Cryptocurrency in the East: Exploring Ethereum's Link to Asian-Pacific Stock Indices through Multivariate-GARCH Approach

Tan, Zi Ling and Lim, Siok Jin

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Tan Zi Ling[1] and Lim Siok Jin[2]

Abstract

This study investigates the dynamic interrelationship between Ethereum and key stock indices in the Asian-Pacific region, focusing on its potential role as a diversification tool for equity investors. Utilizing a Multivariate Generalized Autoregressive Conditional Heteroskedasticity Dynamic Conditional Correlation (MGARCH-DCC) model, we analyse daily closing prices from November 2018 to November 2023 across four developed Asian stock markets—China, Hong Kong, Japan, and Malaysia—alongside Ethereum. The findings reveal that Ethereum exhibits distinctive volatility patterns compared to traditional stock indices, with conditional correlations fluctuating significantly over time. Notably, Ethereum demonstrates weak correlations with Malaysian stocks, suggesting potential diversification benefits for investors in this market. The study contributes to the growing literature on cryptocurrency's financial integration, offering insights into the hedging properties of Ethereum amidst evolving market dynamics in the Asian-Pacific region.

Keywords*:* Ethereum, Asian-Pacific stock indices, Multivariate-GARCH, Dynamic Conditional Correlation (DCC), Cryptocurrency, Financial integration, Diversification, Volatility, Hedging, Emerging markets

[1]Student in Finance and Accounting at New Era University College, Malaysia.

[2]**Corresponding author**, Lecturer of Finance and Investment, New Era University College, Malaysia. Phone: +60149613139 Email: siokjin.lim@newera.edu.my

1.0 Introduction

Portfolio diversification is a risk management strategy wherein investors distribute their investments across different asset classes, industries, and geographical regions (Lioudis, 2022). The goal is to minimize overall risk while striking a balance between potential returns and risk exposure. This approach involves holding a variety of assets, such as stocks, bonds, and real estate, each with distinct risk profiles.

Cryptocurrency, a form of digital or virtual currency, utilizes cryptography for security and operates on decentralized networks, often based on blockchain technology. Investors are drawn to the underlying technology of cryptocurrencies, particularly blockchain, which provides a transparent, secure, and immutable ledger. This technology extends beyond cryptocurrencies and finds applications in areas like supply chain management, smart contracts, and decentralized finance (DeFi) (Hayes, 2023). Cryptocurrencies have demonstrated considerable price volatility, presenting opportunities for investors to generate substantial profits. For instance, Bitcoin investors have witnessed significant returns as the cryptocurrency's value surged over the years.

Ethereum, the second most popular cryptocurrency after Bitcoin, is renowned for its blockchain platform that supports decentralized applications (DApps) and various blockchain-based projects (Frankenfield, 2022). Ethereum's native cryptocurrency, ether (ETH), gained attention for its role in facilitating these applications. Ethereum underwent rapid price growth from its introduction in 2015, with Ether's value reaching a peak on January 13, 2018 (see A. Meshcheryakov and Ivanov, 2020). However, the earlier rapid expansion led to a substantial decline in its value in December 2018, coinciding with a broader downturn in the cryptocurrency market.

Several research studies have explored the hedging opportunities of various cryptocurrencies, including Bitcoin, Ethereum, Ripple, Monero, and Litecoin, within Asia's emerging markets and Islamic financial markets, such as Malaysia, Thailand, Singapore, Vietnam, and other countries (Susilo et al., 2020; Akinlaso et al., 2023; Lim & Neoh, 2023).

The focus of this paper is to investigate the correlation between Ethereum and stock indices in the Asian region. Additionally, the study aims to understand how the adoption of blockchain and smart contract technology influences traditional financial markets. This exploration is particularly relevant for investors seeking a balance between exposure to both traditional and emerging markets, offering valuable insights for risk management and portfolio construction strategies.

The Asian region is characterized by rapidly growing economies and emerging markets. For example, countries like China and Japan exerting substantial influence on international trade and finance which given the significant role of the Asian region in the global economy, thus, understanding the correlation between Ethereum and Asian stock indices becomes crucial. Moreover, the regulatory landscape for cryptocurrencies, including Ethereum, varies across different jurisdictions within Asia. This paper intends to shed light on how market sentiment and regulatory changes impact both traditional and digital asset markets,

Building on the insights from existing studies, our hypothesis posits that Ethereum has the potential to function as an effective hedge for investors in the Asian region stock markets. This study explores the link between Ethereum and Asian region stock markets using the most recent

datasets available. Although the primary focus is on the Asian region stock market and Ethereum, the empirical analysis will disaggregate the Asian market into five distinct developed-country indices (China, Hong Kong, Japan and Malaysia). The implications of the study's findings are particularly relevant for investors aiming to minimize risk through the inclusion of Ethereum in their portfolios.

Using a time-varying volatility model suitable for the variables of interest, our analysis reveals supportive evidence for the hedging potential of Ethereum for Asian region stocks from the end of 2018 to the end of 2023. These results align with the increasing significance of the Asian economy and financial markets. The contributions of this study are threefold. Firstly, it extends the literature by assessing the volatility of Ethereum and Asian region stock markets over the last five years (2018 to 2023). Secondly, it evaluates the hedging potential of Ethereum for Asian region stocks during the specified period. Lastly, it examines whether the hedging properties of Ethereum differ across developed and emerging country stock markets in Asia from the end of 2018 to the end of 2023. The remainder of the paper is organized as follows: Section II delves into the data and methodology, Section III presents the main findings, and Section IV concludes the study.

2.0 Data and Methodology

The data covers daily time series closing prices from November 14, 2018 to November 14, 2023 which are collected from Yahoo Finance. The dataset consists of the closing daily prices of four developed stock markets in the Asian region (China, Hong Kong, Japan, Malaysia) alongside Ethereum prices.

The research employs the multivariate Generalized Autoregressive Conditional Heteroskedasticity Dynamic Conditional Correlation (MGARCH-DCC) method introduced by Pesaran and Pesaran (2007) to investigate the changing volatilities and correlations between stock indices and Ethereum over time. This approach enables the examination and evaluation of specific instances when there are shifts in conditional correlations and volatilities. It replaces the conventional method of relying on historical covariance mixture through a two-stage estimation process. In the initial stage, the study employs a univariate GARCH (X,Y) model to determine the conditional variances of each asset. The model is represented by the equation:

$$h_{it} = \omega_i + \sum_{x=1}^{X_i} \alpha_{ix} r_{it-x}^2 + \sum_{y=1}^{Y_i} \beta_{iy} h_{it-y}, for\ i = 1, 2, \ldots, k$$

where ω_i, α_{ix} and β_{iy} are non-negative and $\sum_{x=1}^{X_i} \alpha_{ix} + \sum_{y=1}^{Y_i} \beta_{iy} < 1$. The parameter α_{ix} denotes shocks to return *X* due to a short-run persistence (ARCH effects), β_{iy} is the contribution of shocks to return *Y* due to a long-run persistence (GARCH effects) and *k* represents the number of assets.

In the second stage, the time-varying conditional correlation between index returns is calculated using the Dynamic Conditional Correlation (DCC) estimator as follow:

$$H_t = D_t R_t D_t$$

whereby H_t denotes multivariate conditional covariance matrix, D_t represents a *k* x *k* matrix of conditional time-varying standardized residuals (ε_t), which will be generated from the univariate GARCH model at the first step as follows:

$$D_t = diag(\sqrt{h_{11,t}}, \sqrt{h_{22,t}}, \ldots, \sqrt{h_{kk,t}}$$

It is a symmetric positive definitive matrix having on $\sqrt{h_{ii,t}}$ its diagonals, *I* = 1, 2, . . ., k. The matrix R_t stand for the time-varying correlation matrix (off-diagonal elements).

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}$$

where $Q_t = (q_{ij,t})$ is derived from

$$Q_t = (1 - \emptyset - \gamma)\underline{Q} + \gamma Q_{t-1} + \emptyset \sigma_{i,t-1}\sigma_{j,t-1}$$

the *k* x *k* symmetric positive definitive matrix, where Q_t is a *k* x *k* symmetric positive definitive conditional (time-varying) covariance matrix of standardized residual:

$$\sigma_{it} = \frac{\varepsilon_{it}}{\sqrt{h_{it}}}$$

and $\underline{Q}$ is the unconditional correlations of $\sigma_{i,t}\sigma_{j,t}$, ϕ and γ are non-negative scalar parameters satisfying $\emptyset + \gamma < 1$. The matrix Q_t^* is the diagonal matrix consisting of the square root of the diagonal elements of Q_t:

$$Q_t^* = diag(\sqrt{q_{11}}, \sqrt{q_{22}}, \ldots, \sqrt{q_{kk}}$$

Thereby, the conditional correlation of X and Y stock indices at time *t* can be calculated as follows:

$$\rho_{ij,t} = \left[(1 - \emptyset - \gamma)\, \underline{q}_{ij} + \emptyset \sigma_{i,t-1}\sigma_{j,t-1} + \gamma q_{ij,t-1}\right] \div \left\{\left[(1 - \emptyset - \gamma)\, \underline{q}_{ij} + \emptyset \sigma_{i,t-1}^2 + \gamma q_{ii,t-1}\right]^{\frac{1}{2}} \left[(1 - \emptyset - \gamma)\, \underline{q}_{jj} + \emptyset \sigma_{j,t-1}^2 + \gamma q_{jj,t-1}\right]^{\frac{1}{2}}\right\}$$

where q_{ij} denotes the element on the *i*th line and *j*th columns on the matrix Q_t (Bollerslev, 1988). By Bollerslev's (1988) model, the conditional log-likelihood of the parameters based on the Gaussian assumption can be summarized as:

$$L = -\frac{1}{2}\sum_{t=1}^{T} [(k\ log\ (2\pi)\ + log\ |D_t|^{\ 2} + \varepsilon_t' D_t^{-1} D_t^{-1} \varepsilon_t) + (log\ |R_t| + \sigma_t' R_t^{-1} \sigma_t - \sigma_t' \sigma_t)]$$

where *k* denotes the number of equations and T denotes the number of observations.

In the initial stage, the focus is solely on maximizing the volatility component (D_t), which entails reducing the log-likelihood to the sum of the log-likelihood of the univariate GARCH model. Subsequently, in the second stage, the emphasis shifts to maximizing the correlation component (R_t), conditional on the previously estimated parameters, using the standardized residuals obtained from stage one. It's worth noting that relying on the Gaussian assumption

for daily returns is a topic of controversy. This assumption, while convenient, leads to an underestimation of portfolio risk. Despite the consistency observed under the two-stage estimation of the likelihood approach (Engle & Sheppard, 2001), it may prove to be inefficient under Gaussianity, as highlighted by Pesaran and Pesaran in 2010.

In a nutshell, the DCC modelling allows identification of changes (when and how it occurs) in the interdependence between variables of a time series. Therefore, it allows identification of possible diversification benefits provided by Ethereum. The MGARCH-DCC model is known to be a reliable estimator of portfolio estimators and has been used by Fantazzini (2009), Chevallier (2012), and Aas and Berg (2013) to investigate Value at Risk, time-varying correlations, and multivariate dependence structures.

3.0 Findings and Results

Table 1. Results of multivariate GARCH with underlying t-Distribution on the Asian region stock index return series

Parameter	Estimate	Standard Error	T-Ratio[Prob]
lambda1_MS	0.97148	0.0097316	99.8273[.000]
lambda1_CHN	0.93114	0.020214	46.0639[.000]
lambda1_JPN	0.89168	0.040843	21.8318[.000]
lambda1_HK	0.95841	0.022373	42.8386[.000]
lambda1_ETH	0.92692	0.026674	34.7497[.000]
lambda2_MS	0.02596	0.0067525	3.8445[.000]
lambda2_CHN	0.051811	0.013041	3.9728[.000]
lambda2_JPN	0.054244	0.016161	3.3564[.001]
lambda2_HK	0.028709	0.0093322	3.0763[.002]
lambda2_ETH	0.066276	0.021069	3.1456[.002]
delta1	0.94114	0.024015	39.1897[.000]
delta2	0.013123	0.0030236	4.3400[.000]
df	6.5546	0.44734	14.6523[.000]
Maximized Log-Likelihood = 14685.6			

Note: df is the degrees of freedom of the multivariate t-distribution

The maximized log-likelihood value obtained from the *t*-DCC model (14,685.6) is higher than the Gaussian model (14,423). Additionally, the estimated degree of freedom for the *t*-normal distribution is 6.5546, which is below 30. This outcome suggests that the fat-tailed and Ethereum tend to be best captured by the *t*-distribution model. Based on Table 1, it is evident that the *t*-DCC model is the most suitable model for the study of the Asian region's stock market and Ethereum. In the *t*-DCC model, the volatility parameters are highly significant, with the estimates of λ_{1i}, i = 1, 2, 3, 4, 5, 6, 7 being close to one, indicating a slow volatility decay. Furthermore, the sum of *lambda 1* and *lambda 2* for all Asian region stock indices and Ethereum is equal to or less than 1 (e.g., *lambda1_MS* + *lambda2_MS* = 0.9974).

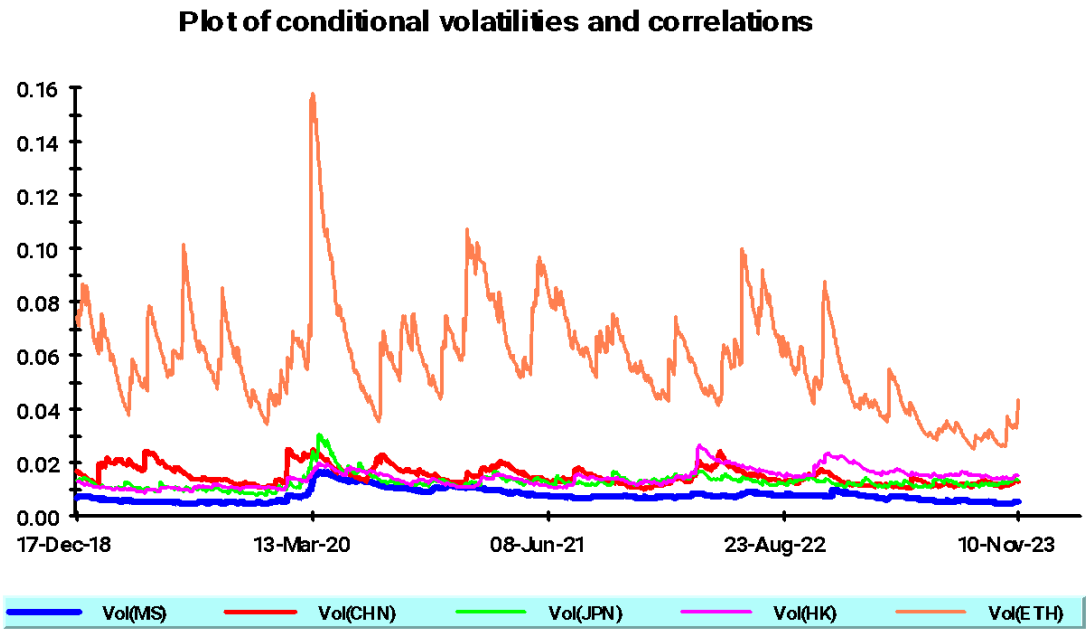

Figure 1. Conditional volatilities of Asian region stock indices and Ethereum

Figure 1 illustrates the dynamic conditional volatilities for each Asian country's stock index and Ethereum return. According to these estimates, the conditional volatilities of stock indices follow nearly the same path, except for Ethereum. The Malaysia stock index return exhibits the lowest conditional volatility, while Ethereum demonstrates the highest volatility. These findings align with the findings on unconditional volatilities presented in Table 2.

Within the time interval of the study, the conditional volatility of Ethereum started at a moderate level. A. Meshcheryakov and Stoyu Ivanov. (2020) highlight a significant downturn in Ethereum's value, along with the broader cryptocurrency market in December 2018. This downturn followed the rapid price growth since its introduction in 2015 and reaching maximum of $1,432.88 on January 13, 2018.

In 2019, there was a slight increase in the convergence of volatility among stock indices with Ethereum. The correlation between Ethereum and Asian region stock indices was notably lowest during this period, particularly at the beginning of 2020.

However, the conditional volatility spiked to its highest level after the World Health Organization (WHO) declared COVID-19 a pandemic on March 11, 2020. The studies indicate that volatility among all Asian region stock indexes is convergent, while Ethereum did not consistently correlate with the stock indices. As a result, due to Ethereum's weak correlation with the stock markets, it may be advantageous for investors and portfolio managers to consider it as a tool to improve their portfolio diversification strategies.

From the end of 2020 until the end of 2022, Ethereum's return volatility remained higher than that of Asian region stock index returns. The volatility in Asian equity markets stabilized by the end of 2021, responding to increased vaccination rates, the removal of lockdowns, reduced COVID-19-related deaths, and improved awareness of virus spread prevention measures.

In previous market cycles, Ethereum often outperformed Bitcoin (BTC) during bullish trends. However, a shift occurred in early 2023, with both Ether and various altcoins facing challenges. The narrative surrounding their utility in Web3, DeFi, and NFTs came under pressure in 2022 and 2023 (Brackett, 2023). Additionally, Ethereum's performance suffered due to a steady increase in Bitcoin dominance, further impacting sentiment for Ethereum.

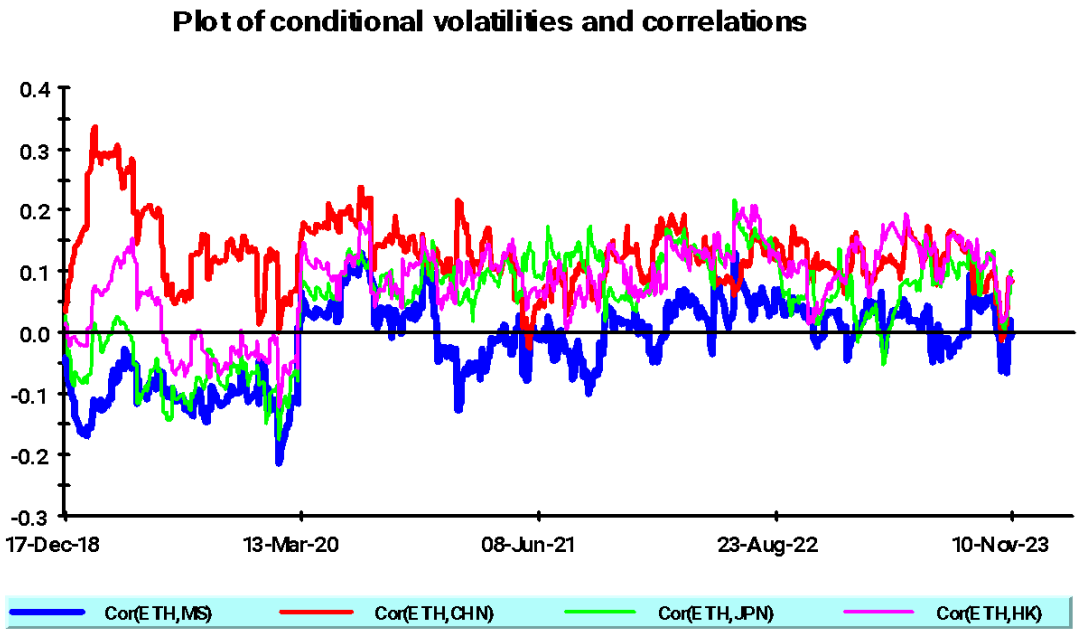

Figure 2. Conditional correlation of Asian region stock indices and Ethereum

Figure 2 illustrates the conditional correlation of Ethereum returns with Asian region stock index returns. The plot reveals that the return correlations of Ethereum with Asian region stock indices appear to trend towards zero around the end of 2018 and the beginning of 2020, with the exception of China. Furthermore, from the middle of 2020 to the end of 2023, the return correlations of Ethereum with Asian region stock indices seem to move slightly above zero except for Malaysia's stock index. Moreover, this observation aligns with the results of the unconditional correlations presented in Table 2, indicating that Ethereum returns exhibit a lowest correlation with Malaysia's stock returns compared to other stock returns. Consequently, it can be inferred that for Malaysia equity investors contemplating asset allocation, the inclusion of Ethereum in their portfolios could offer diversification benefits. The evidence suggests that Ethereum's returns are less correlated with Malaysia's stock returns relative to other stock returns, emphasizing its potential as a tool for enhancing portfolio diversification strategies in the Malaysian market.

Table 2. Unconditional volatilities of Asian region stock indices alongside Ethereum & Unconditional correlations between Asian region stock indices and Ethereum

Asian Region Stock Index & Ethereum	Unconditional volatility	Unconditional correlation
Malaysia (MS)	0.0080753	0.023418
China (CHN)	0.014943	0.10508
Japan (JP)	0.013057	0.092153
Hong Kong (HK)	0.015217	0.11609
Ethereum (ETH)	0.61366	-

4.0 Conclusion

This research is conducted to assist Asian equity investors, particularly in developed Asian countries, in identifying potential portfolio diversification benefits. The study employs the multivariate GARCH-DCC model to analyse the time-varying relationships between Ethereum returns and the returns of developed stock markets in the Asian region over the last five years, from the end of 2018 to the end of 2023. The analysis reveals a period of moderate volatility for Asian region stock indices and Ethereum returns from the end of 2018 to the beginning of 2020. In March 2020, there is a notable increase in the conditional volatilities of both Asian region stock indices and Ethereum returns. Subsequently, volatility fluctuates from the end of 2020 to the end of 2022, with a slight reduction observed in 2023. This reduction is attributed to stringent regulations against the crypto industry and an increase in Bitcoin dominance.

The findings also indicate a low correlation between Ethereum and Asian region stock indices, except for China, at the end of 2018 and the beginning of 2020. However, from the middle of 2020 to the end of 2023, there is a slight increase in the correlation between Ethereum and Asian region stock. Notably, the conditional correlation between Malaysia's stock index and Ethereum is weak, suggesting a potential diversification benefit for Malaysia equity investors.

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