**International Journal of Electrical and Computer Engineering (IJECE)**
Vol. 13, No. 6, December 2023, pp. 6637~6645
ISSN: 2088-8708, DOI: 10.11591/ijece.v13i6.pp6637-6645 

# Correlation between capital markets and cryptocurrency: impact of the coronavirus

**Kanyawut Ariya, Somsak Chanaim, Ahmad Yahya Dawod**
International College of Digital Innovation, Chiang Mai University, Chiang Mai, Thailand

**Article Info**

***Article history:***

Received Nov 9, 2022
Revised Mar 12, 2023
Accepted Mar 28, 2023

***Keywords:***

Capital market
Correlation matrix
Cryptocurrencies
Digital asset pricing
Minimum spanning tree

**ABSTRACT**

The objective of the study is to use daily Thai data analysis to strengthen correlations between Bitcoin and conventional asset measurements. The most popular asset prices and indices include gold, oil, the SET50 index, Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Ripple (XRP), Dashcoin (DASH), Stellar Lumens (XLM), Binance coin (BNB), and Dogecoin (DOGE). We find a significant correlation between cryptocurrencies and the digital economy using a matrix approach to the Pearson correlation coefficient. With the help of a minimal spanning tree model and random matrix theory, we can determine the shortest route between assets. Yet, as predicted, only a small percentage of the greatest eigenvalues diverge. We are also developing a novel technique to find the SET-50 index. In an investment portfolio during the coronavirus period, alternatives to the gold price and the DOGE may offer possibilities for risk diversification.



***Corresponding Author:***

Kanyawut Ariya
International College of Digital Innovation, Chiang Mai University
239 Nimmanhaemin Road, Muang District, Chiang Mai-50200, Thailand
Email: kanyawut_ariya@cmu.ac.th

## 1. INTRODUCTION

When it comes to cryptocurrencies, it is undeniable that cryptocurrencies have played a massive role in the world's financial system today, whether it is a cash payment, exchange, investment, or savings that attracts more investors to study and invest. Hedge funds and asset managers have begun implementing cryptocurrency trading strategies and investment plans in their product offerings [1]. The fact that cryptocurrencies are decentralized ledgers independent of political processes or government oversight makes them a popular replacement for traditional payment systems [2]. While finance traditionalists disagree that cryptocurrencies serve as a means of value transfer between people worldwide and provide no more value [3]. The established financial systems may be affected or disrupted by Bitcoin and/or other digital currencies. They can independently offer financial services, lessen or perhaps do away with the need for money transfers across state lines, expanding commercial options. However, in contrast to traditional financial assets, the price of digital currencies is erratic. Investors have several severe concerns due to price volatility. These worries prompt calls for cryptocurrency regulation. This study shows that after the coronavirus disease 2019 (COVID-19) situation, Bitcoin, Ethereum, and other cryptocurrencies vary in value.

In 2013 a trading platform in Thailand began to trade cryptocurrency. The trading platform enables traders to convert baht into cryptocurrency. Market participants assert that they can earn a significant sum of money. Financial analysts, economists, and even Thailand's investment regulatory body have all criticized the profit to various degrees. Individuals who engage in trading or investment activities in the market should exercise caution and remain mindful of potential risks, given the market's high volatility and level of uncertainty, which can be significantly higher than that of the regular market. It is essential to stay informed

about the market's current conditions and developments, as well as to have a solid understanding of the underlying factors that drive market fluctuations [4]. There are two primary types of financial markets: money markets and capital markets. In money markets, short-term financial instruments with high liquidity, such as promissory notes and bills of exchange, are frequently traded [5]. On the other hand, governments, financial institutions, and large corporations typically issue long-term debt or equity securities that provide funding for periods exceeding one year, which capital markets focus on. Securities traded in capital markets often have longer maturities and can be traded on exchanges or over-the-counter markets [6].

Due to the COVID-19 epidemic, we are interested in analyzing how investing in digital asset markets compares to investing in traditional assets in the Thai capital market. We are interested in researching how the Thai capital market and the cryptocurrency industry are related. The research will compare asset price data to determine the direct relationship between the market returns. We believe that cryptocurrency trading will be liquid in the Thai market as a result of the regulator's securities and exchange commission (SEC) development of legislation and regulation, allowing the economic mechanism to function effectively [7].

## 2. LITERATURE REVIEW

This section comprises a compilation of literature reviews directly pertinent to the present investigation. The subsequent study of literature will function as a guiding framework for ensuring effective operations within this research endeavor. Specifically, the literature reviews encompass three distinct topics: the digital asset market, the capital market in Thailand, and comparative theory.

### 2.1. Digital asset market

The reliability of cryptocurrencies is due to the technology that underpins them. The technology that underpins cryptocurrencies is blockchain technology. Blockchain, a technology that decentralizes information, is described in the paper. The technology that underpins cryptocurrency is what makes it trustworthy [8] and released a paper on blockchain technology, which powers cryptocurrency. Blockchain is defined in the paper as a technology that decentralizes information. To encourage the use of a coin while maintaining information transparency, it does not save data in any local systems that can verify its accuracy and cannot be edited or amended. According to [9], the combination of blockchain technology and cryptocurrencies can reduce the risk of a bubble, which benefits investors and digital market operators. Blockchain technology, a secure network that can analyze and distribute data in real-time, enables large-scale transactions [10].

Ethereum is a cryptocurrency that uses blockchain technology. Despite its enormous variation in composition, use, service life, and asset trading volumes, the Ethereum ecosystem adheres to global architecture. Furthermore, show that, contrary to popular belief, this economy has a steady and balanced structure. The document concentrates on the developing phenomena of cryptocurrencies and examines the benefits and drawbacks of digital assets [11]. Digital currency price increases may be driven by factors such as supply and demand, institutional adoption, technological advancements, and geopolitical events. However, the volatility of the cryptocurrency market presents risks, including scams, regulatory uncertainties, and environmental concerns. The sustainability and behavior of cryptocurrencies remain under debate, with proponents highlighting potential benefits such as increased efficiency in the investment market, while others express concerns about socio-economic challenges and the lack of regulations. A thorough investigation into these factors is necessary to fully understand the potential advantages and limitations of digital currencies. However, there are also concerns with cryptocurrencies that are not adequately controlled, resulting in instances of financial crime such as money bubbles and the theft of cryptocurrency benefits [12].

Digital assets have been invested in and researched in Thailand, interviewed 25 Thai cryptocurrency investors for research on their perspectives on the digital currency market. The goal of this research is to acquire a better knowledge of the overall market position as well as Thai investors' attitudes toward investing in digital currency and the sector [13]. Based on the findings of the study, it appears that the interviewees were knowledgeable about the cryptocurrency market and expressed a strong interest in investing in cryptocurrencies. Despite fluctuations in market conditions, the majority of interviewees indicated that they continue to expand their investments in cryptocurrencies. Additionally, the study suggests that investors may not be overly cautious when selecting digital currencies, indicating a high level of confidence in the potential of these assets [14].

### 2.2. Capital market in Thailand

As a developing country, Thailand requires significant capital to invest in various companies and industries. However, due to limited government savings, capital markets have become a crucial long-term source of finance. The commercial banking industry remains the country's primary economic sector. Due to the Thai baht currency crisis in 1997, Thailand's financial organizations revised their rules and legislation to

meet international standards and provided chances for foreigners to participate in Thai commercial banking and examine the capital market's impact on Thailand's economy's growth since the 1997 financial crisis [15]. Three techniques were used to find the correlation between 1997 and 2016: the unit root test, the cointegration test, and the causality test. The results show that the stock and bond markets benefited from economic growth. The stock market simultaneously encourages economic growth by allocating funds to private investment, which results in more output and employment [16]. On the other hand, the bond market has little impact on economic expansion. However, it helps the stock market grow by giving investors a choice for investment management and diversification [17].

### 2.3. Comparative theory

According to the "reflection effect," people frequently take less risk when there are wins and more risk when there are losses. The study examines the empirical features of the reflection effect theory by analyzing the behavior of winning and losing trades from a dataset of over 28.5 million trades carried out by 81.3 thousand traders on an online financial trading platform over a period of two years and four months. The reflection effect theory suggests that people tend to take less risk after experiencing gains and more risk after experiencing losses [18]. By evaluating and comparing the behavior of winning and losing trades in the dataset, the study aims to shed light on the existence and extent of the reflection effect in financial decision-making. Using the information, it examines the growth of online social commerce potential [19]. The study's findings suggest that individual human decisions can influence whether or not financial trading behavior can alter, which suggests that trading efficiency would rise dramatically if people were more informed about investing.

Prim's algorithm is a popular algorithm for finding the minimum spanning tree (MST) of a graph, which is an independent tree that connects all vertices in the graph with the minimum possible edge weight. This algorithm finds the shortest path for developing the MST. By utilizing the distance between assets in the research, it is employed to determine the relationship between assets [20]. A recent study analyzed the fluctuations in cryptocurrency prices, focusing on data from trades within the Bitcoin market and between the Bitcoin and traditional markets [21]. To understand the interplay between these markets, the researchers employed the MST approach, which provides a method for analyzing direct links between markets. The analysis revealed that the traditional market and the market for digital assets did not have a direct relationship [22].

## 3. DATA

This study will use daily asset prices over three years, from January 1, 2019 to September 30, 2022, to analyze how the COVID-19 outbreak has affected the relationship between cryptocurrencies and the Thai capital markets. The datasets utilized in this study are from the Bank of Thailand database and trading economics website. It consists of the Thai capital market, the SET50, gold, oil, and the THB/USD exchange rate. The finance yahoo website [23] is used to collect daily digital asset values for the market for cryptocurrencies like Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Ripple (XRP), Dashcoin (DASH), Stellar Lumens (XLM), Binance coin (BNB), and Dogecoin (DOGE). The website determines prices by using the volume-weighted average of values distributed for several exchange marketplaces, including missing data if the cryptocurrency had not been exchanged on a given day.

## 4. METHOD

The data used in the research was gathered from a variety of sources. The random matrix theory (RMT) was used to eliminate noise from the correlation matrix. The data was susceptible to noise contamination. Using RMT, were able to filter out the noise and produce a more accurate correlation matrix. We employ PG+filtering techniques [24]. Then, we use networks to show the relationship between assets in two ways: direct and inverse during times of crisis, using an MST to determine the shortest route between any two graph vertices. Let $P_i(t)$ be the price and $r_i(t)$ be the return of an asset "$i$" and "$t$" be the time, to found $r_i(t)$ following the (1).

$$r_i(t) = \log\big(P_i(t)\big) - \log\left(P_i(t-1)\right) \quad (1)$$

Then let $r_i(t)$ be deployed by $r_i$ to find the correlation matrix $C_{i,t}$ defined as (2),

$$C_{i,j} = \frac{E(r_i r_j) - E(r_i)E(r\_j)}{\sigma(r_i)\sigma(r_j)} \quad (2)$$

where $C_{i,j}$ is the correlation matrix between $i$ and $j$ asset, let $(\sigma)$ be the standard deviation [25], and let $(E)$ be the mean value. Let $Q = \frac{L}{N}$ where $(L)$ is the number of days, and $(N)$ is the number of assets. Let $(\lambda)$ be a noisy eigenvalue if $\lambda_- \leq \lambda \leq \lambda_+$ where $\lambda_-$ be the minimum eigenvalue, $\lambda_+$be the maximum eigenvalue, following the (3).

$$\lambda_{\pm} = 1 + \frac{1}{Q} \pm 2\sqrt{\frac{1}{Q}} \quad (3)$$

Let $\mathrm{D}_{\mathrm{filtered}}$ be a correlation matrix by replacing with zero in the position where the noisy eigenvalues of the $C$ eigenvalue matrix, let $E$ be an eigenvectors matrix of $C$. Then replacing with 1 in the diagonal of $E\mathrm{D}_{\mathrm{filtered}}\,E^{-1}$ [26].

To display the relationship between assets, we applied the networks with a node as an asset and connected a distance line between the nodes. The distance relationship between assets follows the (4).

$$\mathrm{D}_{(\mathrm{i,j})} = \sqrt{(2 - 2C_{(i,j)})} \quad (4)$$

Then we used the MST model to display the relationship in the distance networks [27]. To find the expected return among the assets that have the greatest distance from the MST, following the (5).

$$Expected\ return = \mu_x w + (1 - w)\mu_y \quad (5)$$

Let $\mu_x$ be an average return of asset *"x"*, $\mu_y$ be an average return of asset *"y"* and *W* be the weight.

## 5. RESULT AND DISCUSSION

Table 1 displays the original correlation matrix that shows the relationship between the returns of each asset studied in the previous section. The values in the correlation matrix range from -1 to 1, where a value of 1 indicates a strong positive correlation (direct relationship) between two assets and a value of -1 indicates a strong negative correlation (inverse relationship). The closer the value is to 1 (or -1), the stronger the correlation (direct or inverse) between the financial assets.

Using *N*=12 assets and *L*=1004 days, we compute $Q$ using PG+filtering techniques. As a result, *Q*=83.667, and from the equation, we discovered the minimum eigenvalue $(\lambda_+) = 0.793$ and the greatest eigenvalue $(\lambda_+) = 1.230$ shown in (3). Finding the eigenvalue matrix for the correlation matrix *C*, and replacing any noisy eigenvalues inside the $[\lambda_-, \lambda_+]$ range with zero. Figure 1 shows the eigenvalues of digital assets and capital assets from correlation matrix *C*, SET50 is the highest eigenvalue and DOGE is the lowest eigenvalue. In the study, the researchers focused on the area of the eigenvalue spectrum that noise had affected and identified the oil price eigenvalue as 0.850 within this region. To remove noise from the data, the researchers replaced the eigenvalues with zero in this area.

The procedure in section 4 can then be used to obtain the correlation matrix following *C*-filtered filtering. As shown in Table 2, we discovered that the filtered correlation matrix $C$ filtered differs little from the original correlation matrix $C$. As shown in (4) can be used to determine, from Table 2, the direct distance relationship between assets. The distance can then be drawn as a network map and displayed using a MST. The stronger the association displayed in Figure 2, the tighter the distance between assets.

Table 1. Correlation matrix between statistics return series

| Currency | SET50 | GOLD | OIL | THB-USD | BTC | ETH | LTC | XLM | XRP | DASH | BNB | DOGE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| SET50 | 1 | 0.136 | 0.562 | 0.241 | 0.491 | 0.523 | 0.357 | 0.335 | 0.418 | 0.245 | 0.533 | 0.366 |
| GOLD | | 1 | 0.580 | 0.619 | 0.248 | 0.432 | **-0.006** | 0.024 | 0.225 | **-0.165** | 0.445 | 0.247 |
| OIL | | | 1 | 0.807 | 0.308 | 0.437 | 0.067 | 0.107 | 0.221 | **-0.100** | 0.531 | 0.282 |
| THB-USD | | | | 1 | 0.094 | 0.343 | **-0.173** | **-0.148** | 0.103 | **-0.291** | 0.438 | 0.172 |
| BTC | | | | | 1 | 0.897 | 0.896 | 0.882 | 0.847 | 0.766 | 0.864 | 0.724 |
| ETH | | | | | | 1 | 0.745 | 0.708 | 0.863 | 0.587 | 0.957 | 0.814 |
| LTC | | | | | | | 1 | 0.968 | 0.860 | 0.941 | 0.730 | 0.778 |
| XLM | | | | | | | | 1 | 0.837 | 0.921 | 0.703 | 0.754 |
| XRP | | | | | | | | | 1 | 0.803 | 0.873 | 0.888 |
| DASH | | | | | | | | | | 1 | 0.598 | 0.718 |
| BNB | | | | | | | | | | | 1 | 0.829 |
| DOGE | | | | | | | | | | | | 1 |

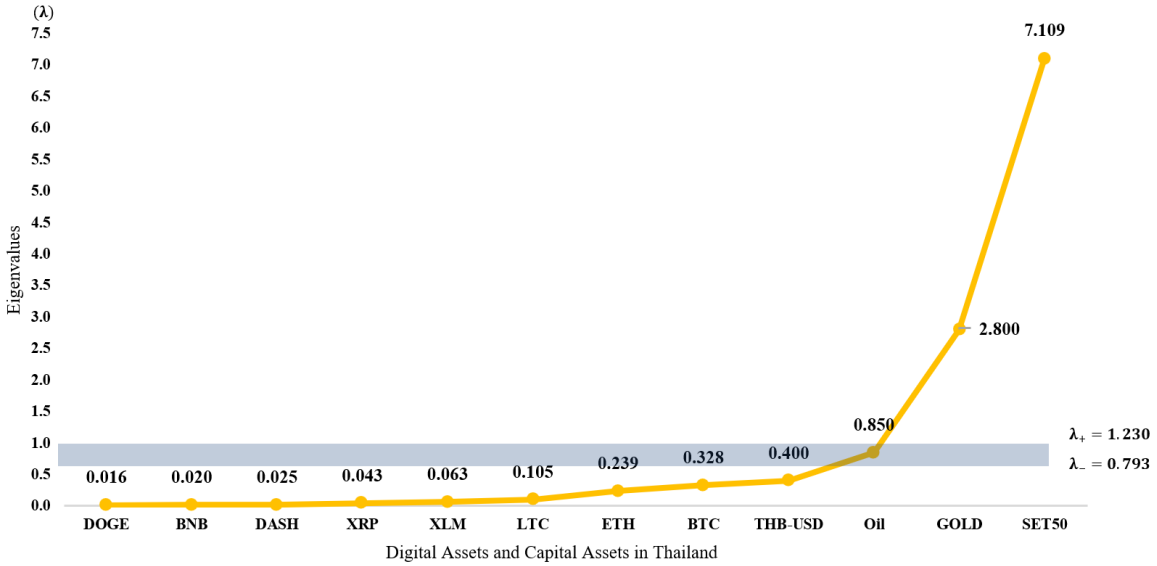



Figure 1. The noisy eigenvalue area $[\lambda_-, \lambda_+]$ of correlation matrix $C$

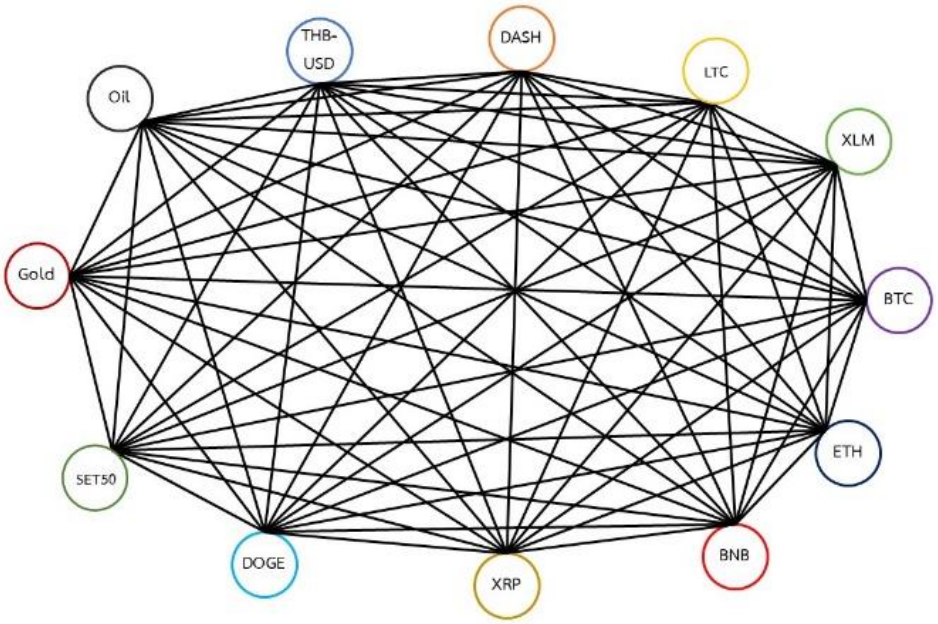
Table 2. Thailand's capital market and digital asset market have filtered correlations

| Currency | SET50 | GOLD | OIL | THB-USD | BTC | ETH | LTC | XLM | XRP | DASH | BNB | DOGE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| SET50 | 1 | 0.461 | 0.389 | 0.312 | 0.475 | 0.576 | 0.352 | 0.342 | 0.496 | 0.250 | 0.576 | 0.481 |
| GOLD | | 1 | 0.682 | 0.577 | 0.258 | 0.402 | **-0.004** | 0.020 | 0.179 | **-0.168** | 0.420 | 0.180 |
| OIL | | | 1 | 0.829 | 0.303 | 0.454 | 0.066 | 0.109 | 0.246 | **-0.099** | 0.544 | 0.318 |
| THB-USD | | | | 1 | 0.096 | 0.337 | **-0.172** | -0.149 | 0.093 | **-0.291** | 0.433 | 0.157 |
| BTC | | | | | 1 | 0.899 | 0.895 | 0.883 | 0.850 | 0.766 | 0.866 | 0.727 |
| ETH | | | | | | 1 | 0.746 | 0.707 | 0.856 | 0.586 | 0.952 | 0.803 |
| LTC | | | | | | | 1 | 0.968 | 0.860 | 0.941 | 0.730 | 0.779 |
| XLM | | | | | | | | 1 | 0.836 | 0.921 | 0.703 | 0.752 |
| XRP | | | | | | | | | 1 | 0.803 | 0.867 | 0.872 |
| DASH | | | | | | | | | | 1 | 0.598 | 0.717 |
| BNB | | | | | | | | | | | 1 | 0.820 |
| DOGE | | | | | | | | | | | | 1 |

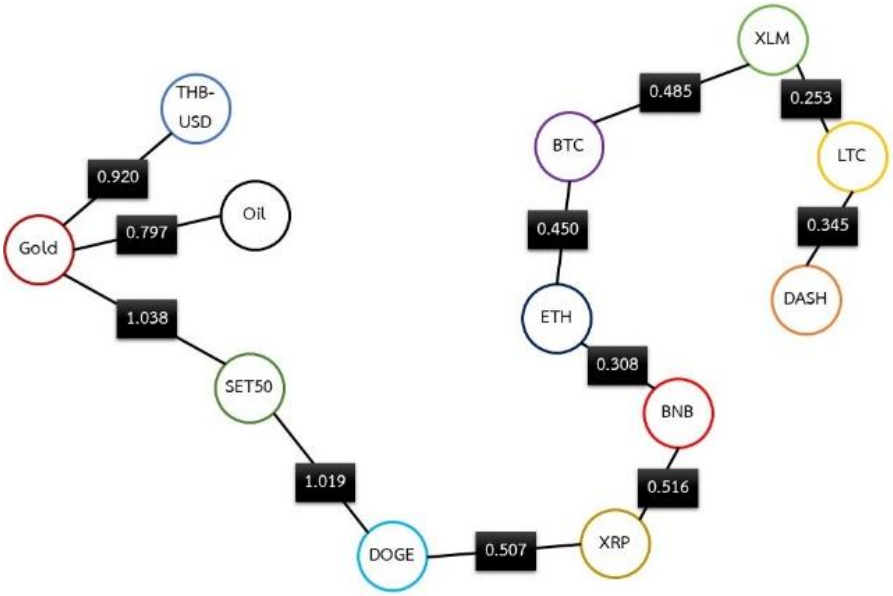
Figure 2 depicts the MST of partial cross-correlations in the cryptocurrency market, where nodes represent various cryptocurrencies that connect to different parts of the distance matrix. The node sizes are inversely correlated with the respective cryptocurrency's position in the market capitalization hierarchy. The distance between XLM and LTC is the shortest, indicating the most positive relationship, while the distance between SET50 and GOLD is the greatest, suggesting no relationship. Figure 2(a) shows a network where each asset is connected to one another using filtered correlations, while Figure 2(b) shows the network after using the MST to identify strong direct relationships between assets.

Table 3 presents the shortest distance between each asset illustrated in Figure 2. The findings indicate that there is no overall connectedness observed between traditional markets in Thailand and cryptocurrencies. This signifies a fundamental contrast between the behavior of cryptocurrencies and traditional markets. However, our model predicts that during periods of declining prices in the traditional market, investors tend to shift their focus towards cryptocurrency markets to diversify their investment portfolios. Conversely, when traditional markets experience a rise in prices, investors may allocate their resources away from cryptocurrencies.

Table 3 provides an estimate of the direct relationships between assets, with each asset having an equal level of correlation except for SET50 and GOLD, SET50 and DOGE, and THB-USD and GOLD, which have no relationship as their distance is close to $\sqrt{2}$. From Table 3 we infer that the SET50 index and DOGE coin is a strong inverse relationship between digital assets and capital assets in Thailand. We selected the SET50 index and DOGE coin to diversify the portfolio by using weighted average returns. In Figure 3 we have used expected return by (5) to show that at the 99% weight of SET50 and 1% weight of DOGE the return is below zero. According to the analysis, the low-risk, low-return point is 15% weight of SET50 and 85% weight of DOGE at a weighted average return of 0.0003, and the high-risk, high-return point is 75% weight of SET50 and 25% weight of DOGE at a weighted average return of 0.0012. The investment is based on the investors' risk tolerance level.




(a)




(b)

Figure 2. The MST of the direct relationships network: (a) before MST and (b) after MST

Table 3. The distance between different assets value

| No. | ASSET1 | ASSET2 | Distance |
|---|---|---|---|
| 1 | XLM | LTC | 0.2533 |
| 2 | BNB | ETH | 0.3083 |
| 3 | DASH | LTC | 0.3446 |
| 4 | BTC | ETH | 0.4503 |
| 5 | XLM | BTC | 0.4846 |
| 6 | DOGE | XRP | 0.5068 |
| 7 | BNB | XRP | 0.5157 |
| 8 | GOLD | OIL | 0.7969 |
| 9 | THB-USD | GOLD | 0.9200 |
| 10 | SET50 | DOGE | 1.0192 |
| 11 | SET50 | GOLD | 1.0384 |

In previous studies, we conducted an analysis using a dataset encompassing the time period from January 1, 2016 to December 31, 2019. The primary objective was to determine the relative distance between each asset, enabling us to identify correlations among the assets with the most significant correlation and those with minor correlations. The findings from these studies reveal the existence of strong correlations between oil prices in traditional markets, the SET50 index (representing the top 50 companies in the Thai stock market), and cryptocurrencies within the digital market. This research contributes to a comprehensive understanding of the interrelationships among these financial assets, providing valuable insights for investors, policymakers, and researchers navigating the complexities of modern financial markets.

Coronaviruses begin to change Bitcoin prices with more impact, the other cryptocurrencies. We focus on how the influence of cryptocurrency markets and traditional markets have contributed to obtaining high-performance results in this study research by using the Pearson correlation coefficient model to determine the relationship between assets. Following that, we used the RMT model to differentiate causes from the correlation matrix to make the data more efficient and filter the noise from the dataset we obtained, and finally, we used the MST model to display these relationships. The stronger the connection, the tighter the distance between assets.

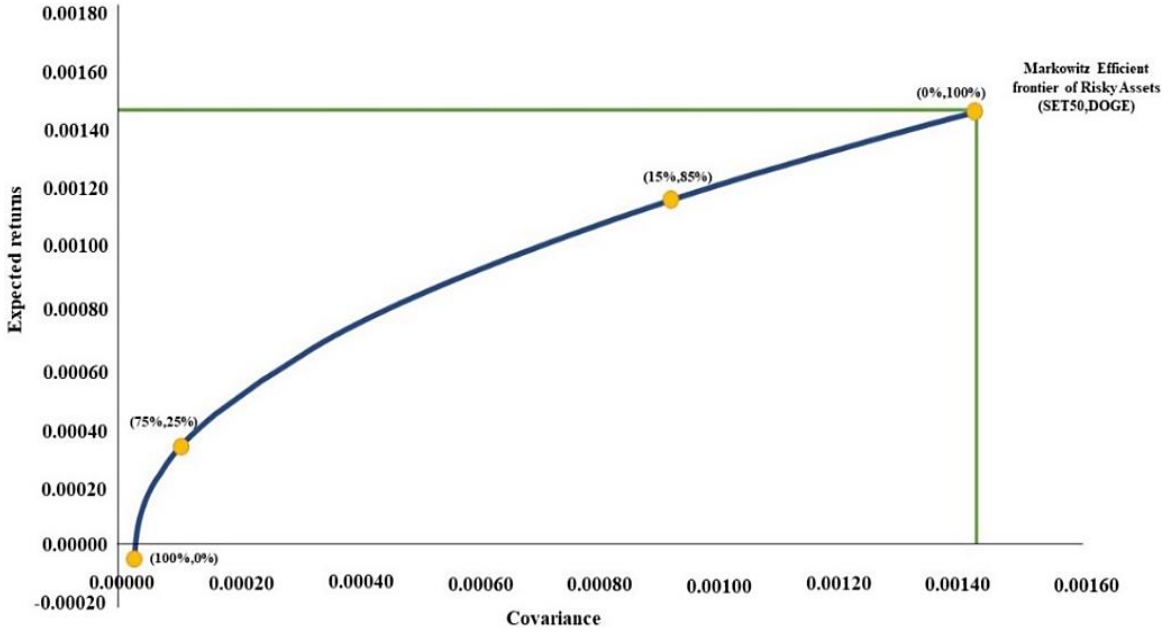



Figure 3. Markowitz efficient frontier of risky assets (SET50, DOGE)

## 6. CONCLUSION

This study adds to the body of research work showing that there is a relationship between market prices for some traditional assets and asset prices for cryptocurrencies. The COVID-19 epidemic was shown to have a significant direct impact on cryptocurrencies in the digital market, according to three years' worth of daily data on cryptocurrency assets and conventional assets in Thailand's traditional markets between 2019 and 2022. It is interesting to note that cryptocurrencies like Stellar, Litecoin, Ethereum, DASH, BNB, and Bitcoin have greater ties than traditional assets do. This may lead one to believe that correlations between digital assets are stronger than those between traditional ones. This would indicate that there is a better correlation between digital assets than between traditional ones. It would be interesting to look further into the phenomenon that digital assets exhibit greater correlations than traditional assets. This phenomenon could be attributed to variations in trading platforms or other variables. The connections between digital assets may be seen in the strong correlations between Stellar and Litecoin as well as between Ethereum and the price of BNB. We analyzed the correlations of the Market of cryptocurrency as a complicated network and identified various community structures in its MST. To diversify the risk in a portfolio of investments, digital assets could be used as extra investment strategy options. The SET-50 index's tenuous ties to the DOGE and gold prices, as well as the SET-50 index's poor signal, may indicate that local investors account for the majority of trade, with little outside involvement. Research articles on these suspicious hypotheses may be fascinating if they are further investigated.

## REFERENCES


[1] F. Fang *et al.*, "Cryptocurrency trading: A comprehensive survey," *Financial Innovation*, vol. 8, no. 1, Dec. 2022, doi: 10.1186/s40854-021-00321-6.

[2] S. Corbet, D. J. Cumming, B. M. Lucey, M. Peat, and S. A. Vigne, "The destabilising effects of cryptocurrency cybercriminality," *Economics Letters*, vol. 191, Jun. 2020, doi: 10.1016/j.econlet.2019.108741.

[3] S. Corbet, B. Lucey, A. Urquhart, and L. Yarovaya, "Cryptocurrencies as a financial asset: A systematic analysis," *International Review of Financial Analysis*, vol. 62, pp. 182–199, Mar. 2019, doi: 10.1016/j.irfa.2018.09.003.

[4] D. Bianchi, "Cryptocurrencies as an asset Class? An empirical assessment," *The Journal of Alternative Investments*, vol. 23, no. 2, pp. 162–179, Sep. 2020, doi: 10.3905/jai.2020.1.105.

[5] E. Mnif, A. Jarboui, and K. Mouakhar, "How the cryptocurrency market has performed during COVID 19? A multifractal analysis," *Finance Research Letters*, vol. 36, Oct. 2020, doi: 10.1016/j.frl.2020.101647.

[6] M. Uddin, A. Chowdhury, K. Anderson, and K. Chaudhuri, "The effect of COVID–19 pandemic on global stock market volatility: Can economic strength help to manage the uncertainty?," *Journal of Business Research*, vol. 128, pp. 31–44, May 2021, doi: 10.1016/j.jbusres.2021.01.061.

[7] D. E. Allen, "Cryptocurrencies, Diversification and the COVID-19 Pandemic," *Journal of Risk and Financial Management*, vol. 15, no. 3, Feb. 2022, doi: 10.3390/jrfm15030103.

[8] J. Batten and X. V. Vo, "Determinants of Bank profitability-evidence from Vietnam," *Emerging Markets Finance and Trade*, vol. 55, no. 6, pp. 1417–1428, May 2019, doi: 10.1080/1540496X.2018.1524326.

[9] H. Chitsazan, A. Bagheri, and M. Tajeddin, "Initial coin offerings (ICOs) success: Conceptualization, theories and systematic analysis of empirical studies," *Technological Forecasting and Social Change*, vol. 180, 2022, doi: 10.1016/j.techfore.2022.121729.

[10] H. Hassani, X. Huang, and E. S. Silva, "Blockchain and cryptocurrency," in *Fusing Big Data, Blockchain and Cryptocurrency*, Cham: Springer International Publishing, 2019, pp. 49–76. doi: 10.1007/978-3-030-31391-3_3.

[11] E. Kromidha and M. C. Li, "Determinants of leadership in online social trading: A signaling theory perspective," *Journal of Business Research*, vol. 97, pp. 184–197, Apr. 2019, doi: 10.1016/j.jbusres.2019.01.004.

[12] B. Aditya Pai, L. Devareddy, S. Hegde, and B. S. Ramya, "A time series cryptocurrency price prediction using LSTM," in *Emerging Research in Computing, Information, Communication and Applications*, 2022, pp. 653–662. doi: 10.1007/978-981-16-1342-5_50.

[13] D. Stosic, D. Stosic, T. B. Ludermir, and T. Stosic, "Collective behavior of cryptocurrency price changes," *Physica A: Statistical Mechanics and its Applications*, vol. 507, pp. 499–509, Oct. 2018, doi: 10.1016/j.physa.2018.05.050.

[14] J. Bun, J.-P. Bouchaud, and M. Potters, "Cleaning large correlation matrices: Tools from random matrix theory," *Physics Reports*, vol. 666, pp. 1–109, Jan. 2017, doi: 10.1016/j.physrep.2016.10.005.

[15] F. Casino, T. K. Dasaklis, and C. Patsakis, "A systematic literature review of blockchain-based applications: Current status, classification and open issues," *Telematics and Informatics*, vol. 36, pp. 55–81, Mar. 2019, doi: 10.1016/j.tele.2018.11.006.

[16] O. Sattarov *et al.*, "Recommending cryptocurrency trading points with deep reinforcement learning approach," *Applied Sciences*, vol. 10, no. 4, Feb. 2020, doi: 10.3390/app10041506.

[17] J. Kurka, "Do cryptocurrencies and traditional asset classes influence each other?," *Finance Research Letters*, vol. 31, pp. 38–46, Dec. 2019, doi: 10.1016/j.frl.2019.04.018.

[18] Z.-Q. Jiang, W.-J. Xie, W.-X. Zhou, and D. Sornette, "Multifractal analysis of financial markets: a review," *Reports on Progress in Physics*, vol. 82, no. 12, Dec. 2019, doi: 10.1088/1361-6633/ab42fb.

[19] A. Agosto and A. Cafferata, "Financial bubbles: A study of co-explosivity in the cryptocurrency market," *Risks*, vol. 8, no. 2, Apr. 2020, doi: 10.3390/risks8020034.

[20] S. Saberi, M. Kouhizadeh, J. Sarkis, and L. Shen, "Blockchain technology and its relationships to sustainable supply chain management," *International Journal of Production Research*, vol. 57, no. 7, pp. 2117–2135, Apr. 2019, doi: 10.1080/00207543.2018.1533261.

[21] Z. Zhang, M. Zargham, and V. M. Preciado, "On modeling blockchain-enabled economic networks as stochastic dynamical systems," *Applied Network Science*, vol. 5, no. 1, Dec. 2020, doi: 10.1007/s41109-020-0254-9.

[22] A. Chursook, A. Yahya Dawod, S. Chanaim, N. Naktnasukanjn, and N. Chakpitak, "Twitter sentiment analysis and expert ratings of initial coin offering fundraising: Evidence from Australia and Singapore markets," *TEM Journal*, pp. 44–55, Feb. 2022, doi: 10.18421/TEM111-06.

[23] "Yahoo Finance," Yahoo. https://finance.yahoo.com/ (accessed Apr. 15, 2021).

[24] F. Han *et al.*, "A data driven approach to robust event detection in smart grids based on random matrix theory and Kalman filtering," *Energies*, vol. 14, no. 8, Apr. 2021, doi: 10.3390/en14082166.

[25] Z. Šverko, M. Vrankić, S. Vlahinić, and P. Rogelj, "Complex pearson correlation coefficient for EEG connectivity analysis," *Sensors*, vol. 22, no. 4, Feb. 2022, doi: 10.3390/s22041477.

[26] P. Giudici and G. Polinesi, "Crypto price discovery through correlation networks," *Annals of Operations Research*, vol. 299, no. 1–2, pp. 443–457, Apr. 2021, doi: 10.1007/s10479-019-03282-3.

[27] S. Pettie and V. Ramachandran, "An optimal minimum spanning tree algorithm," *Journal of the ACM*, vol. 49, no. 1, pp. 16–34, Jan. 2002, doi: 10.1145/505241.505243.


## BIOGRAPHIES OF AUTHORS

**Kanyawut Ariya** received a B.Sc. degree in computer science from Chiang Mai University, Thailand. He is currently working as a computer technical officer at International College of Digital Innovation at Chiang Mai University since 2017 present. He works as a researcher with the group FabLab with 10 projects as a developer programming. He can be contacted by email: kanyawut.ariya@cmu.ac.th.

**Somsak Chanaim** received a B.Sc. degree in mathematics from Kasetsart University, Thailand, an M.Sc. degree in insurance from Chulalongkorn University, Thailand, an M.Sc. degree in applied mathematics from Chiang Mai University, Thailand, and a Ph.D. degree in economics from Chiang Mai University, Thailand, he currently works at lecturer at International College of Digital Innovation Chiang Mai University since 2020 present. He has supervised and co-supervised more than 4 masters and 1 Ph.D. student. He is particularly researching and interested in Insurance, Finance, and econometrics. He can be contacted by email: somsak.c@cmu.ac.th.

**Ahmad Yahya Dawod** received a B.Sc. degree in computer science from the University of Mustansiriyah, Baghdad, Iraq, an M.Sc. degree in Faculty of Computing and Informatics FCI from the Multimedia University in Malaysia MMU, and the Ph.D. degree in Faculty of Information Science and Technology FTSM from National University of Malaysia UKM, he currently works at lecturer at International College of Digital Innovation Chiang Mai University since 2019 present. He has supervised and co-supervised more than 7 masters and 6 Ph.D. students. He is particularly researching interested in artificial intelligence, computer vision, image processing, NLP, robotics, and machine learning. He has acted as a reviewer for several international journals and conferences regularly. You can reach him via email at: ahmadyahyadawod.a@cmu.ac.th.