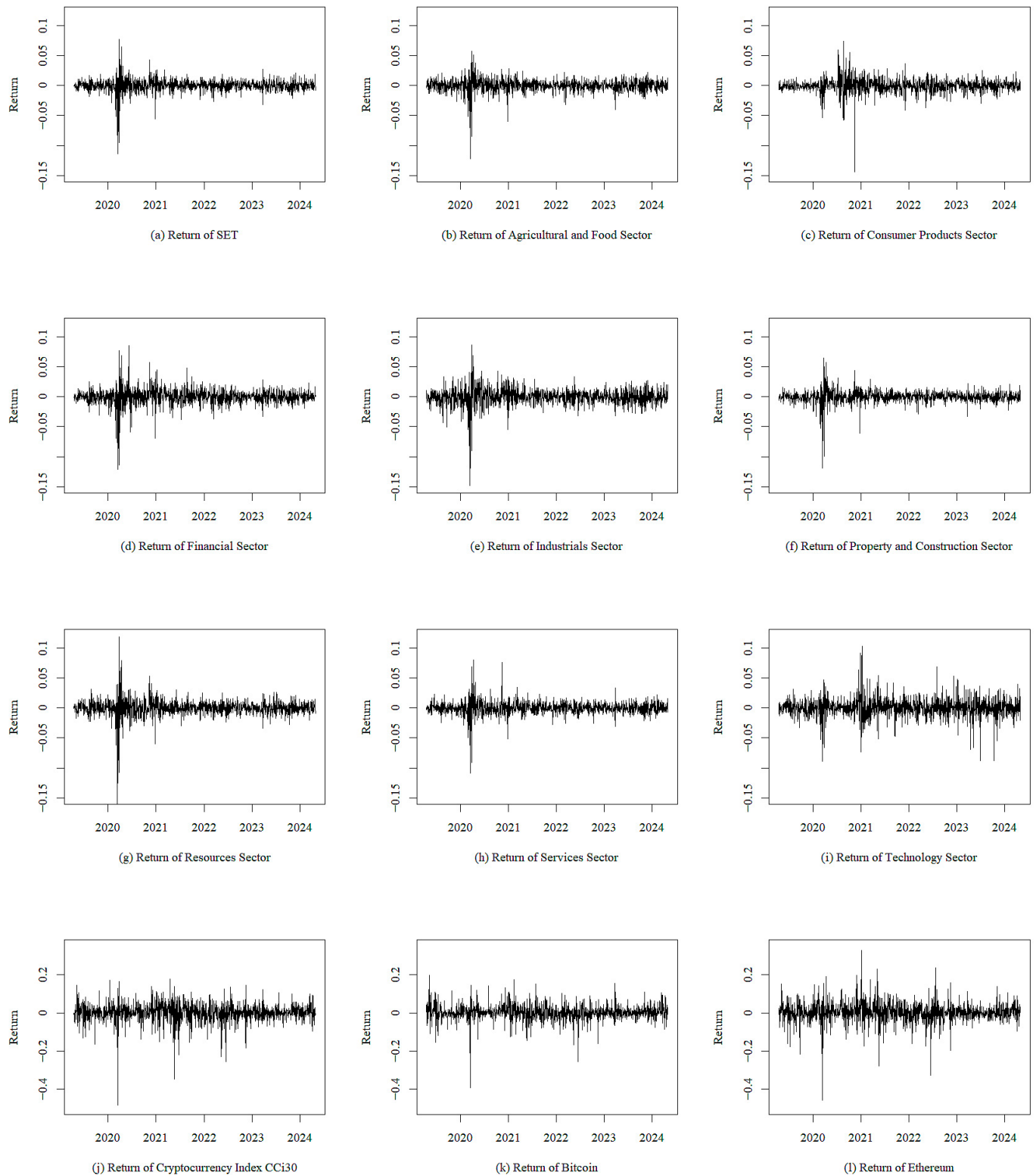


Figure 2. Daily return series of Thai stock market and major cryptocurrencies.

All the data on the assets are reported on a daily basis. Daily data are available for cryptocurrency, including the Cryptocurrency Market Index, Bitcoin, and Ethereum. Bitcoin is the largest cryptocurrency according to market capitalization, and Ethereum is the second largest cryptocurrency according to market capitalization; Ethereum is the largest Altcoin. Thus, Bitcoin and Ethereum are included in this research.

The Cryptocurrency Index CCI30 is also included in this study because the CCI30 index is created to gauge the overall growth and movement of the cryptocurrency market. Including the top 30 largest cryptocurrencies by market capitalization provides researchers with a reliable and standardized benchmark to assess the performance of the cryptocurrency market.

Based on data availability, and since the research context is in Thailand, the prices for Bitcoin and Ethereum are denominated in Thai Baht to reflect the situation in Thailand better. The cryptocurrency closing price data were sourced from Orbix (Satang), a leading cryptocurrency exchange in Thailand. The historical data for the CCI30 index were obtained from CCI30.com. All daily data for the Thai stock market indices are obtained from the Stock Exchange of Thailand (Stock Exchange of Thailand 2024b).

The daily closing price natural logarithm returns of the assets i , $r_{i,t}$, are defined as follows:

$$r_{i,t} = \frac{\ln(p_{i,t})}{\ln(p_{i,t-1})} = \ln(p_{i,t}) - \ln(p_{i,t-1}) \quad (1)$$

where $p_{i,t}$ is the price or index of the asset i on time t .

4.2. Bivariate Vector Autoregressive Model—VAR (1) Model

The bivariate VAR (1) model is the conditional mean equation, and the matrix form of the bivariate VAR (1) model can be expressed as follows:

$$\begin{bmatrix} r_{1,t} \\ r_{2,t} \end{bmatrix} = \begin{bmatrix} a_{01} \\ a_{02} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \times \begin{bmatrix} r_{1,t-1} \\ r_{2,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} \quad (2)$$

where $r_{1,t}$ and $r_{2,t}$ are the returns of asset 1 and asset 2 at time t , a_{01} and a_{02} are the constants or intercept terms, the β_{11} coefficient measures the impact of the return of the first asset at time $t - 1$ on its return at time t , the β_{12} coefficient measures the impact or the mean spillover effect of the return of the second asset at time $t - 1$ on the return of the first asset at time t , the β_{21} coefficient measures the impact or the mean spillover effect of the return of the first asset at time $t - 1$ on the return of the second asset at time t , the β_{22} coefficient measures the impact of the return of the second asset at time $t - 1$ on its return at time t , and $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are the error terms of at time t .

4.3. BEKK GARCH Model with Asymmetry

The BEKK GARCH model of Engle and Kroner (1995) was applied. In addition, the asymmetric effect term of Kroner and Ng (1998) was also considered. The asymmetry effect refers to the phenomenon where adverse shocks (e.g., market downturns) have a greater impact on volatility than positive shocks (e.g., market upturns) of the same magnitude. This is often attributed to investor behavior, as market participants tend to react more strongly to bad news, leading to higher volatility. The BEKK GARCH model with asymmetry is the conditional variance equation. The BEKK GARCH model with asymmetry can be expressed as follows:

$$H_t = CC' + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + G'H_{t-1}G + D'v_{t-1}v'_{t-1}D \quad (3)$$

Further, after matrix multiplication and addition, the BEKK GARCH model with asymmetry can be expressed as three main equations, as follows:

$$h_{11,t} = c_{11}^2 + a_{11}^2 \varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1} + a_{21}^2 \varepsilon_{2,t-1}^2 + g_{11}^2 h_{11,t-1} + 2g_{11}g_{21}h_{21,t-1} + g_{21}^2 h_{22,t-1} + d_{11}^2 v_{1,t-1}^2 + 2d_{11}d_{21}v_{1,t-1} + d_{21}^2 v_{2,t-1}^2 \quad (4)$$

$$\begin{aligned}
h_{12,t} = h_{21,t} = & c_{11}c_{21} + a_{11}a_{12}\varepsilon_{1,t-1}^2 + (a_{11}a_{22} + a_{12}a_{21})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}a_{22}\varepsilon_{2,t-1}^2 \\
& + g_{11}g_{12}h_{11,t-1} + (g_{11}g_{22} + g_{12}g_{21})h_{12,t-1} + g_{21}g_{22}h_{22,t-1} \\
& + d_{11}d_{12}v_{1,t-1}^2 + (d_{11}d_{22} + d_{12}d_{21})v_{1,t-1}v_{2,t-1} \\
& + d_{21}d_{22}v_{2,t-1}^2
\end{aligned} \quad (5)$$

$$\begin{aligned}
h_{22,t} = & c_{21}^2 + c_{22}^2 + a_{12}^2\varepsilon_{1,t-1}^2 + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{22}^2\varepsilon_{2,t-1}^2 + g_{12}^2h_{11,t-1} + 2g_{12}g_{22}h_{12,t-1} + g_{22}^2h_{22,t-1} \\
& + d_{12}^2v_{1,t-1}^2 + 2d_{12}d_{22}v_{1,t-1}v_{2,t-1} + d_{22}^2v_{2,t-1}^2
\end{aligned} \quad (6)$$

H_t is the dynamic conditional or time-varying variance-covariance matrix between asset 1 and asset 2 for a bivariate BEKK GARCH model, $h_{11,t}$ stands for the dynamic conditional or time-varying variance of asset 1, $h_{22,t}$ stands for the dynamic conditional or time-varying variance of asset 2, and $h_{12,t} = h_{21,t}$, which stands for the dynamic conditional or time-varying covariance between asset 1 and asset 2.

In addition, to better understand the direction of the volatility spillover effect between asset 1 and asset 2, we conducted a Wald test based on estimated coefficients from BEKK-GARCH with an asymmetry model. In terms of the direction of the volatility spillover effect from asset 1 to asset 2, the null hypothesis is $a_{12} = g_{12} = d_{12} = 0$. Regarding the direction of the volatility spillover effect from asset 2 to asset 1, the null hypothesis is $a_{21} = g_{21} = d_{21} = 0$. If the p -value of the Wald test statistic is less than 5%, reject the null hypothesis.

This research selected the VAR (1)-BEKK-GARCH (1,1) with asymmetry as the econometric model to investigate the mean and volatility spillover effects between stock and cryptocurrency because the VAR (1)-BEKK-GARCH (1,1) with asymmetry has the conditional mean equation to directly capture the mean spillover effects between stock and cryptocurrency and also the conditional variance equation to capture the volatility spillover effects between stock and cryptocurrency directly. Other multivariate GARCH models, like the DCC-GARCH model, estimate the conditional correlations and conditional covariances separately according to their frameworks, failing to capture the volatility spillover effects between stock and cryptocurrency directly. The BEKK-GARCH model ensures a positive-definite variance-covariance matrix by combining variance and covariance dynamics into one framework. Additionally, the BEKK-GARCH model allows for the Wald test to be conducted on the combined significance of volatility spillover effects, representing a robust test for the significance of volatility spillover effects between stock and cryptocurrency. Moreover, previous financial research papers have successfully applied VAR (1)-BEKK-GARCH (1,1) with asymmetry to investigate mean and volatility spillovers between financial assets (Özdemir and Bilgiç 2023; Wang et al. 2019; Wang et al. 2023; Yu et al. 2020). Furthermore, empirical research has revealed that the VAR-BEKK-GARCH model showed better goodness-of-fit and robustness compared to other multivariate GARCH models such as CCC-GARCH, DCC-GARCH, and E-GARCH (Maharana et al. 2024). Therefore, given the advantages discussed, the VAR (1)-BEKK-GARCH (1,1) with asymmetry model was selected to investigate the mean and volatility spillover effects between stock and cryptocurrency.

5. Discussion

This study provides empirical evidence of mean and volatility spillover effects between the cryptocurrency and stock markets in Thailand.

Regarding the mean spillover effect, the results indicate that all the studied cryptocurrencies, including the Cryptocurrency Market Index, Bitcoin, and Ethereum, had a positive and significant mean spillover effect on the Stock Exchange of Thailand (SET) in terms of returns. However, the return of the SET did not exhibit a significant mean spillover effect on any of the cryptocurrencies. Specifically, this research revealed that the mean spillover effect was strongest from the Cryptocurrency Market Index, followed by

Ethereum and Bitcoin. This mean spillover effect pattern may be attributed to the fact that cryptocurrency market capitalization was larger than that of the Thai stock market. These mean spillover effect findings align with [Uzonwanne \(2021\)](#) and [Elsayed et al. \(2022\)](#), who also found evidence of the return spillovers between cryptocurrencies and equities. However, the result reporting a significant mean spillover effect from cryptocurrencies to stock is different from the findings of [Wang et al. \(2019\)](#), who did not find a significant mean spillover effect between cryptocurrency and stock. The variation in the findings compared with the previous literature highlights the fact that during financial crises or uncertain times, the spillovers among different financial assets generally increase sharply ([Diebold and Yilmaz 2012](#)).

The findings of the mean spillover effects between the Thai equity sectoral indices and cryptocurrencies represent the novel contribution of this article. This research revealed that the mean spillover effect mechanism between different equity sectors and cryptocurrencies was varied. The mean spillover effects on sectoral analysis revealed that all the cryptocurrencies studied had a stronger positive mean spillover effect on the returns of the technology and industrials sectors. The magnitude of the mean spillover effects from cryptocurrencies to sectors like consumer products, finance, property and construction, and resources was relatively lower. However, this research revealed that all studied cryptocurrencies exerted insignificant mean spillover effects on the agricultural and food sector. This could be because the price movement of the agricultural and food sector is mainly affected by factors such as pesticide and fertilizer prices, weather conditions, and agricultural policies. In addition, this research found that the cryptocurrency market index and Bitcoin exerted insignificant mean spillover effects on the service sectors, but Ethereum exerted a statistically significant mean spillover effect on the service sector. Ethereum, the second largest cryptocurrency with decentralized finance and smart contracts, is more relevant to service-based industries. The varied findings of the mean spillover effects among equity sectors could be explained by differences in the magnitude of market capitalization, sectoral-specific characteristics, and aggregate or global shocks such as the COVID-19 pandemic and the Russia–Ukraine conflict. Equity sectors, such as industrial and technology, are more globally integrated and innovation-driven. The industrial and technology sectors may be more susceptible to speculative capital flows from cryptocurrency markets, leading to stronger mean spillover effects from external shocks. The stability of the traditional equity sectors such as consumer products, finance, property and construction, and resources stems from their reliance on domestic economic conditions rather than external shocks.

For volatility spillover effects, the findings revealed that volatility spillover effects dominantly transferred from stock to cryptocurrency. As a part of the global stock market, the Thai stock market exerted a significant volatility spillover effect on cryptocurrency. These findings are consistent with [Symitsi and Chalvatzis \(2018\)](#), who found spillover effects from traditional stock markets to Bitcoin, but different from [Wang et al. \(2019\)](#), who did not find a significant volatility spillover effect between cryptocurrency and stock.

The volatility spillover effect mechanism found in this study aligns with the mechanism that aggregate or global shocks increase interaction among different financial assets. [Forbes and Rigobon \(2002\)](#) demonstrated that aggregate or global events such as international capital supply fluctuations, increases in international interest rates, or decreases in international demand can disrupt economic fundamentals in multiple countries. Equity markets in any country affected by such aggregate or global shock will move in the same direction to some extent, so cross-market integration between affected countries will increase after the aggregate or global shock. The COVID-19 pandemic can be treated as a typical example of aggregate or global shock. During the COVID-19 pandemic, international

travel restrictions, increases in international inflation rates, rises in international interest rates, and declines in international demand disrupted economic fundamentals in every country globally. In times of financial uncertainty, investors re-evaluate their portfolio risk exposures, leading to capital flows fluctuating across different financial asset categories. These fluctuating capital movements increased financial asset interactions (Bouri et al. 2022; Yousaf and Yarovaya 2021).

Furthermore, the sectoral analysis revealed that the consumer products, financial, industrial, and technology sectors exhibited volatility spillover patterns similar to SET, whereas the service sector demonstrated bidirectional volatility spillovers with cryptocurrencies (Cryptocurrency Market Index, Bitcoin, and Ethereum). This aligns with Vardar and Aydogan (2019), who observed bidirectional spillovers between Bitcoin and conventional financial assets in emerging countries. The bidirectional linkage in Thailand's service sector may reflect the country's tourism-dependent economy, where businesses responded to pandemic-related revenue declines by adjusting their investment strategies, amplifying cross-market volatility spillovers.

The findings of the asymmetric effects of positive and negative shocks between the emerging equity sectoral indices and cryptocurrency are the novel contribution of this article. The findings reveal that the SET Index, financial, and service sectors exhibited unidirectional asymmetry effects of positive and negative shocks on cryptocurrencies such as the Cryptocurrency Index and Ethereum. However, the SET Index, financial, and service sectors did not exhibit unidirectional asymmetry effects of positive or negative shocks on Bitcoin. In addition, unidirectional asymmetry effects of positive and negative shocks were observed in the consumer products, industrials, and technology sectors and in cryptocurrencies. Notably, the resources sector exerted a bidirectional asymmetry effect of positive and negative shocks with the Cryptocurrency Index. These varied findings reveal the specific sectoral differences in the transmission mechanisms of asymmetric positive and negative shocks between cryptocurrency and equity sectoral indices. These findings align with prior research demonstrating the presence of asymmetric effects between cryptocurrencies and traditional financial assets (Bouri et al. 2018; Cao and Xie 2022; Hsu et al. 2021; Kurka 2019). Specifically, Symitsi and Chalvatzis (2018) revealed the presence of asymmetric effects of positive and negative shocks between equity and cryptocurrency. In addition, Hsu et al. (2021) found that after 2020, spillover effects between cryptocurrencies and traditional financial instruments became more asymmetric, with negative return shocks exerting a greater influence on volatility than positive return shocks. This phenomenon may be driven by investor sentiment and market reactions to negative financial news, which tend to increase volatility spillovers among different financial assets.

6. Conclusions

This article investigated the mean and volatility spillover effects between the Thai stock market and major cryptocurrencies. The findings reveal significant mean and volatility spillover effects between cryptocurrencies and the Thai stock market. Regarding the mean spillover effects, cryptocurrencies exerted a statistically significant mean spillover effect on the Thai stock market. In contrast, volatility spillovers were dominantly from the Thai stock market to cryptocurrencies. The asymmetry effect followed a similar pattern, with the stock market exerting a stronger asymmetric influence on cryptocurrencies. Sectoral analysis revealed varying degrees of mean and volatility spillovers across different industries.

Investors need to carefully consider cryptocurrency's spillover effect on the stock market to make better risk and portfolio management decisions. While cryptocurrencies offer high returns, their substantial volatility requires adequate strategies to reduce portfolio risks, such as asset diversification, clear investment goals, and stop-loss limits. The stronger

positive mean spillover effects from cryptocurrency to industrial and technology sectors highlight the need to control cryptocurrency allocation to reduce portfolio risks. The weaker volatility spillovers in consumer products and financial sectors make them potential hedges. The agricultural and food sector provides stability during global uncertainty, while the service sector's bidirectional volatility spillovers, linked to Thailand's tourism-driven economy, require cautious exposure. Sector-specific investment strategies and due diligence can help balance portfolio risk and return. For policymakers, the results of this study highlight the need to establish a stringent regulatory framework in emerging economies such as Thailand. To reduce market manipulation and systemic financial risks, transparent information disclosure requirements for cryptocurrency exchanges must be strengthened, stricter capital adequacy requirements should be formulated, and financial institutions should be encouraged to improve risk disclosure transparency. In addition, anti-money laundering mechanisms should be strengthened, and the integration and application of blockchain technology in the financial system and public management should be promoted with the help of the "regulatory sandbox" mechanism while ensuring the effectiveness of supervision to balance the relationship between regulation and innovation. At the same time, attention should be paid to public education and financial literacy, and investor education and publicity activities should be carried out to enhance investors' understanding of crypto assets and risk management capabilities to promote the healthy and sustainable development of the market.

Although this study provides valuable insights into the mean and volatility spillover effects between cryptocurrencies and the Thai stock market, the research does have some limitations. Firstly, the study period presents a limitation in that the research time range is from April 2019 to April 2024. Although this study period covers several key aggregate or global events, this period may not fully reflect longer-term structural changes or extreme market shocks. Therefore, future studies may consider extending the sample period or introducing high-frequency (such as intraday) data to obtain more detailed dynamic feature analysis. Secondly, in terms of method selection, although this study uses the asymmetric VAR (1)-BEKK-GARCH (1,1) model to capture the mean and volatility spillover effects between cryptocurrency and stock, future studies could try to use other advanced econometric models such as the time-varying parameter vector autoregression model (TVP-VAR) or Copula-based methods to comprehensively capture nonlinear dependencies and tail risk spillover effects between cryptocurrencies and stock. Thirdly, this study selected Thailand as a representative of the emerging market, and future studies could conduct similar mean and volatility spillover effect research in other emerging markets. Finally, since the cryptocurrency market develops continuously, future studies should include alternative crypto assets such as stablecoins and decentralized financial tokens to comprehensively analyze their potential mean and volatility spillover effect on other financial assets.

Author Contributions: Conceptualization, Y.Z., S.-t.L. and D.S.; methodology, Y.Z.; software, Y.Z.; validation, Y.Z., S.-t.L. and D.S.; formal analysis, Y.Z.; investigation, Y.Z.; resources, Y.Z., S.-t.L. and D.S.; data curation, Y.Z.; writing—original draft preparation, Y.Z.; writing—review and editing, Y.Z., S.-t.L. and D.S.; supervision, S.-t.L. and D.S.; project administration, S.-t.L. and D.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data that support the findings of this study are available on request from the corresponding author due to privacy reason.

Acknowledgments: The authors would like to express sincere gratitude to the reviewers and editors for their insightful comments and valuable suggestions, which have significantly contributed to improving the quality and clarity of this article.

Conflicts of Interest: The authors declare no conflicts of interest.

References

- Alkan, Buket, and Serkan Çiçek. 2020. Spillover effect in financial markets in Turkey. *Central Bank Review* 20: 53–64. [CrossRef]
- Anamika, Madhumita Chakraborty, and Sowmya Subramaniam. 2021. Does Sentiment Impact Cryptocurrency? *Journal of Behavioral Finance* 24: 202–18. [CrossRef]
- Antonakakis, Nikolaos, Ioannis Chatziantoniou, and David Gabauer. 2019. Cryptocurrency market contagion: Market uncertainty, market complexity, and dynamic portfolios. *Journal of International Financial Markets Institutions and Money* 61: 37–51. [CrossRef]
- Aydoğan, Berna, Gülin Vardar, and Caner Taçoğlu. 2022. Volatility spillovers among G7, E7 stock markets and cryptocurrencies. *Journal of Economic and Administrative Sciences* 40: 364–87. [CrossRef]
- Bouri, Elie, Ladislav Kristoufek, and Nehme Azoury. 2022. Bitcoin and SandP500: Co-movements of high-order moments in the time-frequency domain. *PLoS ONE* 17: e0277924. [CrossRef]
- Bouri, Elie, Mahamitra Das, Rangan Gupta, and David Roubaud. 2018. Spillovers between Bitcoin and other assets during bear and bull markets. *Applied Economics* 50: 5935–49. [CrossRef]
- Cao, Guangxi, and Wenhao Xie. 2022. Asymmetric dynamic spillover effect between cryptocurrency and China's financial market: Evidence from TVP-VAR based connectedness approach. *Finance Research Letters* 49: 103070. [CrossRef]
- Choi, Sun-Yong. 2022. Volatility spillovers among Northeast Asia and the US: Evidence from the global financial crisis and the COVID-19 pandemic. *Economic Analysis and Policy* 73: 179–93. [CrossRef]
- Corbet, Shaen, Andrew Meegan, Charles Larkin, Brian Lucey, and Larisa Yarovaya. 2018. Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters* 165: 28–34. [CrossRef]
- Diebold, Francis X., and Kamil Yilmaz. 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting* 28: 57–66. [CrossRef]
- Elsayed, Ahmed H., Giray Gozgor, and Chi Keung Marco Lau. 2022. Risk transmissions between bitcoin and traditional financial assets during the COVID-19 era: The role of global uncertainties. *International Review of Financial Analysis* 81: 102069. [CrossRef]
- Engle, Robert F., and Kenneth F. Kroner. 1995. Multivariate Simultaneous Generalized ARCH. *Econometric Theory* 11: 122–50. [CrossRef]
- Forbes, Kristen J., and Roberto Rigobon. 2002. No contagion, only interdependence: Measuring stock market comovements. *Journal of Finance* 57: 2223–61. [CrossRef]
- Gaies, Brahim, Mohamed Sahbi Nakhli, Jean Michel Sahut, and Khaled Guesmi. 2021. Is Bitcoin rooted in confidence? Unraveling the determinants of globalized digital currencies. *Technological Forecasting and Social Change* 172: 121038. [CrossRef]
- He, Pinglin, Yulong Sun, Ying Zhang, and Tao Li. 2021. COVID-19's impact on stock prices across different sectors—An event study based on the Chinese stock market. *Emerging Markets Finance and Trade* 56: 2198–212. [CrossRef]
- Hsu, Shu-Han, Chwen Sheu, and Jiho Yoon. 2021. Risk spillovers between cryptocurrencies and traditional currencies and gold under different global economic conditions. *The North American Journal of Economics and Finance* 57: 101443. [CrossRef]
- Joshi, Prashant, Jinghua Wang, and Michael Busler. 2022. A Study of the Machine Learning Approach and the MGARCH-BEKK Model in Volatility Transmission. *Journal of Risk and Financial Management* 15: 116. [CrossRef]
- Koutmos, Dimitrios. 2018. Return and volatility spillovers among cryptocurrencies. *Economics Letters* 173: 122–27. [CrossRef]
- Kroner, Kenneth F., and Victor K. Ng. 1998. Modeling Asymmetric Comovements of Asset Returns. *Review of Financial Studies* 11: 817–44. [CrossRef]
- Kurka, Josef. 2019. Do cryptocurrencies and traditional asset classes influence each other? *Finance Research Letters* 31: 38–46. [CrossRef]
- Lehnert, Thorsten. 2022. Flight-to-safety and retail investor behavior. *International Review of Financial Analysis* 81: 102142. [CrossRef]
- Maharana, Narayana, Ashok Kumar Panigrahi, and Suman Kalyan Chaudhury. 2024. Volatility persistence and spillover effects of Indian market in the global economy: A pre-and post-pandemic analysis using VAR-BEKK-GARCH model. *Journal of Risk and Financial Management* 17: 294. [CrossRef]
- Malhotra, Nidhi, and Saumya Gupta. 2019. Volatility spillovers and correlation between cryptocurrencies and Asian equity market. *International Journal of Economics and Financial* 9: 208–15. [CrossRef]
- Markowitz, Harry. 1952. Modern portfolio theory. *Journal of Finance* 7: 77–91.
- Özdemir, Ferda Nur, and Abdulkali Bilgiç. 2023. Determining the short and long term volatility spillovers between wheat, cotton and corn prices in Turkey using the asymmetric BEKK-GARCH-mean equation model. *Scientific Papers Series Management, Economic Engineering in Agriculture & Rural Development* 23: 475–90.
- Polkuamdee, Nuntawun. 2021. Thai Traders Surge into Crypto Market. Bangkok Post. Available online: <https://www.bangkokpost.com/business/2178707/thai-traders-surge-into-crypto-market> (accessed on 12 March 2024).

- Stock Exchange of Thailand. 2024a. Investor Types (SET). Available online: <https://www.set.or.th/en/market/statistics/investor-type?market=SET> (accessed on 10 April 2024).
- Stock Exchange of Thailand. 2024b. Trading and Statistics Historical Data. Available online: <https://www.set.or.th/en/services/connectivity-and-data/data/historical> (accessed on 10 May 2024).
- Stock Exchange of Thailand. 2025. Market Capitalization (Sep 1988 to Present). Available online: <https://www.set.or.th/en/market/statistics/market-statistics/main> (accessed on 10 February 2025).
- Symitsi, Efthymia, and Konstantinos J. Chalvatzis. 2018. Return, volatility and shock spillovers of Bitcoin with energy and technology companies. *Economics Letters* 170: 127–30. [\[CrossRef\]](#)
- Tangwattananarat, Natnicha. 2017. A Study of the Perception of Thai Cryptocurrency Investors Towards Digital Currency Market. Ph.D. dissertation, Thammasat University, Bangkok, Thailand.
- Thailand Board of Investment. 2024a. Thailand's Advantages. Available online: https://www.boi.go.th/index.php?page=thailand_advantages (accessed on 15 November 2024).
- Thailand Board of Investment. 2024b. Thailand's Rankings. Available online: https://www.boi.go.th/index.php?page=thailand_rankings (accessed on 15 November 2024).
- Tjondro, Elisa, Saarcce Elsy Hatane, Retnaningtyas Widuri, and Josua Tarigan. 2023. Rational versus Irrational Behavior of Indonesian Cryptocurrency Owners in Making Investment Decision. *Risks* 11: 17. [\[CrossRef\]](#)
- Trabelsi, Nader. 2018. Are There Any Volatility Spill-Over Effects among Cryptocurrencies and Widely Traded Asset Classes? *Journal of Risk and Financial Management* 11: 66. [\[CrossRef\]](#)
- Uddin, Md Akther, Md Hakim Ali, and Mansur Masih. 2020. Bitcoin—A hype or digital gold? Global evidence. *Australian Economic Papers* 59: 215–31. [\[CrossRef\]](#)
- Uzonwanne, Godfrey. 2021. Volatility and return spillovers between stock markets and cryptocurrencies. *The Quarterly Review of Economics and Finance* 82: 30–36. [\[CrossRef\]](#)
- Vardar, Gulin, and Berna Aydogan. 2019. Return and volatility spillovers between Bitcoin and other asset classes in Turkey. *EuroMed Journal of Business* 14: 209–20. [\[CrossRef\]](#)
- Wang, Gangjin, Yanping Tang, Chi Xie, and Shou Chen. 2019. Is bitcoin a safe haven or a hedging asset? Evidence from China. *Journal of Management Science and Engineering* 4: 173–88. [\[CrossRef\]](#)
- Wang, Jia, Huang Xun, and Wang Xu. 2023. Risk spillovers and hedging in the Chinese stock market: An asymmetric VAR-BEKK-AGARCH analysis. *Acadlore Transactions on Applied Mathematics and Statistics* 1: 111–29. [\[CrossRef\]](#)
- Yasir, Muhammad, Muhammad Attique, Khalid Latif, Ghulam Mujtaba Chaudhary, Sitara Afzal, Kamran Ahmed, and Farhan Shahzad. 2020. Deep-learning-assisted business intelligence model for cryptocurrency forecasting using social media sentiment. *Journal of Enterprise Information Management* 36: 718–33. [\[CrossRef\]](#)
- Yousaf, Imran, Afsheen Abrar, and John W. Goodell. 2022. Connectedness between travel and tourism tokens, tourism equity, and other assets. *Finance Research Letters* 53: 103595. [\[CrossRef\]](#)
- Yousaf, Imran, and Larisa Yarovaya. 2021. Spillovers between the Islamic gold-backed cryptocurrencies and equity markets during the COVID-19: A sectorial analysis. *Pacific-Basin Finance Journal* 71: 101705. [\[CrossRef\]](#)
- Yu, Lean, Rui Zha, Dimitrios Stafylas, Kaijian He, and Jia Liu. 2020. Dependences and volatility spillovers between the oil and stock markets: New evidence from the copula and VAR-BEKK-GARCH models. *International Review of Financial Analysis* 68: 101280. [\[CrossRef\]](#)

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.