Is cryptocurrency a hedge, safe haven, diversifier against Thailand, Indonesia, Philippine stock market on pre-COVID-19 and during COVID-19?

Mr. Suphawit Keakultanes

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คริปโตเคอเรนซี่เป็นสินทรัพย์เพื่อป้องกันความเสี่ยง สินทรัพย์ปลอดภัย หรือสินทรัพย์เพื่อกระจายความเสี่ยง สำหรับตลาดหุ้นไทย ฟิลิปปินส์ และอินโดนีเซีย ในช่วงก่อนและช่วงเกิดโควิด 19 หรือไม่?

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สารนิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต
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By	Mr. Suphawit Keakultanes
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INDEPENDENT STUDY COMMITTEE

.... Chairman

()

.... Advisor

(Associate Professor BOONLERT JITMANEEROJ, Ph.D.)

.... Examiner

(Tanawit Sae-Sue, Ph.D.)

.... Examiner

(Assistant Professor RUTTACHAI SEELAJAROEN, Ph.D.)

ศุภวิชญ์ เกื้อกูลธเนศ : คริปโตเคอเรนซี่เป็นสินทรัพย์เพื่อป้องกันความเสี่ยง สินทรัพย์ปลอดภัย หรือสินทรัพย์เพื่อกระจายความเสี่ยง สำหรับตลาดหุ้นไทย ฟิลิปปินส์ และอินโดนีเซีย ในช่วงก่อนและช่วงเกิดโควิด 19 หรือไม่?. (Is cryptocurrency a hedge, safe haven, diversifier against Thailand, Indonesia, Philippine stock market on pre-COVID-19 and during COVID-19?) อ.ที่ปรึกษาหลัก : รศ. ดร.บุญเลิศ จิตรมณีโรจน์

งานวิจัยนี้ศึกษาว่า คริปโตเคอเรนซี่ มีคุณสมบัติในการป้องกันความเสี่ยง (hedge) สินทรัพย์ที่ปลอดภัย (safe haven) หรือ สินทรัพย์เพื่อกระจายความเสี่ยง (diversifier)ต่อตลาดหุ้นไทย ฟิลิปปินส์ และอินโดนีเซีย โดยใช้แบบจำลอง DCC-GARCH และการทดสอบสมมติฐาน เราจะตรวจสอบอัตราส่วนการป้องกันความเสี่ยงและความสัมพันธ์แบบมีเงื่อนไขระหว่างสกุลเงินดิจิทัลกับตลาดหุ้นของประเทศไทย ฟิลิปปินส์ และอินโดนีเซีย การวิจัยครอบคลุมช่วงเวลาและครอบคลุมผลตอบแทนของข้อมูลดัชนีของ กลุ่มตลาด TIP, Bitcoin, Ethereum, Tether และ Litecoin ตั้งแต่วันที่ 1 มกราคม พ.ศ. 2559 ถึง 31 ธันวาคม พ.ศ. 2564 ผลเชิงประจักษ์แสดงให้เห็นว่าสกุลเงินดิจิทัลดั้งเดิม เช่น Bitcoin และ Litecoin สามารถทำหน้าที่เป็นตัวกระจายความเสี่ยง Ethereum สามารถทำหน้าที่เป็น เครื่องมือป้องกันความเสี่ยงในดัชนี PSEI และเหรียญTether สามารถทำหน้าที่เป็นตัวป้องกันความเสี่ยงและเป็นที่หลบภัยในดัชนี PSEI และ JKSE ความสามารถที่ปลอดภัยของ Tether สามารถเปลี่ยนแปลงได้ตามสภาวะตลาด ประโยชน์ของการวิจัยครั้งนี้คือการช่วยให้นักลงทุนมีความเข้าใจที่สำคัญเกี่ยวกับการกระจายตัวของสกุลเงินดิจิทัล นอกจากนี้ภาครัฐหรือหน่วยงานที่เกี่ยวข้องและนักลงทุนจะสนใจในการค้นพบของเรา หากพวกเขามีส่วนร่วมในการอภิปรายเชิงลึกเกี่ยวกับบทบาทของ Cคริปโตเคอเรนซี่ ในตลาดการเงิน การศึกษานี้มีส่วนช่วยในการอภิปรายอย่างต่อเนื่องเกี่ยวกับศักยภาพการลงทุนของสกุลเงินดิจิทัลหรือคริปโตเคอเรนซี่

สาขาวิชา	การเงิน	ลายมือชื่อนิสิต	
ปีการศึกษา	2564	ลายมือชื่อ อ.ที่ปรึกษาหลัก	

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Suphawit Keakultanes : Is cryptocurrency a hedge, safe haven, diversifier against Thailand, Indonesia, Philippine stock market on pre-COVID-19 and during COVID-19?. Advisor: Assoc. Prof. BOONLERT JITMANEEROJ, Ph.D.

This research study whether cryptocurrencies act as a hedge, safe haven or diversifier against Thailand, Philippines, and Indonesia stock exchange market. Using DCC-GARCH model and hypothesis test, we examine the hedge ratio and the conditional correlation between cryptocurrencies and TIP's stock exchange market. The sample cover data on the return of the TIP's index, Bitcoin, Ethereum, Tether and Litecoin from 1st January 2016 to 31st December 2021. The empirical results show that traditional cryptocurrencies, such as Bitcoin and Litecoin can act as diversifier, Ethereum can act as hedge instrument in PSEI index. Tether can act as the hedge and safe haven in PSEI and JKSE index. The safe-haven capability of Tether can change across market condition. The benefits of this research are to help investors the important understanding into diversification of cryptocurrencies. Moreover, authorities and governments would be interested in our findings if they were to engage in a deeper discussion on the role of cryptocurrencies in financial markets. This study contributes to the continuing discussion regarding the investment potential of cryptocurrencies.

Field of Study:	Finance	Student's Signature ....
Academic Year:	2021	Advisor's Signature ....

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Suphawit Keakultanes

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Chapter 1
Introduction

Cryptocurrency is decentralized networks based on the blockchain technology that allows online payments to flow directly between individuals without the middleman or without the need of a financial institution to interfere. Bitcoin is one of the most popular cryptocurrencies since the cryptocurrency launched. In 2021, It constituted around 60% of the total market capitalization of cryptocurrencies and following by Ethereum, it constituted around 10% in 2021. And over 20,000 businesses are already accepting cryptocurrency payments. Moreover, some of the countries have already approved Bitcoin and Ethereum as legal tender, and many regional policymakers are keen on investing in these cryptocurrencies.

In recent years, cryptocurrencies have emphasized cryptocurrency limited supply as a way to prevent the monetary inflation associated with fiat currency. The idea is that a rise in the supply of fiat money, particularly in reaction to the COVID-19 epidemic, will eventually result in price inflation and a financial market downturn. (Dyhrberg 2016) concluded that Bitcoin is similar to gold by using GARCH techniques, meaning that Bitcoin can act as hedging potential. And the current bull run in cryptocurrencies can be linked to its newly discovered potential as a hedging investment similar to gold and silver, which can maintain value in the presence of inflationary pressures and devaluation of fiat currencies. Additionally, (Demir, Gozgor et al. 2018)demonstrated how Bitcoin might be used to hedge economic policy uncertainty. Similarly, Bitcoin has a potential to be a hedge against unpredictability by inferred volatilities method (Bouri, Molnár et al. 2017).

Meanwhile, cryptocurrencies have seen an uptrend. At the end of November 2017, over 80% of Bitcoin trading activities are accounted in Japan, South Korea, and Vietnam. In comparison to the prices of Bitcoin, Bitcoin had increased by 800%, Ethereum had the most highest increasing which is 1293% in 2020. Following by Litecoin and XRP had increased by 591%, and 849%, respectively. Bitcoin trading volume peaked in February 2021, marking as one of the significant months in the coin's history. Bitcoin and other cryptocurrencies decentralized or blockchain technology allows a simple access to the global investors while giving a safe alternative to conventional financial assets. Consequently, cryptocurrencies in other countries than the United States have grown significantly. The COVID-19 pandemic has far impacted on every sector of society, resulting in a serious economic downturn, multiple business shutdowns, critical corporate instability, and major jobs lost, along with other consequences. Also, many countries are dealing with a serious health crisis, a major external shock of demand, a large downturn of global financial market, and the significant decline in a commodity index, which have a very huge impact on market activity in commodity-exporting countries (IMF, 2020). The consequences are reflected on the stock exchange market. The SET, which represents the Thailand stock exchange, is comprised of the top 100 stocks sorted by average daily market capitalization. The IDX or JKSE, representing the Indonesian stock exchange and the index is composed of 80 companies that have relatively large market capitalization, high fund flow or liquidity, and solid fundamentals. The PSE Composite Index is a stock market index consisting of 30 companies listed on the Philippine Stock Exchange.

The World Health Organization declared COVID19 a Public Health Emergency of International Concern on January 30, 2020, and a pandemic on March 11, 2020, SET and PSEI index went down around 10% on the next day after the WHO announced but the IDX index slightly decreased around 5%. Investors knew that the tourism sector was the most affected by the Covid-19, which reflected on the stock exchange of these three countries. Thailand's tourism industry contributed to the GDP of around 3 billion THB in 2019 to 1 billion THB in 2020 or contributed around 6.78%, a 65.4% decline and the overall GDP fell by 6.1% in 2020, and it is the largest recession since the Asian financial crisis. For Indonesia, contribution of travel and tourism sector to GDP is around 4.97% in and it went down from around 940 trillion RP to 502 trillion RP, a 53.4% decline. In 2020, travel and tourism contribute around 5.4 percent to the Philippine economy as measured by Gross Domestic Product (GDP). In addition, the three stock exchange markets became more volatile and unpredictable due to number of the infections, scarcity in covid vaccines, new covid variant, and unclear quantitative easing which led to market's volatility and inflation. As a result, investors require information to safeguard against this increased uncertainty of market and more precisely, the properties of cryptocurrencies to operate as a hedge and safe-haven instrument during uncertainty period, such as COVID-19 period.

Objective:

The purpose of this research is to examine and investigate the hedging, safe-haven, and diversification characteristics of alternative assets, such as cryptocurrency and cryptocurrency indexes, in comparison to Thailand, Indonesia, and the Philippines stock exchanges prior to and during the COVID-19 crisis, using the DCC-GARCH framework. Additionally, the DCC GARCH framework is used to compute ratio of hedging instrument and effectiveness of hedge in order to evaluate the hedging qualities of two assets, such as Bitcoin and the stock market index, Ethereum and the stock market index, or Cryptocurrency index and the stock market index. Additionally, investors will be able to find hedge assets and analyze the hedging capabilities of other asset classes, since there are several cryptocurrencies that have created new options for investors seeking risk diversification.

Contribution:

Firstly, existing research on Bitcoin makes no distinction between the benefits of Bitcoin for investors in established and emerging economies. In general, the trading of financial assets in developed markets and developing markets differ significantly. Often, developing markets are defined by political instability, lack of regulation, and a weak financial structure. For example, (Dyhrberg 2016)showed that Bitcoin could be the hedger against the US dollar and London Stock Exchange (FTSE100). This paper provides a clearer aspect of the properties of Bitcoin, which can be used as an alternative instrument against the developed stock exchange market or top 5 market capitalization but provide more information for domestic investors or foreign investors who want to invest in developing countries as well. So, we focus on Thailand, Indonesia, and Philippine, because they share many similarities. These countries’ GDP is heavily reliant on tourism industry. It directly impacts on the GDP and indirectly impacts on the capital investment, impact on the production and supply chains in USA, European Unions, and China. Also, research on cryptocurrencies using the Thailand, Indonesian and Philippine stock exchange market as a variable is limited, especially the recent pandemic, COVID-19.

Secondly, most research papers described hedge and safe haven on bitcoin or gold during the global economic crisis in 2008 but this paper provides a deeper understanding not only of Bitcoin but also of how the characteristics of other cryptocurrency differ for domestic or foreign investors. Other large market capitalization cryptocurrencies, such as Ethereum and Litcoin, can act as hedgers and diversifiers, particularly against Nikkei 225 index and other Asian Pacific’s stock index, implying that investors should consider other cryptocurrencies besides Bitcoin, these results found by (Bouri, Shahzad et al. 2020)

Furthermore, the conditional hedge ratios and hedging effectiveness of cryptocurrency and stock index are also determined in this paper. In addition, this paper can assist risk managers and investors looking for hedge or safe-haven assets, particularly during COVID-19 crises. It will be fascinating to see if future research examines cryptocurrency's utility as a hedge against other financial assets such as currency, bonds, and uncertainty.

Chapter 2
Literature Review:

Meaning of hedge, safe haven, diversifier

The definitions of diversifier, hedge, and safe haven assets were introduced enabling the examination and identification of an asset's capabilities. The following definitions are provided: "A diversifier is defined as an asset that is on average (but not perfectly) connected with another asset or portfolio." A hedge, on average, is an asset that is uncorrelated or has a negative correlation with another asset or portfolio. "A safe haven asset is one that is uncorrelated or has a negative correlation with another asset or portfolio during times of market stress or volatility." By differentiating between weak and strong forms, (Baur and McDermott 2010)greatly improved these criteria. "On average, a hedge is an asset that is negatively associated with (or uncorrelated with) another asset or portfolio. A strong (weak) safe haven is defined as an asset that is uncorrelated (negatively correlated) with another asset or portfolio during certain times, such as market downturns."

Many of the cryptocurrency research papers have mainly focused on Bitcoin because of its capability to performance as a hedger or safe-haven and its market capitalization. (Dyhrberg 2015), began to explore the capability of Bitcoin as hedging instrument against gold and US dollar. Later in the same year, further studied of Dyhrberg can say that Bitcoin may be used as hedging instrument against the United Kingdom stock exchange market and the US currency. (Wang, Zhang et al. 2019)investigated the mean and volatility spillover effect between Bitcoin and other tradition assets and inspect the hedging and safe-haven capability of Bitcoin by using VAR-GARCH-BEEK. The results of this paper showed that Bitcoin is an excellent hedge against stock and bond market and can encounter the losses due to the negative correlation with stocks and bonds. According to (Stensås, Nygaard et al. 2019), this article examines a hedge, safe-haven, or diversifier characteristic of Bitcoin to operate against developed and developing stock exchange markets, as well as commodities. According to the findings, Bitcoin is more likely to act as a hedge for emerging markets, while operate as a diversifier for developed markets and commodities. Using a quantile correlation technique, (Kristoufek 2020) concluded that gold was a stronger safe-haven asset than bitcoin relative to the US equities market during the COVID-19 crisis. (Yousaf and Ali 2020)tested the spillover effect between Bitcoin, gold, and oil during pandemic by using DCC-GARCH and checked the robustness by using VAR-GARCH and BEKK-GARCH. They also analyzed the hedge ratio and hedge effectiveness between Bitcoin-oil and gold-oil to help investors for construct portfolio and reduce the risk exposure during COVID-19. (Marobhe 2021)examined the properties of Bitcoin, Ethereum and Litecoin as a safe haven during uncertainty period, such as COVID-19 pandemic(Shahzad, Bouri et al. 2019) argued that Bitcoin and gold are weak safe haven asset against the major commodities and stock market during COVID-19 by applied cross-quantilogram approach, showing that Bitcoin have the better potential to act diversifier due to the uncorrelation with other traditional assets. Some of the research had examine using many types of method and the results showed the difference perspectives and arguments. (Kliber, Marszałek et al. 2019)applied the Stochastic Volatility Model with DCC-GARCH to verify the capability of Bitcoin to act as a hedger, safe-haven, or diversifier against the stock exchange market. The results suggested that Bitcoin is a weak hedge with all analyzed markets.

Additionally, numerous recent study studies, in order to get a better knowledge of the features of cryptocurrencies as a store of wealth, such as (Vukovic, Maiti et al. 2021), this research paper examines whether the cryptocurrency market is a safe haven and, in comparison to traditional assets such as gold, oil, could have served as a diversifier during the early stage of COVID-19 spreading using OLS, quantile, and robust regression. (Wang, Ma et al. 2020) employed a DCC-GARCH technique and dummy variable regression to examine the stable coins' qualities as a hedge or safe-haven against regular cryptocurrencies. The research concludes with the critical finding that stable coins may act as a safe haven during market downturns and as a diversifier in normal circumstances. (Tiwari, Kumar et al. 2019) used a different type of GARCH model called Copula to examine the dynamic linkage between cryptocurrency and the S&P 500, resulting in cryptocurrency playing an essential role as a hedging instrument against uncertainty. Next, (Marobhe 2021)examined the properties of Bitcoin, Ethereum and Litecoin as a safe haven during COVID-19 crisis and concluded that all of them can act as a safe haven during COVID-19 crisis. (Abakah, Gil-Alana et al. 2020)concluded that risk-averse investors may utilize bitcoin as a risk diversification tool. (Bouri, Shahzad et al. 2020)investigated the properties of cryptocurrency to act as the hedger and safe haven against the S&P 500 index by using the cross-quantilogram approach to, concluding that Bitcoin, Ripple, and Stellar have a hedging ability against the stock index, meanwhile, Litecoin and Monero may serve as a safe- haven. (Caferra and Vidal-Tomás 2021)discussed the properties of cryptocurrencies that make them suitable for use as a safe-haven instrument and how they were used to test the relationship between cryptocurrency and the global COVID-19 fear index using a technique called Wavelet Coherence and Markov switching.

Chapter 3
Research Hypothesis:

(Robiyanto, Nugroho et al. 2021)promoted cryptocurrencies in Indonesia as a hedger and safe haven tools. (Stensås, Nygaard et al. 2019)revealed that Bitcoin has great safe haven attributes during situations of high uncertainty. (Dyhrberg 2016)found that Bitcoin is equivalent to gold using GARCH approaches, stating that Bitcoin has the potential to be used as a hedge. Numerous research articles assert that Bitcoin will serve as a hedging and safe-haven tool. These results lead to the following hypothesis:

H1: The conditional correlations between the top 4 cryptocurrencies by market capitalization and stock index of Thailand, Indonesia, and Philippines will be a negative pre-COVID-19 crisis and during COVID-19 crisis, and we expected that during COVID-19 crisis, the correlation would be higher.

(Corbet, Meegan et al. 2018, Iqbal, Fareed et al. 2021)provided evidence to support that Bitcoin, Ethereum, and Litecoin act as a hedging instrument. (Bouri, Shahzad et al. 2020) Ethereum and Litecoin are the safe haven against some of the US' equity sectors. Bitcoin has a maximum limit of 21 million on the supply, whereas the Ethereum has an unlimited supply but an annual maximum limit of 18 million on supply. So, we compare this characteristic with gold, the total supply of gold in 2020 is around 4,633 tons and this characteristic of Bitcoin, Ethereum, and gold, it can act against inflation. This argument leads to the following hypothesis.

H2: Bitcoin and Ethereum have better hedge property than other 2 cryptocurrencies during pre-COVID-19 crisis because of their limited supply as a gold.

Some recent research found that cryptocurrencies, such as Tether or stable coin can act as a safe haven instrument when compared with other cryptocurrencies during market turmoil. (Bianchi 2017)used a VAR model to examine the link between stable coins and traditional cryptocurrencies, concluding that Tether does correlate with the returns of lagging cryptocurrencies. In general, when Bitcoin's price goes down, investors will invest in the stable coin because stable coin offer more stability than traditional cryptocurrencies, which means that stablecoins may be used to create portfolios that outperform traditional cryptocurrencies. This leads to the following hypothesis. This argument leads to the following hypothesis.

H3: Tether has better safe haven property than other 3 cryptocurrencies pre COVID-19 crisis because of their low volatility. (i.e., stablecoins)

Chapter 4
DATA:

2,191 daily observations from 1st January 2018 to 31st December 2021 are collected into our sample. We focus on the TIP countries stock index, which is SET index, from Thailand's stock market exchange, IDX or JKSE index, from Indonesia's stock market exchange, and PSE index from Philippines's stock market exchange. The closing price of each stock market in three difference countries are downloaded from Datastream Thomson Reuters. The stock market exchanges are designated in USD dollars. We select the average of the top 4 cryptocurrencies by market capitalization before the COVID-19 crisis from 1st January 2016 and end on 12th March 2020 and during COVID-19, beginning on March 11th, 2020, the day the World Health Organization proclaimed COVID-19 a pandemic and ending on 31st December 2021. The top 4 cryptocurrencies are Bitcoin, Ethereum, Tether, and Litecoin. All the cryptocurrencies' daily prices are collected in US dollars and are downloaded from Investing.com and coingecko.com. The daily return of all index and cryptocurrencies data are calculated as follows:

$$Return_{i,t} = \left(\frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}}\right) \tag{1}$$

The cryptocurrency market can be traded 24 hours per day like foreign exchange market, but for the stock exchange markets, the markets are open from roughly 9:30 am EDT until 4 pm EDT on Mondays through Fridays and are closed on weekends and holidays. We set and collect the return of cryptocurrencies and stock market index with the timeframe of the stock exchange market trading hours as the benchmark, so we will be able to compare and observe the results. For the cryptocurrency index, the set of data obtained from the S&P Cryptocurrency Large capitalization index that reflects the largest and most liquid cryptocurrencies into one index that is weighted by the equivalent of the market capitalization of cryptocurrencies (coin supply multiplied with coin price) The index is generated using the mean of the S&P DJI digital asset indexes' divisor approach.

According to (Stensås, Nygaard et al. 2019), Bitcoin serves as an excellent hedge for investors in developing economies. The supply model of Ethereum may differ from the supply model of Bitcoin in some cases. Bitcoin will have a total supply of 21 million coins, while Ethereum will have an infinite supply but a maximum yearly output of 18 million coins. Tether was nominated to be worth around $1.00, and it is what's known as a stablecoin. Additionally, stablecoins offer liquidity in a fluctuating cryptocurrency market when it is difficult to convert between cash and a cryptocurrency such as Bitcoin.(Wang, Ma et al. 2020) mentioned the true value of Tether, and it mentioned that on 14th March 2019. It announced that just $0.70 in backing was available for each Tether, implying that the value of this stablecoin had dropped by almost 30 percent. Next, XRP, a cryptocurrency that is used on the Ripple network to facilitate transfers of money between different currencies. XRP can be used as a bridge currency because it allows the financial institutions a cheaper way to trade currencies by holding XRP instead of various types of fiat money. Litecoin is a cryptocurrency that is quite close to Bitcoin in terms of technical specifications. Bitcoin and Litecoin have a finite number of coins in circulation; Litecoin has 84 million LTC in total.

Chapter 5
METHODOLOGY:

Previous research has examined whether gold may operate as a hedge or a safe-haven asset using the GARCH model. In contrast, (Beckmann, Berger et al. 2015)contributed the smooth transition regression with an exponential transition function. The problem of this method is that it can’t addressed aggregation of the models for each individual economy. The wavelet transformation approach was used by (Mensi, Rehman et al. 2020) to investigate the correlation between Bitcoin and the Dow Jones Index and the Islamic Stock Exchange. This study demonstrated that in the short run, Bitcoin may be a greater diversifier than in the long term. (Conlon, Corbet et al. 2020) investigated the safe-haven property of cryptocurrencies during COVID-19 crisis by using two-moment VaR. With the two moment VaR, this method is unable to capture the potential losses with the normal return distribution.

Additionally other academics looked at several variations of multivariate GARCH models. Numerous models have been developed in the literature to quantify an asset's hedging and safe haven potential. The BEKK model is one of these models, as is the Constant Conditional Correlation (CCC) model. The CCC model is limited by its assumption of continuous conditional correlation and its inability to explain how assets interact. (Bouri, Molnár et al. 2017) cautioned, however, that those models are likely to be unable to establish a stable convergence point and may include incorrect parameter values. As discussed in the literature section, the goal of this study was to use the DCC-GARCH technique in order to capture the dynamic behavior of cryptocurrencies as a hedge, diversifier, or safe haven. The purpose of this work is to determine time-varying correlation coefficients across series and to compare them between stable and distressed periods.

After we obtain all the daily return of the stock market index, individual cryptocurrency and its index. We used DCC-GARCH model Estimation, start with the following equation

$$R_t = \mu + \gamma R_{t-1} + e_t \ with \ \ e_t = H_t^{1/2} \eta_t \qquad (2)$$

Where R_t= $(R_t{}^x, R_t{}^y)'$is the vector of the price return on the x (stock market) and y (cryptocurrencies) asset at time t. μ is a constant term. γ refers to a two-by-two matrix of factors indicating the effect of the two assets' own lagged and cross mean transmission; $e_t = e_t{}^x, e_t{}^y$ is the vector of the residuals of the conditional mean equations at time t; $\eta_t = \eta_t{}^x, \eta_t{}^y$ indicates a sequence of random errors that are both independently and identically distributed; and $H_t{}^{1/2} = diag\left(\sqrt{h_t{}^x}, \sqrt{h_t{}^y}\right)$, where $h_t{}^x$ and $h_t{}^y$ represent the conditional variances of stock market return with the price return of the cryptocurrencies.

$$H_t = D_t R_t D_t \tag{3}$$

$$h_t = c + a\, e^2{}_{t-1} + b\, h_{t-1} \tag{4}$$

$$R_t = diag\,\{Q_t\}^{-1}\; Q_t\, diag\,\{Q_t\}^{-1} \tag{5}$$

$$Q_t = (1-\alpha\; -\beta)\bar{Q} + \alpha\, \tilde{e}_{t-1}\, \widetilde{e'}_{t-1} + \beta Q_{t-1} \tag{6}$$

The definitions of variables in equations 3 to 6 can be referred to the following table.

Table 1: Variable in Equations and Definition

Variables in Equation 3 to 6	Definitions
$\boldsymbol{H_t}$	the conditional covariance matrix.
$\boldsymbol{D_t = diag\left(\sqrt{h_t{}^x}, \sqrt{h_t{}^y}\right)}$	the diagonal matrix of conditional standard deviations for the x and y return series at time t,
$\boldsymbol{R_t = [\rho_{xy,t}]}$	represents the time-varying conditional correlation matrix.
$\boldsymbol{h_t}$	represents the conditional variance.
c	the constant term
a	is the parameter that captures the ARCH effect.
b	is the parameter that captures the GARCH effect.
$\boldsymbol{Q_t}$	a conditional variance-covariance matrix of $\tilde{e}, \beta, \alpha$
$\boldsymbol{\bar{Q}}$	represents the time-varying unconditional correlation matrix of standardised residuals.
et	is a vector of standardized residuals obtained from equation 4.

Next, conditional correlations between the two assets are calculating by the following equation:

$$\rho_{xy,t} = \frac{q_{xy,t}}{\sqrt{q_{x,t}}\sqrt{q_{y,t}}} \tag{7}$$

Where $q_{xy,t}$ is the unconditional correlation matrix of e_t and a symmetric positive definite matrix.

The next following steps, the capabilities of cryptocurrencies as hedge, safe-haven, diversifier against stock market are examined using t- test to classify the properties of cryptocurrencies act against TIP's stock exchange market during twoperiods (pre COVID-19 and during COVID-19 crisis.

Table 2: Hypothesis Test

Pre-COVID-19 Crisis	During COVID-19 Crisis
H_0: $\bar{\rho}_{xy,t} = 0$ H_1: $\bar{\rho}_{xy,t} \neq 0$ If it rejects, H_0 then it is diversifier or strong hedge but if it fails to reject H_0 then it is weak hedge.	H_0: $\bar{\rho}_{xy,t} = 0$ H_1: $\bar{\rho}_{xy,t} \neq 0$ If it rejects, H_0 then it is diversifier or strong safe haven but if it fails to reject H_0 then it is weak safe haven.

The minimum conditional variance hedge ratio at time t are calculated for a portfolio of the TIP countries stock index using each cryptocurrency or cryptocurrency index as a hedging instrument based on the DCC GARCH framework. (Jitmaneeroj 2018)

$$\beta_{xy,t} = \frac{h_{xy,t}}{h_{y,t}} \tag{8}$$

Where $\beta_{xy,t}$ is the minimum conditional hedge ratio at time t and the object of this is to minimize risk rather than to maximize return. The conditional covariance between the stock market index and individual cryptocurrencies and the cryptocurrency index is represented by $h_{xy,t}$ Where $h_{y,t}$ is the conditional variance of the cryptocurrencies. Next, the minimum static hedge ratio is used to compare with the minimum conditional hedge ratio. The aim of this comparison is to estimate optimal hedge ratio and to be able to help fund manager decide the strategies for the various of portfolio investment.

Chapter 6
Empirical results

Summary Statistics:

According to the daily yield data of cryptocurrencies and stock market index from January 1st, 2016 to December 29th, 2021, cryptocurrencies and stock market index had positive yields except for Tether. If we considered the risk of each cryptocurrency with S.D., Tether has the lowest risk and ETH has the highest risk. And for the stock market index, Thailand stock market index or SET has the lowest risk. Ethereum has the highest return and highest risk among other cryptocurrencies.

We found that return of three stock market indices have a positive unconditional correlation with every cryptocurrency except Tether and Ethereum with PSEI index. These are the earliest indications that these cryptocurrencies may serve as diversifiers against the equities in Thailand, Philippines, and Indonesia. The unconditional correlation between SET, PSEI, JKSE index and Tether are negative, which suggests that Tether can used as a hedging or safe-haven instrument against stock markets. All cryptocurrencies except Tether have lower kurtosis than the SET index. This denotes that the SET index has higher tailed risk than those cryptocurrencies.

Next, testing the distribution of the data with Jarque-Bera statistic) and the testing of autocorrelation up to 5 lags in all the daily returns with Ljung-Box test. Before applying the DCC-GARCH model, the stability of the data is testing by Unit root tests with Augmented Dickey Fuller test (ADF) and heteroscedasticity of all daily returns' series are confirmed with ARCH testing. So, when Lagrange Multiplier (LM) statistics are used to test for ARCH effects, they show that the time-varying variance is present in all the daily returns. The presence of ARCH effects suggests that a GARCH model is the right choice, and the dynamic hedge is likely to be a good way to protect against risk.

Table 3.: Summary statistics of daily return for the SET, PSEI, and JKSE index and Cryptocurrencies

Market Index and Cryptocurrencies	Mean	Min	Max	Stand Div	Skewness	Kurtosis	observation	Jarque-Bera	p-value
PANEL A: TIP's Stock Exchange Markets									
SET	0.0002	-0.1080	0.0795	0.0101	-1.7125	25.1985	1324	35675.9994	0.0000
PSEI	0.0002	-0.1334	0.0744	0.0128	-1.2600	14.5872	1324	12089.0880	0.0000
JKSE	0.0004	-0.0658	0.1019	0.0102	0.1097	11.3849	1324	7153.0970	0.0000
PANEL B: Cryptocurrencies									
BTC	0.0019	-0.4022	0.2001	0.0434	-1.2012	9.9745	1324	5806.9389	0.0000
ETH	0.0050	-0.2779	0.4667	0.0597	0.8401	6.1419	1324	2236.7543	0.0000
Tether	-0.0002	-0.3200	0.1204	0.0128	-11.3902	311.4771	1324	5380788.6972	0.0000
Litecoin	0.0015	-0.3759	0.6726	0.0612	1.3945	18.3045	1324	18913.0343	0.0000

Table 4: Unconditional Correlation between the SET, PSEI, and JKSE index and Cryptocurrencies

Unconditional Correlation between Stock Market Exchanges and Cryptocurrencies

	SET	PSEI	JKSE	BTC	ETH	TETHER	LITECOIN
SET	1.0000						
PSEI	0.3903	1.0000					
JKSE	0.3915	0.4710	1.0000				
BTC	0.1768	0.0794	0.0627	1.0000			
ETH	0.0577	-0.0074	0.0118	0.3126	1.0000		
TETHER	-0.0049	-0.0244	-0.0236	-0.0079	0.0172	1.0000	
LITECOIN	0.0533	0.0296	0.0440	0.3655	0.2810	0.0012	1.0000

Table 5: Summary statistics of daily return for the SET, PSEI, and JKSE index and Cryptocurrencies

Market Index and Cryptocurrencies	Ljung-Box Test (Q5)	ADF Unit root Test lag(5)	ARCH-LM Test lag(5)
SET	37.7126***	-13.42***	241.115***
PSEI	18.083***	-15.343***	310.141***
JKSE	23.1643***	-14.6***	222.933***
BTC	18.7157***	-16.446***	40.414***
ETH	7.7813***	-14.693***	84.478***
Tether	223.0445***	-14.95***	11.666***
Litecoin	4.5003***	-15.532***	28.811***

Note:Under the null hypothesis of no autocorrelation, the Ljung-Box test returns the Q (5) statistic for up to fifth-order serial correlation. The unit root test gives the ADF statistic based on the number of lags with the smallest Schwarz Information Criterion value. The null hypothesis is the existence of a unit root. The ARCH-LM test presents the LM-statistic with ARCH effects of the fifth order. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

DCC-GARCH Model Estimation:

The estimate results of a bivariate DCC-GARCH model for the daily returns of the TIP national stock market index and cryptocurrencies are presented in Table 6 The conditional mean of the daily returns is represented as a VAR process with optimal lag lengths determined using the Schwarz Information Criteria (SIC). Representing the conditional covariance as a DCC-GARCH process where the variance of each disturbance term follows a GARCH (1,1) process.

The coefficients (ω0), (ω1) and (ω2) of all indices are highly statistically significant, indicating that variance, covariance, and therefore the risk-minimizing hedge ratio are definitely time-varying. However, the coefficient on the lagged squared error (ω1) is fairly small, whereas the coefficient on the lagged conditional variance (ω2) is significantly bigger. Therefore, the fitted conditional variance from the previous day is more significant for forecasting the present conditional variance than information about the previous day's volatility. Lambda1 and Lambda2 are the parameters that govern the dynamics of conditional quasi-correlations. Both lambda1 and lambda2 are statistically significant for all cases, which mean that DCC-GARCH is appropriate for this study.

Table 6: Dynamic conditional correlation MGARCH model

SET/BTC	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
SET (-1)	.052	.03	1.75	.079	-.006	.111	*
SET (-2)	-.056	.029	-1.92	.055	-.113	.001	*
SET (-3)	.022	.029	0.76	.445	-.035	.079	
BTC (-1)	.007	.004	1.81	.07	-.001	.015	*
BTC (-2)	.002	.004	0.41	.681	-.006	.01	
BTC (-3)	.005	.004	1.25	.212	-.003	.013	
Arch (ω1)	.083	.012	7.00	<0.001	.06	.106	***
Garch (ω2)	.907	.012	74.87	<0.001	.883	.931	***
Constant (ω0)	<0.001	<0.001	3.08	.002	<0.001	<0.001	***
SET (-1)	.342	.117	2.92	.003	.113	.571	***
SET (-2)	-.367	.1	-3.69	<0.001	-.562	-.172	***
SET (-3)	.127	.102	1.25	.211	-.072	.327	
BTC (-1)	.136	.034	4.02	<0.001	.07	.203	***

BTC (-2)	-.126	.033	-3.80	<0.001	-.19	-.061	***
BTC (-3)	-.071	.032	-2.24	.025	-.134	-.009	**
Arch (ω1)	.331	.053	6.22	<0.001	.227	.436	***
Garch (ω2)	.676	.035	19.42	<0.001	.608	.745	***
Constant (ω0)	<0.001	0	5.36	<0.001	<0.001	<0.001	***
lambda1	.025	.015	1.64	.1	-.005	.054	
lambda2	.909	.074	12.24	<0.001	.764	1.055	***

Log likelihood = 6963.397

**** p<.01, ** p<.05, * p<.1*

Dynamic conditional correlation MGARCH model

PSEI/BTC	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
PSEI (-1)	-.065	.03	-2.18	.029	-.123	-.007	**
PSEI (-2)	-.044	.03	-1.50	.133	-.102	.014	
PSEI (-3)	.011	.029	0.39	.698	-.046	.068	
PSEI (-4)	.006	.029	0.22	.828	-.05	.063	
BTC (-1)	.01	.007	1.51	.131	-.003	.023	
BTC (-2)	.008	.007	1.28	.201	-.004	.021	
BTC (-3)	.001	.007	0.08	.934	-.013	.014	
BTC (-4)	.019	.007	2.89	.004	.006	.032	***
Arch (ω1)	.096	.02	4.68	<0.01	.056	.136	***
Garch (ω2)	.869	.029	29.47	<0.01	.811	.927	***
Constant (ω0)	<0.001	<0.001	2.70	.007	<0.001	<0.001	***
PSEI (-1)	.008	.099	0.08	.933	-.187	.203	
PSEI (-2)	-.258	.079	-3.29	.001	-.412	-.105	***
PSEI (-3)	.128	.082	1.57	.117	-.032	.289	
PSEI (-4)	-.069	.083	-0.83	.408	-.231	.094	
BTC (-1)	.152	.034	4.45	<0.001	.085	.219	***
BTC (-2)	-.148	.033	-4.43	<0.001	-.214	-.083	***
BTC (-3)	-.064	.032	-2.00	.046	-.127	-.001	**
BTC (-4)	.001	.032	0.04	.966	-.061	.063	
Arch (ω1)	.365	.059	6.13	<0.001	.248	.481	***
Garch (ω2)	.672	.034	19.72	<0.001	.605	.739	***
Constant (ω0)	<0.001	<0.001	4.60	<0.001	<0.001	<0.001	***
lambda1	.034	.013	2.68	.007	.009	.059	***
lambda2	.905	.043	21.16	<0.001	.821	.989	***

Log likelihood = 6450.509

**** p<.01, ** p<.05, * p<.1*

Dynamic conditional correlation MGARCH model

JKSE/BTC	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
JKSE (-1)	-.007	.031	-0.22	.828	-.067	.054	
JKSE (-2)	-.056	.03	-1.87	.062	-.114	.003	*
BTC (-1)	.006	.005	1.22	.222	-.004	.017	
BTC (-2)	.004	.005	0.81	.415	-.006	.014	
Arch (ω1)	.181	.035	5.18	<0.001	.112	.249	***
Garch (ω2)	.734	.052	14.22	<0.001	.633	.835	***
Constant (ω0)	<0.001	<0.001	3.48	.001	<0.001	<0.001	***
JKSE (-1)	-.122	.154	-0.80	.426	-.423	.179	
JKSE (-2)	-.365	.086	-4.24	<0.001	-.534	-.196	***

BTC (-1)	.144	.035	4.09	<0.001	.075	.213	***
BTC (-2)	-.119	.035	-3.41	.001	-.188	-.051	***
Arch (ω1)	.321	.055	5.81	<0.001	.212	.429	***
Garch (ω2)	.686	.038	18.11	<0.001	.612	.76	***
Constant(ω0)	<0.001	<0.001	4.63	<0.001	<0.001	<0.001	***
lambda1	.019	.021	0.88	.377	-.023	.061	
lambda2	.880	.195	4.52	<0.001	.499	1.262	***
Log likelihood = 6783.895							

*** p<.01, ** p<.05, * p<.1*

Dynamic conditional correlation MGARCH model

SET/ETH	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
SET (-1)	.049	.03	1.62	.104	-.01	.107	
SET (-2)	-.045	.029	-1.54	.124	-.103	.012	
SET (-3)	.017	.029	0.58	.56	-.04	.074	
ETH (-1)	.004	.003	1.33	.182	-.002	.009	
ETH (-2)	.005	.003	1.83	.067	<0.001	.01	*
ETH (-3)	.001	.003	0.34	.732	-.004	.006	
Arch (ω1)	.088	.013	6.99	<0.001	.063	.112	***
Garch (ω2)	.903	.013	71.68	<0.001	.879	.928	***
Constant (ω0)	<0.001	<0.001	3.11	.002	<0.001	<0.001	***
SET (-1)	.376	.145	2.60	.009	.092	.659	***
SET (-2)	.173	.148	1.17	.243	-.117	.464	
SET (-3)	.043	.153	0.28	.78	-.257	.342	
ETH (-1)	.087	.032	2.72	.006	.024	.15	***
ETH (-2)	-.014	.031	-0.44	.656	-.076	.048	
ETH (-3)	.01	.031	0.32	.748	-.05	.07	
Arch (ω1)	.158	.032	4.88	<0.001	.094	.221	***
Garch (ω2)	.774	.046	16.80	<0.001	.684	.864	***
Constant (ω0)	<0.001	<0.001	3.42	.001	<0.001	<0.001	***
lambda1	.01	.013	0.77	.441	-.015	.035	
lambda2	.897	.14	6.40	0	.622	1.172	***
Log likelihood = 6538.902							

*** p<.01, ** p<.05, * p<.1*

Dynamic conditional correlation MGARCH model

SET/Tether	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
SET (-1)	.052	.03	1.76	.078	-.006	.111	*
SET (-2)	-.041	.029	-1.42	.156	-.099	.016	
SET (-3)	.014	.029	0.50	.62	-.043	.072	
SET (-4)	.024	.03	0.82	.412	-.034	.082	
TETHER (-1)	.001	.016	0.07	.943	-.03	.032	
TETHER (-2)	-.008	.017	-0.46	.646	-.041	.025	
TETHER (-3)	-.013	.017	-0.77	.443	-.045	.02	
TETHER (-4)	.025	.016	1.55	.122	-.007	.057	
Arch (ω1)	.087	.012	7.03	<0.001	.063	.111	***
Garch (ω2)	.904	.012	72.67	<0.001	.88	.928	***
Constant (ω0)	<0.001	<0.001	3.10	.002	<0.001	<0.001	***
SET (-1)	-.017	.015	-1.16	.247	-.046	.012	
SET (-2)	.009	.011	0.89	.374	-.011	.03	
SET (-3)	-.013	.01	-1.28	.2	-.033	.007	

SET (-4)	.015	.009	1.70	.089	-.002	.031	*
TETHER (-1)	-.298	.063	-4.71	0	-.423	-.174	***
TETHER (-2)	-.041	.055	-0.75	.455	-.15	.067	
TETHER (-3)	-.018	.053	-0.34	.73	-.123	.086	
TETHER (-4)	.014	.051	0.27	.785	-.087	.115	
Arch (ω1)	.549	.061	9.01	<0.001	.43	.669	***
Garch (ω2)	.622	.019	31.93	<0.001	.584	.661	***
Constant (ω0)	<0.001	<0.001	12.22	<0.001	<0.001	<0.001	***
lambda1	.004	.004	0.98	.328	-.004	.013	
lambda2	.996	.004	261.73	<0.001	.988	1.003	***

Log likelihood = 10013.6

**** p<.01, ** p<.05, * p<.1*

Dynamic conditional correlation MGARCH model

SET/Litecoin	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
SET (-1)	.062	.03	2.09	.037	.004	.121	**
SET (-2)	-.046	.029	-1.57	.117	-.103	.011	
SET (-3)	.019	.029	0.63	.528	-.039	.076	
SET (-4)	.033	.03	1.12	.263	-.025	.092	
SET (-5)	-.071	.029	-2.44	.015	-.128	-.014	**
SET (-6)	.001	.029	0.05	.961	-.056	.059	
SET (-7)	-.017	.029	-0.58	.564	-.074	.04	
SET (-8)	-.027	.028	-0.93	.351	-.082	.029	
SET (-9)	-.011	.029	-0.38	.708	-.067	.045	
SET (-10)	-.021	.028	-0.72	.47	-.076	.035	
LITE (-1)	.002	.002	0.98	.326	-.002	.007	
LITE (-2)	-.003	.002	-1.07	.283	-.007	.002	
LITE (-3)	.004	.002	1.84	.066	<0.001	.009	*
LITE (-4)	-.002	.002	-0.89	.375	-.007	.003	
LITE (-5)	.002	.002	0.90	.37	-.003	.007	
LITE (-6)	.002	.002	0.64	.525	-.003	.006	
LITE (-7)	-.001	.002	-0.46	.645	-.006	.004	
LITE (-8)	.004	.002	1.58	.113	-.001	.009	
LITE (-9)	-.005	.002	-2.26	.024	-.01	-.001	**
LITE (-10)	.002	.002	0.91	.361	-.003	.007	
Arch (ω1)	.091	.013	6.83	<0.001	.065	.117	***
Garch (ω2)	.902	.013	68.80	<0.001	.876	.928	***
Constant (ω0)	<0.001	<0.001	2.85	.004	<0.001	<0.001	***
SET (-1)	.447	.153	2.92	.003	.147	.747	***
SET (-2)	.203	.151	1.34	.179	-.093	.498	
SET (-3)	-.178	.147	-1.21	.228	-.466	.111	
SET (-4)	.324	.142	2.28	.022	.046	.601	**
SET (-5)	-.117	.145	-0.81	.419	-.402	.167	
SET (-6)	.241	.145	1.66	.097	-.044	.526	*
SET (-7)	-.157	.143	-1.10	.272	-.437	.123	
SET (-8)	-.04	.138	-0.29	.775	-.311	.232	
SET (-9)	.035	.139	0.25	.8	-.237	.308	
SET (-10)	.031	.139	0.22	.826	-.241	.302	
LITE (-1)	.012	.035	0.36	.719	-.055	.08	
LITE (-2)	-.046	.034	-1.36	.174	-.113	.02	
LITE (-3)	-.027	.034	-0.79	.428	-.094	.04	
LITE (-4)	.004	.034	0.13	.899	-.063	.072	
LITE (-5)	-.024	.035	-0.68	.494	-.091	.044	
LITE (-6)	-.031	.034	-0.92	.359	-.097	.035	
LITE (-7)	.011	.033	0.32	.746	-.054	.076	

LITE (-8)	-.085	.032	-2.64	.008	-.147	-.022	***
LITE (-9)	-.019	.032	-0.59	.556	-.082	.044	
LITE (-10)	.007	.032	0.22	.827	-.056	.071	
Arch (ω1)	.112	.019	5.84	<0.001	.075	.15	***
Garch (ω2)	.866	.015	58.34	<0.001	.837	.895	***
Constant (ω0)	<0.001	<0.001	4.22	<0.001	<0.001	<0.001	***
lambda1	<0.001	.003	0.12	.905	-.006	.007	
lambda2	.996	.009	105.92	<0.001	.978	1.015	***

Log likelihood = 6461.855

**** p<.01, ** p<.05, * p<.1*

Dynamic conditional correlation MGARCH model

PSEI/ETH	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
PSEI (-1)	-.063	.03	-2.11	.035	-.122	-.004	**
PSEI (-2)	-.031	.03	-1.03	.305	-.089	.028	
PSEI (-3)	.015	.029	0.49	.622	-.043	.072	
PSEI (-4)	<0.001	.029	0.01	.992	-.057	.058	
PSEI (-5)	-.059	.029	-2.04	.042	-.116	-.002	**
ETH (-1)	.005	.005	1.16	.245	-.004	.014	
ETH (-2)	.005	.005	0.97	.332	-.005	.014	
ETH (-3)	.002	.005	0.46	.642	-.007	.011	
ETH (-4)	<0.001	.005	-0.08	.94	-.009	.009	
ETH (-5)	.002	.005	0.54	.591	-.007	.011	
Arch (ω1)	.100	.023	4.38	<0.001	.055	.145	***
Garch (ω2)	.859	.035	24.80	<0.001	.791	.926	***
Constant (ω0)	<0.001	<0.001	2.58	.01	<0.001	<0.001	***
PSEI (-1)	.172	.109	1.58	.115	-.042	.385	
PSEI (-2)	.179	.111	1.61	.107	-.039	.398	
PSEI (-3)	.088	.114	0.77	.44	-.135	.311	
PSEI (-4)	.023	.106	0.21	.831	-.186	.231	
PSEI (-5)	.026	.107	0.24	.808	-.184	.236	
ETH (-1)	.089	.032	2.76	.006	.026	.152	***
ETH (-2)	-.013	.032	-0.40	.692	-.075	.05	
ETH (-3)	.011	.031	0.35	.727	-.05	.072	
ETH (-4)	.013	.03	0.43	.664	-.045	.071	
ETH (-5)	-.029	.03	-0.98	.329	-.089	.03	
Arch (ω1)	.168	.032	5.22	<0.001	.105	.231	***
Garch (ω2)	.761	.044	17.48	<0.001	.676	.847	***
Constant (ω0)	<0.001	<0.001	3.80	<0.001	<0.001	<0.001	***
lambda1	.008	.007	1.21	.226	-.005	.022	
lambda2	.977	.019	50.17	<0.001	.939	1.015	***

Log likelihood = 6031.289

**** p<.01, ** p<.05, * p<.1*

Dynamic conditional correlation MGARCH model

PSEI/Tether	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
PSEI (-1)	.006	.019	0.31	.753	-.031	.042	
TETHER (-1)	.005	.005	1.19	.235	-.004	.015	
Arch (ω1)	.099	.022	4.41	<0.001	.055	.142	***
Garch (ω2)	.861	.033	25.70	<0.001	.795	.926	***
Constant (ω0)	<0.001	<0.001	2.66	.008	<0.001	<0.001	***
PSEI (-1)	-.299	.059	-5.12	<0.001	-.414	-.185	***
TETHER (-1)	.002	.002	0.99	.322	-.002	.006	

Arch (ω1)	.529	.055	9.60	<0.001	.421	.638	***
Garch (ω2)	.626	.02	32.08	<0.001	.588	.664	***
Constant (ω0)	<0.001	<0.001	12.05	<0.001	<0.001	<0.001	***
lambda1	.079	.067	1.17	.241	-.053	.211	
lambda2	.537	.33	1.63	.104	-.11	1.183	
Log likelihood = 9529.536							

**** p<.01, ** p<.05, * p<.1*

Dynamic conditional correlation MGARCH model

PSEI/Litecoin	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
PSEI (-1)	-.066	.03	-2.21	.027	-.125	-.007	**
PSEI (-2)	-.047	.03	-1.58	.114	-.105	.011	
PSEI (-3)	.007	.029	0.22	.824	-.051	.064	
PSEI (-4)	-.002	.029	-0.08	.939	-.06	.055	
PSEI (-5)	-.071	.029	-2.48	.013	-.128	-.015	**
PSEI (-6)	-.04	.028	-1.40	.16	-.095	.016	
PSEI (-7)	-.025	.028	-0.88	.38	-.081	.031	
LITE (-1)	.01	.004	2.37	.018	.002	.018	**
LITE (-2)	-.004	.004	-0.95	.345	-.013	.004	
LITE (-3)	.009	.004	2.08	.037	.001	.017	**
LITE (-4)	.003	.004	0.80	.425	-.005	.012	
LITE (-5)	<0.001	.004	-0.10	.918	-.009	.008	
LITE (-6)	.005	.004	1.11	.269	-.004	.013	
LITE (-7)	<0.001	.004	0.02	.987	-.008	.008	
Arch (ω1)	.119	.028	4.22	<0.001	.064	.174	***
Garch (ω2)	.839	.04	21.05	<0.001	.761	.917	***
Constant (ω0)	<0.001	<0.001	2.53	.011	<0.001	<0.001	**
PSEI (-1)	.206	.111	1.86	.063	-.011	.424	*
PSEI (-2)	.17	.111	1.54	.124	-.047	.387	
PSEI (-3)	.027	.112	0.24	.811	-.193	.247	
PSEI (-4)	.231	.107	2.16	.031	.021	.441	**
PSEI (-5)	-.15	.106	-1.42	.157	-.358	.058	
PSEI (-6)	.116	.108	1.07	.287	-.097	.328	
PSEI (-7)	-.137	.108	-1.27	.204	-.348	.074	
LITE (-1)	.02	.035	0.58	.559	-.048	.088	
LITE (-2)	-.045	.035	-1.29	.198	-.113	.023	
LITE (-3)	-.018	.034	-0.54	.59	-.086	.049	
LITE (-4)	.022	.034	0.66	.512	-.045	.089	
LITE (-5)	-.028	.035	-0.80	.425	-.096	.04	
LITE (-6)	-.015	.034	-0.43	.666	-.081	.052	
LITE (-7)	.003	.034	0.08	.937	-.063	.068	
Arch (ω1)	.123	.021	5.97	<0.001	.083	.164	***
Garch (ω2)	.869	.013	65.46	<0.001	.843	.895	***
Constant (ω0)	<0.001	<0.001	3.58	<0.001	<0.001	<0.001	***
lambda1	.009	.01	0.95	.34	-.01	.029	
lambda2	.952	.044	21.46	<0.001	.865	1.039	***
Log likelihood = 5969.337							

**** p<.01, ** p<.05, * p<.1*

Dynamic conditional correlation MGARCH model

JKSE/ETH	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig

JKSE (-1)	-.004	.031	-0.14	.887	-.065	.056	
JKSE (-2)	-.05	.03	-1.68	.092	-.108	.008	*
ETH (-1)	.003	.004	0.89	.373	-.004	.01	
ETH (-2)	.005	.004	1.43	.151	-.002	.012	
Arch (ω1)	.188	.036	5.23	<0.001	.118	.259	***
Garch (ω2)	.727	.052	13.90	<0.001	.624	.829	***
Constant (ω0)	<0.001	<0.001	3.50	<0.001	<0.001	<0.001	***
JKSE (-1)	.179	.144	1.24	.214	-.104	.462	
JKSE (-2)	.128	.144	0.89	.371	-.153	.41	
ETH (-1)	.089	.032	2.75	.006	.026	.152	***
ETH (-2)	-.01	.031	-0.30	.761	-.071	.052	
Arch (ω1)	.169	.032	5.29	<0.001	.107	.232	***
Garch (ω2)	.760	.043	17.47	<0.001	.674	.845	***
Constant (ω0)	<0.001	<0.001	3.81	<0.001	<0.001	<0.001	***
lambda1	.009	.013	0.70	.484	-.016	.034	
lambda2	.942	.066	14.36	<0.001	.814	1.071	***

Log likelihood = 6376.774

**** p<.01, ** p<.05, * p<.1*

Dynamic conditional correlation MGARCH model

JKSE/Tether	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
JKSE (-1)	.004	.031	0.12	.908	-.057	.065	
JKSE (-2)	-.049	.03	-1.64	.1	-.107	.009	
JKSE (-3)	.031	.029	1.05	.292	-.027	.088	
TETHER (-1)	.011	.016	0.69	.491	-.02	.042	
TETHER (-2)	.021	.017	1.27	.204	-.012	.054	
TETHER (-3)	-.04	.02	-2.04	.041	-.079	-.002	**
Arch (ω1)	.19	.036	5.28	<0.001	.119	.26	***
Garch (ω2)	.724	.051	14.13	<0.001	.624	.824	***
Constant (ω0)	<0.001	<0.001	3.64	<0.001	<0.001	<0.001	***
JKSE (-1)	-.026	.009	-3.08	.002	-.043	-.01	***
JKSE (-2)	.036	.009	4.13	0	.019	.052	***
JKSE (-3)	-.02	.01	-2.03	.042	-.039	-.001	**
TETHER (-1)	-.245	.056	-4.40	0	-.354	-.136	***
TETHER (-2)	-.091	.056	-1.63	.104	-.202	.019	
TETHER (-3)	-.033	.047	-0.70	.482	-.125	.059	
Arch (ω1)	.554	.059	9.44	<0.001	.439	.669	***
Garch (ω2)	.624	.019	32.79	<0.001	.586	.661	***
Constant (ω0)	<0.001	<0.001	11.81	<0.001	<0.001	<0.001	***
lambda1	.063	.074	0.86	.392	-.082	.209	
lambda2	.27	.455	0.59	.552	-.621	1.162	

Log likelihood = 9870.892

**** p<.01, ** p<.05, * p<.1*

Dynamic conditional correlation MGARCH model

JKSE/Litecoin	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
JKSE (-1)	-.003	.031	-0.10	.918	-.064	.058	
JKSE (-2)	-.055	.03	-1.85	.065	-.114	.003	*
JKSE (-3)	.024	.029	0.81	.418	-.034	.082	

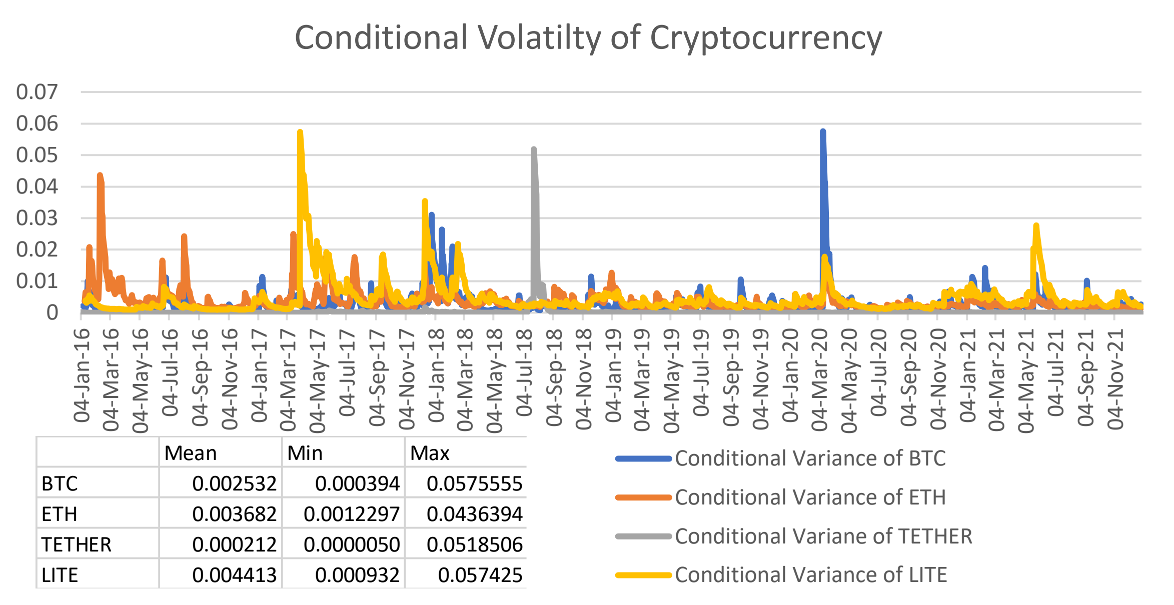
JKSE (-4)	-.032	.028	-1.13	.257	-.088	.023	
JKSE (-5)	-.017	.028	-0.60	.546	-.071	.038	
JKSE (-6)	-.017	.028	-0.61	.544	-.072	.038	
LITE (-1)	.001	.003	0.39	.696	-.005	.008	
LITE (-2)	.003	.003	0.78	.435	-.004	.009	
LITE (-3)	.005	.003	1.52	.128	-.001	.011	
LITE (-4)	.003	.003	0.91	.363	-.004	.01	
LITE (-5)	.003	.003	0.80	.421	-.004	.009	
LITE (-6)	.001	.003	0.38	.703	-.005	.008	
Arch (ω1)	.202	.039	5.19	<0.001	.126	.278	***
Garch (ω2)	.705	.055	12.71	<0.001	.596	.814	***
Constant (ω0)	<0.001	<0.001	3.63	<0.001	<0.001	<0.001	***
JKSE (-1)	.218	.139	1.58	.115	-.053	.49	
JKSE (-2)	.221	.141	1.57	.116	-.055	.498	
JKSE (-3)	-.047	.139	-0.33	.738	-.32	.227	
JKSE (-4)	.321	.132	2.43	.015	.063	.58	**
JKSE (-5)	-.195	.136	-1.44	.151	-.461	.071	
JKSE (-6)	.211	.137	1.54	.122	-.057	.48	
LITE (-1)	.023	.035	0.67	.501	-.044	.091	
LITE (-2)	-.044	.034	-1.28	.2	-.111	.023	
LITE (-3)	-.025	.034	-0.74	.46	-.091	.041	
LITE (-4)	.018	.034	0.54	.586	-.048	.084	
LITE (-5)	-.034	.034	-1.00	.316	-.102	.033	
LITE (-6)	-.026	.034	-0.78	.435	-.093	.04	
Arch (ω1)	.114	.019	6.16	<0.001	.078	.151	***
Garch (ω2)	.873	.014	63.72	<0.001	.843	.896	***
Constant (ω0)	<0.001	<0.001	4.14	<0.001	0	0	***
lambda1	.014	.012	1.18	.238	-.009	.037	
lambda2	.937	.043	21.79	0	.853	1.021	***

Log likelihood = 6299.408

**** p<.01, ** p<.05, * p<.1*

Conditional Volatility:

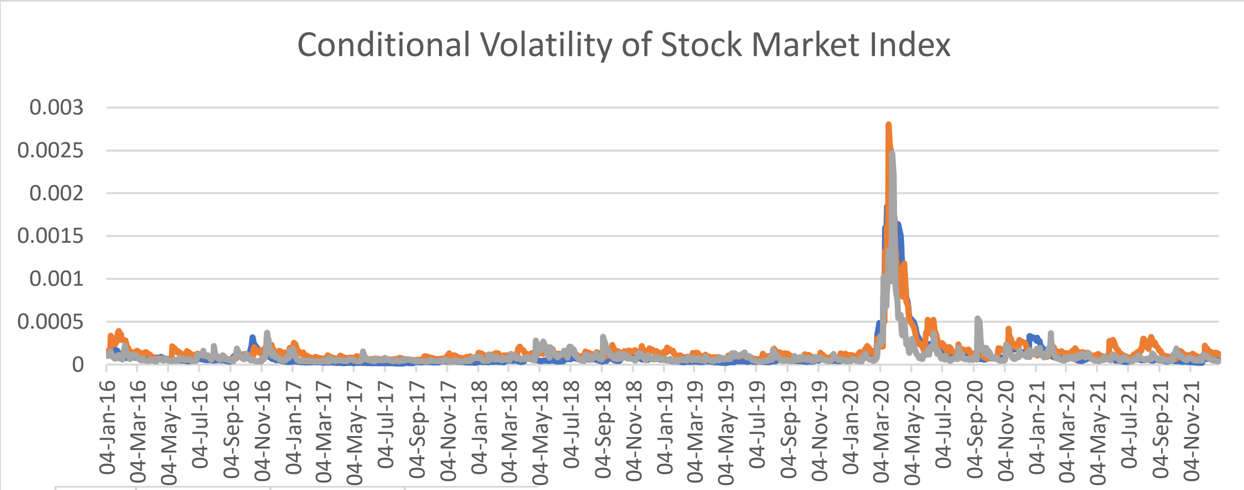
Figure 1: Conditional Volatility of Cryptocurrencies



	Mean	Min	Max
BTC	0.002532	0.000394	0.0575555
ETH	0.003682	0.0012297	0.0436394
TETHER	0.000212	0.0000050	0.0518506
LITE	0.004413	0.000932	0.057425

In general, the patterns in Figures 1 and 2 agree with the fact that cryptocurrencies are much more volatile than the stock market, which is becoming more widely known. Figure 1 demonstrates that the volatility of cryptocurrencies increases from September 2016 to the end of 2017, corresponding with the "bubble" phase in the cryptocurrency market (Ferreira and Pereira 2019). Furthermore, the WHO's announcement that Covid-19 has become a world pandemic is making cryptocurrency and the stock market index more volatile at the beginning of March 2020. Based on the mean of conditional volatility in figure 1, Litecoin are the most volatile, following by Ethereum and Bitcoin. Tether is least volatile, and the reason is that Stable coin, such as Tether was developed to mitigate the risk of excessive volatility in traditional cryptocurrencies. Thus, when the market is under stress, stable coin prices should remain stable or move slightly. The pattern in the figure 2, PSEI index are the most volatile following by SET and JKSE

Figure 2: Conditional Volatility of Stock Market Index



	Mean	Min	Max
SET	0.000102	0.000013	0.002519
PSEI	0.000157	0.000052	0.002805
JKSE	0.000100	0.000033	0.002467

The Conditional Correlation Analysis:

The conditional correlation between SET index and cryptocurrency are reported in Table 7, the average of conditional correlation between SET and Bitcoin are the highest and there are only 2 negative number of conditional correlation. Thus, Bitcoin might not have any hedge properties. Next, conditional correlation of SET and Tether are the lowest in every time periods, they might act as hedger or safe haven because they are very close to zero. To test this assumption, the following sections of this work present more complex empirical models. The conditional correlations increase during the outbreak, although positive dynamic correlations generally lead in most cases. This contributes to the evidence of cryptocurrencies' diversifier capabilities in Thailand's stock market.

The results from Table 8 show that before COVID-19 period and during COVID-19 period, the average of conditional correlation between PSEI and Tether is negative number and there are 86% and 88% of negative number of conditional correlations respectively, which lead to prediction that Tether might act as hedge. The slightly negative average conditional correlations indicate Ethereum's capacity to operate as hedge or may be just the diversifier in times of market stability. To test this assumption, the following sections of this work present more complex empirical model.

Table 7: Summary statistic of conditional correlation of SET Index and Cryptocurrencies

Duration	Index	Observation	Mean	Min	Max	Std. Div	Negative No. of Conditional Correlation	%	Positive No. of Conditional Correlation	%
Whole Period (1/1/2016–31/12/2021)	SET/BTC	1321	0.1726	-0.0233	0.5168	0.0635	2	0.15%	1319	99.85%
	SET/ETH	1321	0.0541	-0.0717	0.1872	0.0258	29	2.20%	1292	97.80%
	SET/TETHER	1320	0.0238	-0.0088	0.0872	0.0251	109	8.26%	1211	91.74%
	SET/LITE	1314	0.0384	-0.0004	0.0523	0.0121	5	0.38%	1309	99.62%
Before Covid (1/1/2016-11/3/2018)	SET/BTC	928	0.1558	-0.0233	0.3190	0.0526	2	0.22%	926	99.78%
	SET/ETH	928	0.0538	-0.0717	0.1872	0.0293	29	3.13%	899	96.88%
	SET/TETHER	927	0.0170	-0.0064	0.0842	0.0195	83	8.95%	844	91.05%
	SET/LITE	921	0.0339	-0.0004	0.0453	0.0117	5	0.54%	916	99.46%
During Covid (12/1/2016-31/12/2021	SET/BTC	393	0.2125	0.0941	0.5168	0.0691	0	0.00%	393	100.00%
	SET/ETH	393	0.0548	0.0086	0.1372	0.0146	0	0.00%	393	100.00%
	SET/TETHER	393	0.0397	-0.0088	0.0872	0.0292	26	6.62%	367	93.38%
	SET/LITE	393	0.0489	0.0416	0.0523	0.0022	0	0.00%	393	100.00%

Table 8: Summary statistic of conditional correlation of PSEI Index and Cryptocurrencies

Duration	Index	Observation	Mean	Min	Max	Std. Div	Negative No. of Conditional Correlation	%	Positive No. of Conditional Correlation	%
Whole Period (1/1/2016–31/12/2021)	PSEI/BTC	1320	0.0698	-0.1946	0.5798	0.0953	275	20.83%	1045	79.17%
	PSEI/ETH	1319	-0.0051	-0.1417	0.1320	0.0463	767	58.15%	552	41.85%
	PSEI/TETHER	1323	-0.0211	-0.3137	0.3974	0.0540	1149	86.85%	174	13.15%
	PSEI/LITE	1317	0.0311	-0.0855	0.1163	0.0329	183	13.90%	1134	86.10%
Before Covid (1/1/2016-11/3/2018)	PSEI/BTC	927	0.0543	-0.1946	0.3355	0.0846	242	26.11%	685	73.89%
	PSEI/ETH	926	-0.0118	-0.1417	0.1320	0.0466	601	64.90%	325	35.10%
	PSEI/TETHER	930	-0.0211	-0.3137	0.3120	0.0522	802	86.24%	128	13.76%
	PSEI/LITE	924	0.0193	-0.0855	0.1118	0.0283	175	18.94%	749	81.06%
During Covid (12/1/2016-31/12/2021	PSEI/BTC	393	0.1062	-0.0977	0.5798	0.1081	33	8.40%	360	91.60%
	PSEI/ETH	393	0.0105	-0.0724	0.1095	0.0416	166	42.24%	227	57.76%
	PSEI/TETHER	393	-0.0209	-0.3101	0.3974	0.0580	347	88.30%	46	11.70%
	PSEI/LITE	393	0.0586	-0.0022	0.1163	0.0258	8	2.04%	385	97.96%

Table 9: Summary statistic of conditional correlation of PSEI Index and Cryptocurrencies.

Duration	Index	Observation	Mean	Min	Max	Std. Div	Negative No. of Conditional Correlation	%	Positive No. of Conditional Correlation	%
Whole Period (1/1/2016– 31/12/2021)	**JKSE/BTC**	1322	0.0645	-0.0735	0.2757	0.0431	63	4.77%	1259	95.23%
	JKSE/ETH	1322	0.0154	-0.0740	0.1652	0.0353	444	33.59%	878	66.41%
	JKSE/TETHER	1322	-0.0120	-0.1800	0.1674	0.0372	919	69.52%	403	30.48%
	JKSE/LITE	1318	0.0473	-0.1074	0.1782	0.0428	195	14.80%	1123	85.20%
Before Covid (1/1/2016- 11/3/2018)	**JKSE/BTC**	929	0.0603	-0.0526	0.5798	0.0391	47	5.06%	882	94.94%
	JKSE/ETH	929	0.0097	-0.0740	0.1095	0.0385	415	44.67%	514	55.33%
	JKSE/TETHER	929	-0.0134	-0.1800	0.3974	0.0369	654	70.40%	275	29.60%
	JKSE/LITE	925	0.0361	-0.1074	0.1163	0.0403	187	20.22%	738	79.78%
During Covid (12/1/2016- 31/12/2021	**JKSE/BTC**	393	0.0745	-0.0735	0.2727	0.0500	16	4.07%	377	95.93%
	JKSE/ETH	393	0.0288	-0.0240	0.1006	0.0210	29	7.38%	364	92.62%
	JKSE/TETHER	393	-0.0087	-0.1142	0.1674	0.0375	265	67.43%	128	32.57%
	JKSE/LITE	393	0.0737	-0.0108	0.1727	0.0364	8	2.04%	385	97.96%

Table 10: Unit root with drift regress lag(5)

List	Whole Period Test Statistic	Before Covid Test Statistic	During Covid Test Statistic
SET/BTC	-6.623***	-6.751***	-4.546***
PSEI/BTC	-5.684***	-4.869***	-4.118***
JKSE/BTC	-7.425***	-6.229***	-2.435***
SET/ETH	-6.996***	-5.602***	-4.687***
PSEI/ETH	-3.421***	-2.608***	-2.073***
JKSE/ETH	-5.266***	-4.087***	-4.087***
SET/TETHER	-1.834**	-2.34***	-1.115**
PSEI/TETHER	-12.455***	-10.938***	-6.152***
JKSE/TETHER	-13.544***	-11.23***	-7.494***
SET/LITE	-4.958***	-4.527***	-3.7***
PSEI/LITE	-4.485***	-4.485***	-2.578***
JKSE/LITE	-5.049***	-3.927***	-3.656***

Notes: ***, ** and * denote statistical significance at the 1%, 5% and 10%, respectively.

According to the figure 3 to figure 5, on average, these conditional correlations have grown. This is the result of two effects. First, the simultaneous collapse of stock markets and the COVID-19 pandemic. In fact, the health crisis has evolved into a severe economic collapse that has impacted the market more severely than any other shock(Baker, Farrokhnia et al. 2020).Some shocks were caused by the direct effects associated with the spread of the virus, such as the infection rate and mortality rate, as well as the economic and psychological effects of social isolation and lockdown measures in various parts of the world, which triggered a massive sell-off on the financial markets. Other (positive or negative) shocks were caused by the direct consequence of central bank monetary policy actions) in different sections of the financial globe and at different times. Second, the fast increase in the prices and the fluctuation of cryptocurrencies, the crisis events drove foreign investors to select an optimal allocation strategy by investing in these assets to safeguard their money (Bofinger, Dullien et al. 2020). However, it appears that the decline in conditional correlation is temporary and of short duration. This study also finds that time-varying correlation between stock markets and cryptocurrencies are stationary using Unit-root with drift regress which implying that if the fund managers know that the results are stationary, then don't have to rebalance the portfolio because there will be no transaction cost for rebalancing the portfolio.

Figure 3: The Conditional Correlation between SET Index and Cryptocurrencies

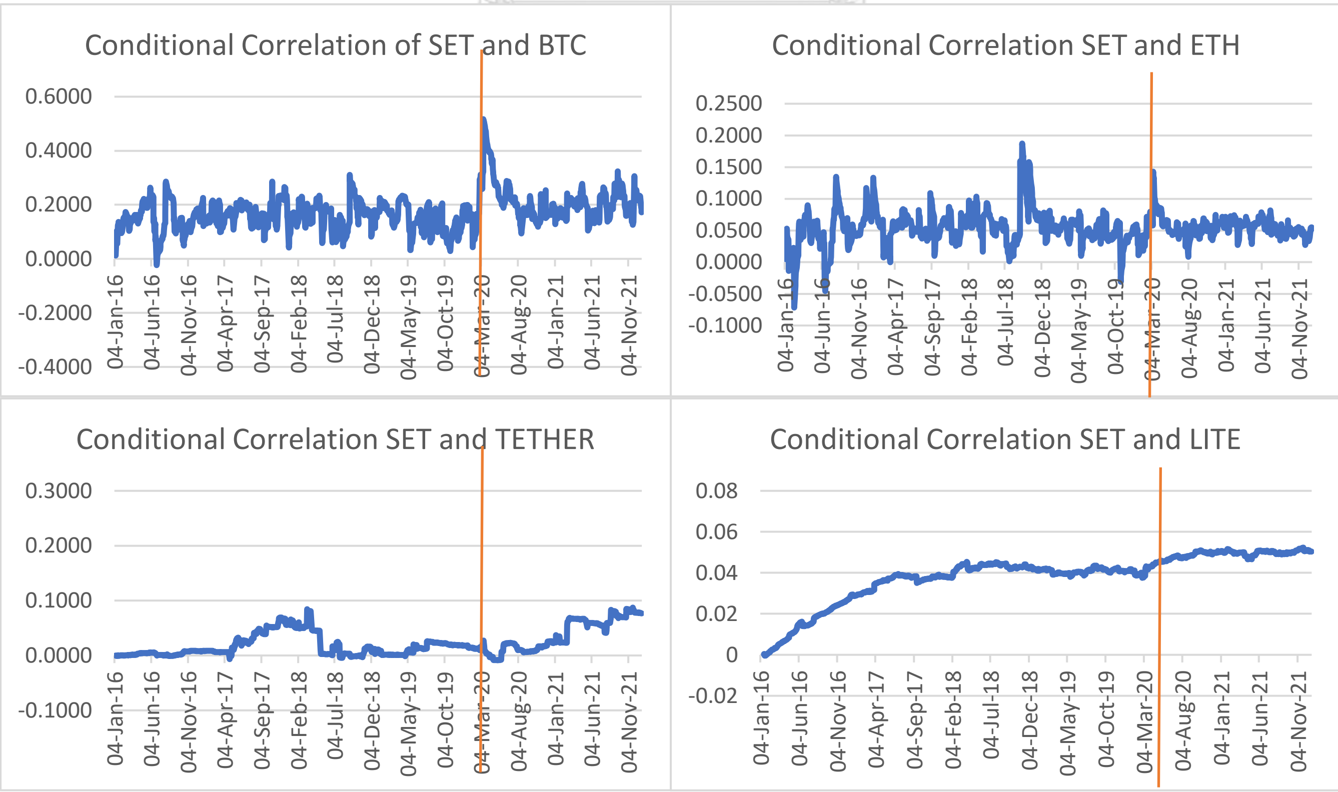


Figure 4: The Conditional Correlation between PSEI Index and Cryptocurrencies

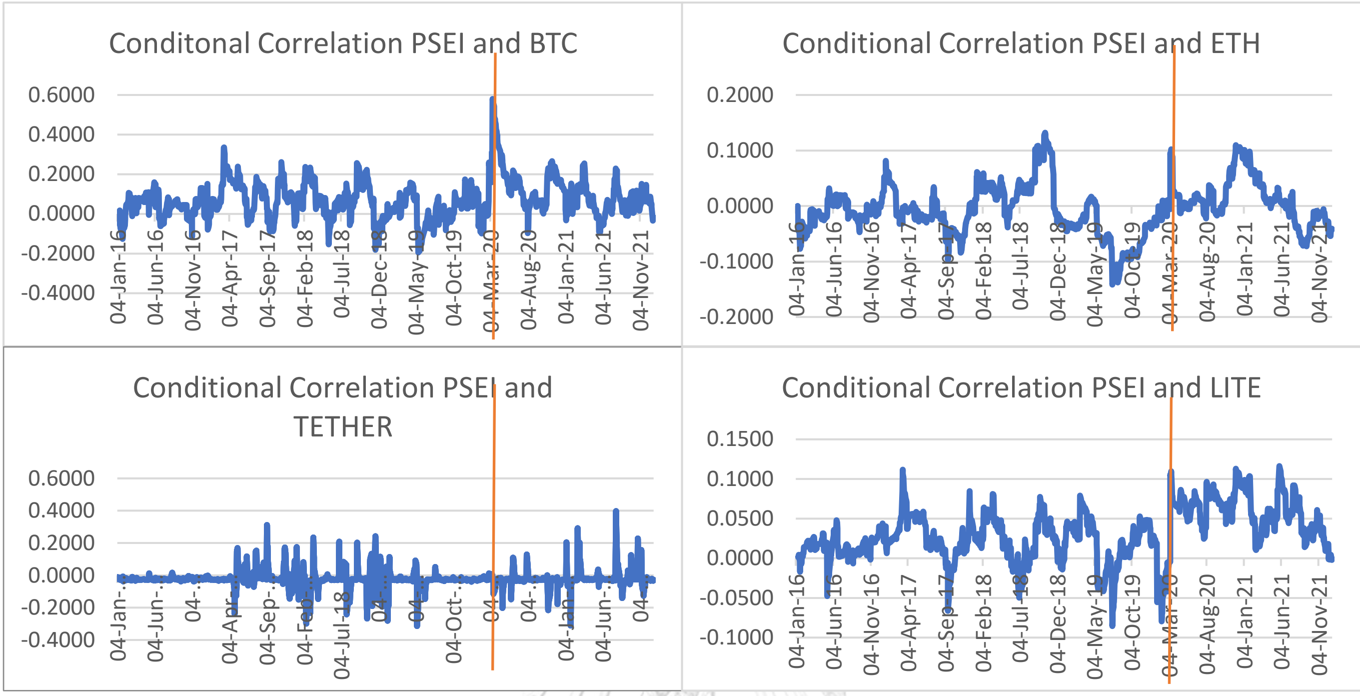
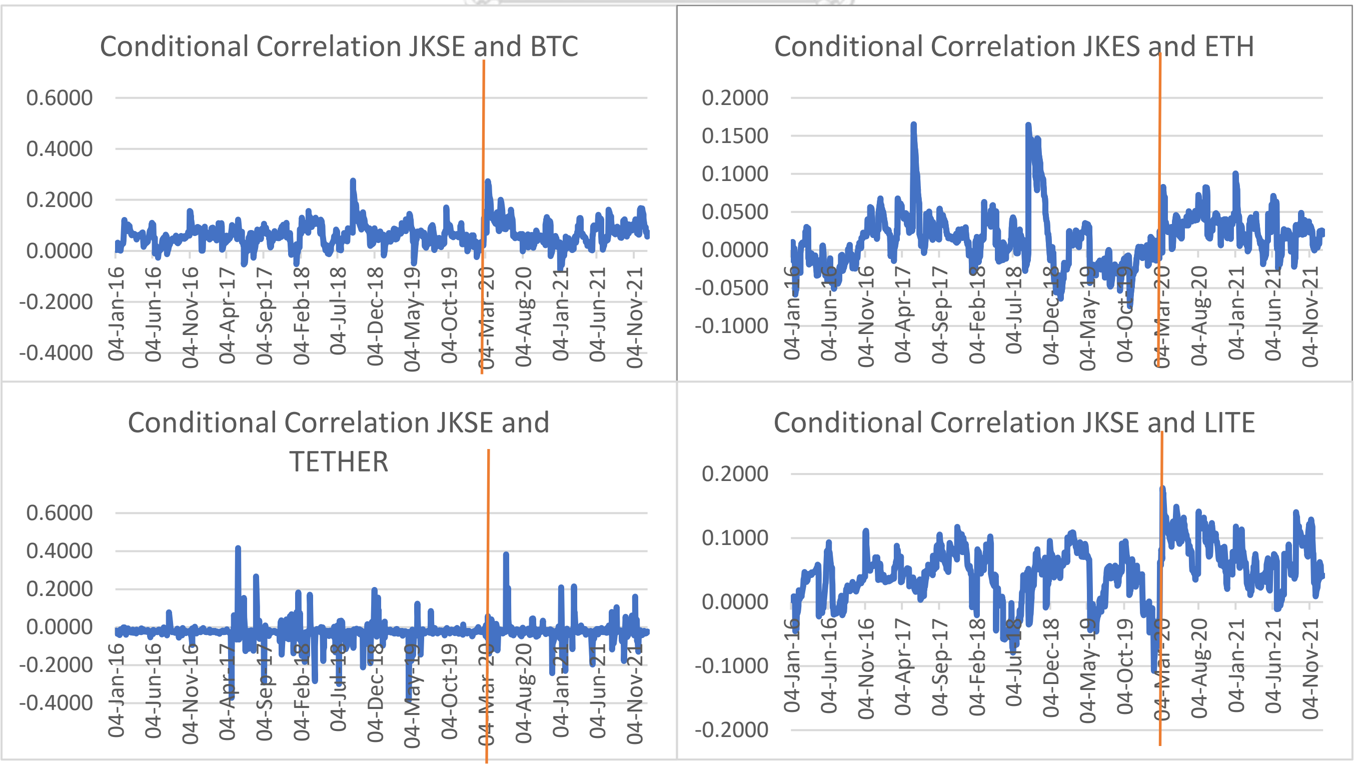


Figure 5: The Conditional Correlation between JKSE Index and Cryptocurrencies.



Hedge Ratio Analysis:

The hedge ratio is an essential risk management strategy. The two types of hedges are static and dynamic. As its name implies, the static hedge's hedging position remains unchanged during the time horizon, whereas the dynamic hedge's hedging position changes over time. The minimum variance hedge ratio, also known as the optimal hedge ratio, is the ratio of futures position to spot position that minimizes the portfolio's variation.

As the result from table 11, the SET/BTC portfolio has the largest hedging ratio, which is about 0.04. This means that a 1 USD long position on the stock market can be hedged with a 0.04 USD short position in BTC to minimize risk. On the other hand, negative hedging ratios are observed for the JKSE/TETHER. Due to the negative conditional covariance between the assets, a negative hedging ratio is calculated. The average hedging ratio for the JKSE/TETHER portfolio is -0.068, which indicates that a long position worth 1 USD on the stock market can be hedged with a long position worth 0.068 USD in Tether.

For dynamic hedge ratio stability, PSEI/Tether has the highest standard deviation of 0.1031. The higher the standard deviation, the more frequently investors rebalance their portfolios. Numerous investors, who typically hedge their portfolios using the hedge ratio computed from previous data, expect a time-varying hedge ratio that is reliable. Cryptocurrencies may lose their hedging value to investors if hedge ratios do not stabilize, as risk diversification and hedging schemes are challenging to implement. (Yao and Wu 2012)

Table 11: Optimal Hedge Ratio

Index	Mean	Max	Min	Std. Div
SET/BTC	0.0412	0.3143	-0.0020	0.0358
PSEI/BTC	0.0236	0.2475	-0.0591	0.0357
JKSE/BTC	0.0166	0.1178	-0.0140	0.0147
SET/ETH	0.0092	0.1071	-0.0036	0.0085
PSEI/ETH	-0.0006	0.0734	-0.0455	0.0112

JKSE/ETH	0.0031	0.0488	-0.0137	0.0066
SET/TETHER	0.0509	0.4500	-0.0732	0.0650
PSEI/TETHER	-0.0890	0.7222	-0.8260	0.1031
JKSE/TETHER	-0.0684	0.5630	-0.8121	0.0825
SET/LITE	0.0059	0.0290	-0.0001	0.0043
PSEI/LITE	0.0070	0.0669	-0.0158	0.0090
JKSE/LITE	0.0083	0.0786	-0.0213	0.0103

Table 12: Average Optimal Hedge Ratio

Average Optimal Hedge ratio		
	Before	**During**
SET/BTC	0.0328	0.0612
SET/ETH	0.0072	0.0139
SET/TETHER	0.0296	0.1013
SET/LITE	0.0043	0.0097
PSEI/BTC	0.0162	0.0410
PSEI/ETH	-0.0022	0.0031
PSEI/TETHER	-0.0800	-0.1103
PSEI/LITE	0.0037	0.0149
JKSE/BTC	0.0152	0.0200
JKSE/ETH	0.0016	0.0067
JKSE/TETHER	-0.0656	-0.0750
JKSE/LITE	0.0053	0.0153

The average optimal hedge ratio for TIP's stock index and cryptocurrencies during the pre-COVID-19 crisis and the COVID-19 crisis is shown in Table 12 For the SET/BTC pair, the optimal hedge ratio is 0.0328 before COVID-19 and 0.0612 during COVID-19 crisis, this result implied that more Bitcoin is needed to minimize the risk of SET, and it follow that the cost of hedging SET risk though Bitcoin is higher during COVID-19. Next, for PSEI/ETH pairs, the results suggest that hedging PSEI index though Ethereum is more expensive during COVID-19.

As we can see, there is a significant fluctuation in the dynamic hedge ratio across all stock and cryptocurrency pairs, which makes it difficult for portfolio managers to rebalance the portfolio and may force them to do so more frequently, which may result in additional costs like transaction fees, exchange rate risk, or tax implications. Sometimes portfolio manager may want to rebalance the portfolio every weekly, monthly, or quarterly based on their preferences or potential benefit of rebalancing the portfolio. Due to volatility of conditional hedge ratio, the unit root tests are applied to confirm the stationarity. The results show that there is stationary which make the rebalancing portfolio easier.

Hypothesis Test Results:

In this section, we evaluate of the conditional correlation obtained from the DCC-GARCH model by using hypothesis test with one sample 2 tailed test. When determining if there is a difference between the groups you are classifying, a two-tailed test is suitable. The two-tailed test is mostly use in the financial research studies because it can compare the 3 conditionals at the same time which make it easier for the research to test the hypothesis. For instance, we would want to apply a two-tailed test to determine if asset A scored higher or lower than asset B. This is so because a two-tailed test makes use of both the distribution's positive and negative tails. To put it another way, it investigates the likelihood of either positive or negative differences or it can detect both positive and negative effects. So, the test split into three periods, which are whole period, before COVID-19, and during Covid.

As you can see in the Table 13, the t-stats from hypothesis test are significantly positive, which mean they all rejected null hypothesis. We can conclude that the 4 sample cryptocurrencies act as the diversifier tool against the SET index so none of them qualified as a hedge in normal situation or safe haven during market turmoil.

Next, the hypothesis test of PSEI and cryptocurrencies are reported in Table 14, we found that when we examine the whole period, Tether and Ethereum have the potential to act as strong hedger against PSEI index, as we compared from the last section, the number of negative numbers of conditional correlation is above 50%.

Tether is all negative at any significance level and every time period, suggesting that hedge and safe haven role against the PSEI index. One possible reason that Tether can act as a safe-haven is that when the market goes down a lot, investors move their money from risky traditional asset to some stablecoins. This tends to make such stablecoins more desirable. Another alternative explanation could be that when negative shocks occur, investors move their funds from cryptocurrencies to traditional safe haven assets (such as USD and gold) to avoid risk, causing the USD and gold prices to rise, which in turn causes the stablecoins to appreciate.

The t-test in Table 15 shows that the percentage of JKSE/TETHER with negative number are above 60% Tether has highest amount of negative number following by Ethereum. As the result, Tether is the only cryptocurrency that all negative at the 1%, 5%, 10% significance level. Tether has the potential to act as the strong hedge and strong safe haven against JKSE index.

Table 14: Hypothesis Test for classify hedge, safe haven or diversify of cryptocurrencies (SET/CRYPTOCURRENCIES

	Whole Period				Before Covid				During Covid			
	SET/BTC	SET/ETH	SET/TETHER	SET/LITE	SET/BTC	SET/ETH	SET/TETHER	SET/LITE	SET/BTC	SET/ETH	SET/TETHER	SET/LITE
Mean	0.1726	0.0541	0.0237	0.03837	0.1554	0.0539	0.017	0.03387	0.2122	0.0546	0.0397	0.04893
t-stat	98.704	70.633	34.4676	115.347	88.6679	55.878	26.5734	87.623	60.8742	66.668	26.9362	447.648
Test	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***
Result	Diversifier	Diversifier	Diversifier	Diversifier	Diversifier	Diversifier	Diversifier	Diversifier	Diversifier	Diversifier	Diversifier	Diversifier

Table 13: Hypothesis Test for classify hedge, safe haven or diversify of cryptocurrencies (PSEI/CRYPTOCURRENCIES)

	Whole Period				Before Covid				During Covid			
	PSEI/BTC	PSEI/ETH	PSEI/TETHER	PSEI/LITE	PSEI/BTC	PSEI/ETH	PSEI/TETHER	PSEI/LITE	PSEI/BTC	PSEI/ETH	PSEI/TETHER	PSEI/LITE
Mean	0.0698	-0.0051	-0.0211	0.0311	0.0543	-0.0118	-0.0211	0.0192	0.1054	0.0105	-0.0209	0.0586
t-stat	26.604	-4.0266	-14.1931	34.1231	19.5391	-7.6932	-12.3522	20.7185	19.3573	4.9994	-7.1306	44.971
Test	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***
Result	Diversifier	Strong Hedge	Strong Hedge	Diversifier	Diversifier	Strong Hedge	Strong Hedge	Diversifier	Diversifier	Diversifier	Strong Safe haven	Diversifier

Table 15: Hypothesis Test for classify hedge, safe haven or diversify of cryptocurrencies (JKSE/CRYPTOCURRENCIES)

	Whole Period				Before Covid				During Covid			
	JKSE/BTC	JKSE/ETH	JKSE/TETHER	JKSE/LITE	JKSE/BTC	JKSE/ETH	JKSE/TETHER	JKSE/LITE	JKSE/BTC	JKSE/ETH	JKSE/TETHER	JKSE/LITE
Mean	0.0645	0.0154	-0.0245	0.0473	0.0603	0.0097	-0.0254	0.0361	0.0741	0.0288	-0.0224	0.0737
t-stat	54.4038	15.8262	-20.0621	40.0932	46.9976	7.6961	-17.6623	27.1899	29.3711	27.1523	-9.7083	40.1105
Test	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***	Reject***
Result	Diversifier	Diversifier	Strong Hedge	Diversifier	Diversifier	Diversifier	Strong Hedge	Diversifier	Diversifier	Diversifier	Strong Safe haven	Diversifier

Chapter 7
Conclusion

The results of our investigation provide three significant insights. First, our findings indicate that cryptocurrencies can be viewed as diversifiers, with the exception of Tether, which can be viewed as a hedge and safe haven for growing stock markets such as Thailand, the Philippines, and Indonesia. Second, our findings enhance our knowledge of the behavior of traditional coins and stable coins over distinct time periods, allowing investors to diversify their portfolios using the hedging ratio. Even though the Tether has a potential to act as hedger and safe haven over the most recent period it and has dollars as collateral. But investors should reconsidered about the USD-pegged coin because in the latest case, The fall of LUNA and UST. There was a crisis happen that made the UST worth almost \$ 0.01. This occurred because it was not backed up by dollar reserves to preserve its peg to the fiat currency. And from this case, the price of Tether started to fluctuate in the past few days after the collapse of UST. So, from the standpoint of asset management, it is unclear why an investor would prefer Tether over US dollar cash holdings. Tether is susceptible to increased counterparty, technological, security, and liquidity risk, in addition to additional concerns regarding the USD peg's resilience during extreme financial crises. Third, Bitcoin and Ethereum have a limited supply, just like gold, but they are only used as diversifiers and hedges in some stock market indexes. This means that they aren't as important as gold as a hedge and safe haven asset.

In contrast to the findings of (Dyhrberg 2016)which identify cryptocurrencies as possessing gold-like properties, cryptocurrencies can act as a strong hedge. However, some research demonstrate that cryptocurrencies are more volatile and riskier than conventional financial assets, leading to limited potential for hedging. Current financial assets carry comparable risks, consistent with the findings of (Bouri, Shahzad et al. 2020, Kakinuma 2022), Investing in alternative financial assets is therefore a hedge against investing in cryptocurrencies. In addition, the findings of (Baur, Hong et al. 2017) investing in cryptocurrencies is essentially diversification. Also, in the context of Thailand, Philippines, Indonesia, cryptocurrencies have limitations. The limitations are due to unclear government policies, both on control, transaction cost and taxation issues. Additionally, the movement of cryptocurrencies may be linked to the global economic situation as well as the differences in risk protection in each industry and price stability, including cryptocurrencies in other groups that are starting to play a more active role. Changes in cryptocurrency's properties as a safe-haven asset and portfolio diversifier depend on the condition of the economy and financial markets, investor behavior, and policy response as this paper mentioned before. In addition, the Federal Reserve's make decisions and take response, followed by those of other central banks, delivered significant liquidity to financial markets, which rapidly restored investor confidence and enhanced the demand for risk assets in addition to the need for safe havens.

Chapter 8
Suggestions and Limitations

Studies have shown a high dynamic correlation between cryptocurrencies and TIP country's stock markets and investing in cryptocurrencies may reduce the risk which depends on the investor’s decision. Cryptocurrency may be offered on the market as a hedge against investments in all other financial assets. However, cryptocurrencies are highly volatile assets with unique risks that differ from other financial assets, so investors are advised to invest in cryptocurrencies that are appropriate for their level of risk and due to exchange rate risk, that may occur when you trade cryptocurrencies across the platforms which may lead to fluctuation of exchange rate. In practical, domestic and foreign investors may face exchange rate risk which can impact on the hedge ratio and volatility as well because when most of the cryptocurrencies are in US dollar and TIP’s index’s returns are in their domestic currency. To spread the risk of the investment portfolio without resulting in lower expected returns, on the other hand, investors who want to avoid risk should manage their portfolios by investing in other financial assets and also investing in cryptocurrencies, which will help their portfolio grow in the future. This is because cryptocurrencies have high yields for Bitcoin, Ethereum and Litecoin at 69.72% and 395.78% per annum, respectively. Investors can accept the findings of this study to describe the overall link between cryptocurrencies and other financial assets and another market index which cannot fully confirm the return on investment that will occur in the future but can help diversify investment risks.

There are still three possible future study directions. The first objective is to examine the possibility of cryptocurrencies to serve as a hedge or safe haven against other traditional assets during economic instability. The second objective is to examine the conditional correlation and volatility between traditional cryptocurrencies and stable cryptocurrencies. The final objective is to assess the hedging capabilities of traditional coin and other type of stable coin, gold, and the US dollar against developing and developed stock market.

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VITA

NAME	Suphawit Keakultanes
DATE OF BIRTH	19 September 1996
PLACE OF BIRTH	Bangkok, Thailand
INSTITUTIONS ATTENDED	Chulalongkorn University
HOME ADDRESS	99/181 Ramkhamhaneg 150 Tararom Village Sapansong Ramkhamhaneg Road Bangkok 10240
PUBLICATION	N/A
AWARD RECEIVED	N/A