ANALYSING THE CORRELATION BETWEEN COLOMBO STOCK EXCHANGE RETURNS AND CRYPTOCURRENCY RETURNS

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Abstract

This research examines the dynamic relationship between returns from the Colombo Stock Exchange (CSE) and cryptocurrency, utilising proxies such as BTC/USD daily returns and the All-Share Price Index (ASPI) daily returns. The primary objective of this study is to investigate whether cryptocurrencies offer diversification potential for Sri Lankan investors. Therefore, this research fills a critical empirical gap by being the first to apply the Dynamic Conditional Correlation Generalised Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model to the Sri Lankan context. The study employs the DCC-GARCH model to analyse time-varying correlations using daily data from 2015 to 2023. A quantitative approach was used with secondary data obtained from Investing.com and analysed in EViews 8. The study shows a weak correlation between ASPI returns and BTC/USD returns, typically around zero, indicating their structural independence. However, during economic shocks like the COVID-19 pandemic, correlations spiked, reflecting investor behaviour, but reverted to near-zero levels post-pandemic. On average, the correlation coefficient remained close to zero, confirming minimal co-movement. Although both markets show persistent volatility, the study concludes that Sri Lankan investors can only profit from limited diversification due to their weak link. Regulatory restrictions and restricted exposure to cryptocurrencies further underscore this. These findings provide practical implications for portfolio diversification and regulatory oversight. The study contributes to the limited regional literature by empirically quantifying the dynamic link between stock and crypto markets in Sri Lanka.

Keywords: ASPI daily returns, Bitcoin, DCC-GARCH, Sri Lanka, time-varying correlation

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Introduction

The relationship between CSE returns and cryptocurrency returns has generated considerable attention from Sri Lankan financial analysts, researchers, and investors. The stock market has traditionally been the primary avenue for investors seeking to accumulate long-term wealth. It is a vital component of a well-diversified investment portfolio due to its historical performance, regulated nature, and inherent stability (Markowitz, 1952). On the contrary, the emergence of cryptocurrencies led by the introduction of Bitcoin in 2009, brought forth a decentralised and frequently volatile asset class that has captured the interest of investors and technologists alike (Bianchi, 2023). The increasing integration of these financial sectors makes it relevant to investigate the relationship between stock returns and cryptocurrency prices worldwide (International Monetary Fund [IMF], 2022; Wątorek et al., 2023). On the other hand, cryptocurrencies oppose traditional monetary systems and support blockchain technology, decentralisation, and transparency (Bianchi, 2023). Conducting a thorough analysis of the current body of research is necessary to investigate the theoretical and practical consequences of this relationship. Some research indicates that there is no relationship between stock returns and cryptocurrency prices, while other studies propose that a relationship may exist, albeit rarely, particularly when considering macroeconomic or market attitudes. These opposing viewpoints highlight the subtleties and complexity that come with examining their relationship.

The popularity and adoption of cryptocurrency have grown rapidly worldwide, including in Sri Lanka. Among Sri Lankan young investors, cryptocurrency investment has become an emerging trend. Additionally, many young investors are assembling well-thought-out portfolios that combine cryptocurrencies with traditional asset types, such as stocks, in the CSE (Evans Rozario et al., 2020). Therefore, it's essential to understand the relationship between stock market performance and the cryptocurrency market to maximise their returns while mitigating risk to a lower level. Despite numerous studies examining this dynamic relationship in developed and developing countries, a significant empirical gap exists regarding the Sri Lankan context. No prior research has employed the Dynamic Conditional Correlation Generalised Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model to investigate the relationship between CSE returns and cryptocurrency returns, leaving a methodological gap that this study seeks to address. Furthermore, this study uniquely compares the pre- and post-COVID-19 periods within the Sri Lankan context to identify how the pandemic reshaped investor sentiment, regulatory policies, and market volatility in both the CSE and cryptocurrency markets. This comparison provides a strong justification for the selected time frame, as the pandemic period marked a structural change in Sri Lanka's financial environment. Accordingly, this research aims to investigate whether a dynamic correlation exists between cryptocurrency returns and CSE returns, and how this relationship behaves during periods of market turbulence. Through a detailed analysis of the relationship dynamics and an attempt to shed light on the nature of their interactions, this research aims to fill this gap.

The organisation of this paper is as follows. Section 2 provides a review of relevant literature. Section 3 details the data sources and variables employed in the study. Section 4 describes the methodology and models employed. Section 5 presents the experimental findings; a discussion of the results and Section 6 concludes the paper.

Literature Review

Overview of the stock market

Stock markets facilitate the exchange of ownership in publicly listed companies and play a vital role in channelling funds between investors and businesses (Mishkin & Eakins, 2021). As regulated and transparent trading platforms, stock exchanges enhance liquidity and price discovery in financial systems (Pagano & Roell, 1996; World Federation of Exchanges [WFE], 2023). According to Modern Portfolio Theory (Markowitz, 1952), the interrelationship among asset returns determines diversification potential, making stock markets a central component of investment portfolios. Major exchanges such as the NYSE, NASDAQ, and TSE serve as global benchmarks for equity performance (WFE, 2023), while in Sri Lanka, the CSE performs a similar function in mobilising domestic capital. The All-Share Price Index (ASPI) serves as a comprehensive measure of market performance and is therefore utilised in this study as the primary indicator of stock market returns (O'Sullivan et al., 2019).

Blockchain and cryptocurrencies

A blockchain is a decentralised ledger that records transactions on a peer-to-peer network, allowing participants to verify exchanges without a central authority (PricewaterhouseCoopers, n.d.). Cryptocurrencies, created and stored electronically on blockchain networks, use cryptographic algorithms to authenticate transactions and control the supply of monetary units. The first and most prominent cryptocurrency, Bitcoin, introduced by Satoshi Nakamoto in 2009, remains the best-performing digital asset in the market. Although blockchain technology has found applications in areas such as tokenisation, fund transfers, and supply chain management, both cryptocurrencies and their underlying systems are still evolving in terms of financial integration and regulatory development (Coursera Staff, 2023).

Relationship between stock market returns and cryptocurrency returns

The relationship between cryptocurrency and stock market returns has become a growing focus in global financial research. Prior studies provide mixed evidence regarding the strength and direction of this linkage. Niyitegeka and Zhou (2023) identified an increase in conditional correlations between Bitcoin and equity markets during the first and second quarters of 2020, indicating contagion effects in times of financial turmoil. Similarly, Kim et al. (2020) found that correlations among Bitcoin, gold, and S&P 500 returns are time-varying and intensify during crises, such as the COVID-19 pandemic. These results align with Contagion Theory, which posits that financial linkages strengthen under market stress.

In contrast, studies such as Bhullar and Bhatnagar (2020) observed no long-run causal relationship between Bitcoin prices and Asian stock indices, suggesting structural independence across markets. Salisu et al. (2019) reported that Bitcoin enhances stock-return predictability in developed economies, implying potential integration, while Sami and Abdallah (2020) found divergent effects across MENA (Middle East and North Africa) markets. Collectively, these findings confirm that stock–crypto interdependence is market-specific and time-varying.

From a theoretical perspective, Modern Portfolio Theory (Markowitz, 1952) emphasises that weak correlations between asset classes offer diversification benefits, whereas Contagion Theory explains the short-term surge in correlations that occurs during shocks. However, empirical evidence from Sri Lanka remains absent. Building on this gap, the present study examines whether the correlation between ASPI and BTC/USD returns is time-varying and whether correlation spikes occur during crisis periods such as the COVID-19 pandemic, using the DCC-GARCH framework.

Gaps identified through the literature review

Insufficient Empirical studies in the context of Sri Lanka: Most studies have been conducted in developed and emerging markets in regions such as Europe, America, the MENA region, and East Asian countries like China. Although research has been conducted on South Asian countries, such as India, there are no empirical studies specifically focused on Sri Lanka. Building on previous international evidence, this study explicitly tests whether the correlation between ASPI and BTC/USD returns is time-varying and whether correlation spikes occur during financial crises, such as the COVID-19 pandemic. This focus provides both empirical and methodological novelty within the Sri Lankan context. In particular, no study has employed the DCC-GARCH model to examine the relationship between CSE returns and cryptocurrency returns, leaving both a contextual and methodological gap that this study seeks to address.

Emerging Market Dynamics: Empirical research is necessary to understand how the distinct features of developing countries, such as Sri Lanka, influence the correlation between stock market returns and cryptocurrencies. From a theoretical standpoint, Contagion Theory explains how correlations intensify during crises, while Modern Portfolio Theory highlights the diversification potential when correlations remain weak. This dual framework motivates the present study's investigation of Sri Lanka's market behaviour before and after the COVID-19 pandemic.

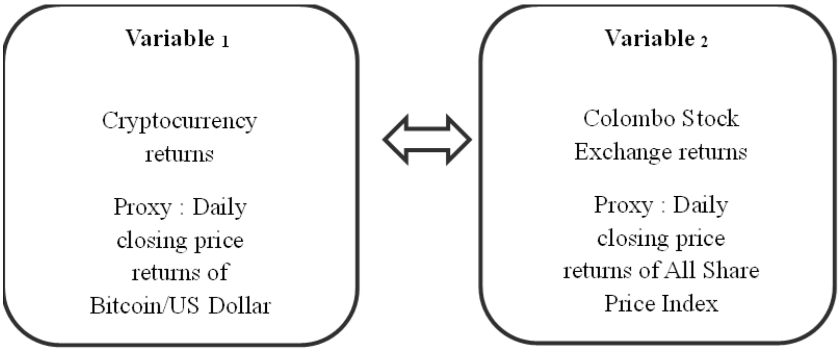
Investor Demographics and Behaviour: Empirical research can shed light on the characteristics and investing habits of Sri Lankans, as well as how they engage with cryptocurrencies in contrast to conventional equities.

Methodology

Conceptual framework

The data used in the study consist of the daily closing price returns of Bitcoin/Tether as a proxy for cryptocurrency returns and the daily closing price returns of the All-Share Price Index as a proxy for the Colombo Stock Exchange returns (Niyitegeka & Zhou, 2023). Every variable and proxy used is in accordance with the existing literature, which has been thoroughly reviewed.

Figure 1
Conceptual framework



((Source: Developed by authors based on literature)

Population and sample selection

Although the population of the cryptocurrency returns consists of all the cryptocurrencies available in the market, we have utilised only the Bitcoin/Tether returns to conduct this study due to the high market capitalisation.

Data collection method

The study utilises daily data from January 1, 2015, to December 31, 2023, to provide a clear picture of the movement of market returns and a significant statistical generalisation. Data was collected from investing.com To achieve more stationary time series data and facilitate detrending, the daily composite price indices were converted into natural logarithmic returns (Niyitegeka & Zhou, 2023), which are stated as follows:

$$R_t = [ln(P_t) - ln(P_{t-1})] \text{ x } 100 \dots \dots \dots (1)$$

P_t represents the period *t* closing price index P_{t-1} represents the period *t-1* closing price index. The formula [ln (P_t) - ln (P_{t-1})] needs to be multiplied by 100 due to numerical problems in the estimation part. This will not affect the model, as it scales linearly.

Research design

This study adheres to a positivist philosophy, focusing on objectively measuring reality through observation and data collection. It uses a deductive approach, beginning with theory and testing it against real-world evidence. By applying a quantitative method, the research systematically analyses numbers to uncover how returns from the CSE relate to those from cryptocurrencies.

Data analysis technique

To conduct this study, the DCC GARCH model is preferred over other multivariate GARCH models because it allows for time-varying correlations in addition to the properties of conditional variances. As a result, the current study can decide whether correlations between two return series are time-varying and change over time in response to market conditions (stable versus turbulent periods) (Ampountolas, 2022).

Dynamic conditional correlation GARCH model

The GARCH (1,1) model assumes that volatility depends on the last period's conditional volatility. It is expressed as follows:

$$r_t = \mu_t + \varepsilon_t \dots \dots \dots \dots \dots \dots . (2)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \dots \dots \dots \dots \dots \quad (3)$$

1st equation is the mean equation, and 2nd equation is the conditional variance equation. α_0 is a constant term, σ^2_t is the volatility at time *t*, ε^2_{t-1} is the squared error term of the previous period, and σ^2_{t-1} is the volatility of the previous period. The presence of clustering would be indicated by statistically significant positive parameter estimates α_1 and β (with the constraint $\alpha_1 + \beta < 1$), with the rate of persistence being defined by how close $\alpha_1 + \beta$ is to unity. The constraint $\alpha_1 + \beta < 1$ enables the process to remain stationary, with the upper limit of $\alpha1 + \beta = 1$ representing an integrated process (Niyitegeka & Zhou, 2023).

1st equation (Mean equation) must be 'White Noice' which means its error term should be serially uncorrelated. Therefore, by using the Durbin-Watson test and/or the Lagrange Multiplier test, the mean equation must be tested for autocorrelation. Lagged values of the dependent variable should be added to the right side of Equation 5 until serial correlation is eliminated, should autocorrelation be detected. To confirm the necessity of proceeding to estimate GARCH models, the appropriate mean equation should also be tested for the Autoregressive Conditional Heteroscedastic effect (Chinzara & Aziakpono, 2009).

Multivariate GARCH models are typically used to study the relationship between equity markets, as the volatilities of financial series are known to move slowly or synchronously across markets. Except for the fact that multivariate GARCH models provide additional equations for the time-varying movements of covariances, they are essentially identical to their univariate counterparts. The literature has presented several multivariate GARCH formulations; the DCC GARCH models are the focus of this section (Niyitegeka & Zhou, 2023).

To capture the dynamic time-varying of conditional covariance, Engle (2002) introduced the DCC GARCH model. It is a dynamic model with a time-varying mean, variance, and covariance of return series r_t (Niyitegeka & Zhou, 2023).

$$r_t = u_t + \varepsilon_t \dots\dots\dots\dots\dots\dots. \quad (4)$$

$$\varepsilon_t|\Omega_{t-1} \rightarrow N(0, H_t)$$

Equation 4 is used to obtain the conditional variance of each return from the residuals of the mean equation:

$$h_{i,t}^2 = \alpha_0 + \sum_{j=1}^{p_l} \alpha_j \varepsilon_{i,t-1}^2 + \sum_{j=1}^{q_l} \beta_j \sigma_{i,t-1}^2 \dots\dots\dots\dots (5)$$

Where, $\sum_{j=1}^{p_l} \alpha_j + \sum_{j=1}^{q_l} \beta_j < 1$

Then, the multivariate conditional variance H_t is estimated as follows:

$$H_t = D_t R_t D_t \dots\dots\dots\dots\dots \quad (6)$$

where H_t the conditional covariance matrix of R_t, D_t represents a (k × k) diagonal matrix of time- varying standard deviations obtained from the univariate GARCH specifications given in 6th formula, and R_t is the (k x k) time-varying correlations matrix derived by first standardizing the residuals of the mean 5th formula of the univariate GARCH model with their conditional standard deviations derived from 6th formula, to obtain $\eta_{it} = \frac{\varepsilon_{it}}{\sqrt{h_{it}^2}}$ (Niyitegeka & Zhou, 2023).

Formulas 7 and 8 are used to estimate the conditional correlation parameters employing the standardised residuals.

$$R_t = \left(diag(Q_t)\right)^{\frac{-1}{2}} Q_t \left(diag(Q)^{\frac{-1}{2}}\right) \dots\dots\dots\dots\dots (7)$$

$$Q_t = (1 - \theta_1 - \theta_2)Q^- + \theta_1 \eta_{t-1}\eta'_{t-1} + \theta_2 Q_{t-1} \dots\dots\dots\dots\dots (8)$$

where QQ^- is the standardised residuals' unconditional covariance. The Q_t does not generally have ones on the diagonal, so it is scaled as in formula 6 above to derive R_t, which is a positive definite matrix. As a result, the conditional correlations in this model are dynamic or change over time. It is assumed that θ_1 and θ_2 from formula 8 are positive scalars such that $\theta_1 + \theta_2 < 1$ (Niyitegeka & Zhou, 2023).

Finally, by following the equation, the conditional correlation coefficient ρ_{ijj} between two market returns, i and j can be expressed:

$$\rho_{ij} = \frac{q_{ij,t}}{\sqrt{q_{ij,t} q_{jj,t}}}, i, j = 1,2, \dots\dots, n, and\ i \neq j \dots\dots\dots (9)$$

This can be expressed in typical correlation form by putting $Q_t = q_{ij,t}$ as follows:

$$\rho_{ij} = \frac{(1 - \theta_1 - \theta_2)q_{12}^- + \theta_1 \eta_{1,t-1}\eta_{2,t-1} + \theta_2 q_{12,t-1}}{\sqrt{[(1 - \theta_1 - \theta_2)q_{11}^- + \theta_1 \eta_{1,t-1}^2 + \theta_2 q_{11,t-1}]}\sqrt{[(1 - \theta_1 - \theta_2)q_{22}^- + \theta_2 \eta_{1,t-1}^2 + \theta_2 q_{22,t-1}]}} \dots\dots\dots (10)$$

Hypotheses development

This hypothesis, that there is a correlation between cryptocurrency returns and CSE returns, served as the basis for this study, which was grounded in a conceptual framework and a literature review. This reflects the expectation that movements in one market may be associated with corresponding changes in the other, indicating potential interlinkages between these two investment domains.

Findings and Discussion

In this study, DCC-GARCH (1,1) was applied to examine the dynamic relationship between the daily returns of the ASPI and the daily returns of BTC/USD. The output from DCC-GARCH (1,1) was based on a two-step estimation procedure. First, univariate GARCH models were estimated for each of the time series: ASPI daily returns and BTC/USD daily returns. In the second step, the model dynamically estimates the conditional correlations between the two series over time.

Univariate GARCH outputs

For ASPI, the mean constant of -0.034708 (p = 0.0100) points to a slight but statistically significant downward drift, possibly reflecting persistent inefficiencies or structural issues in the market. Volatility dynamics exhibit a low baseline level (0.009442, p = 0.0007), strong sensitivity to recent shocks (ARCH = 0.190836, p = 0.0000), and high persistence (GARCH = 0.820708, p = 0.0000), indicating that periods of high or low volatility tend to persist. In contrast, BTC/USD recorded a mean constant of 0.194023 (p = 0.0110), indicating a modest but significant upward drift, consistent with its growth-oriented and speculative nature. Its baseline volatility was much higher (0.971679, p = 0.0017), sensitivity to short-term shocks was lower (ARCH = 0.134292, p = 0.0000), yet persistence remained strong (GARCH = 0.824856, p = 0.0000). Both models converged quickly (30 iterations for ASPI, 21 for BTC/USD), exhibited highly significant coefficients, and produced negative R-squared values typical of volatility models. The Akaike and Schwarz criteria, which support the models, confirmed that they effectively capture the conditional variance patterns in both markets.

DCC-GARCH output

Table 1 presents the summary results of the DCC-GARCH model estimation.

Table 1
Summary table of the DCC Output

	Coefficient	Standard Error	Z-Statistic	P-Values
Theta 1 (α)	-0.003763	0.004702	-0.800354	0.4235
Theta 2 (β)	0.975743	0.034104	28.61051	0.0000
Convergence achieved after 29 iterations				
Stability condition: Theta (1) + Theta (2) < 1 is met				

(Source: EViews 8)

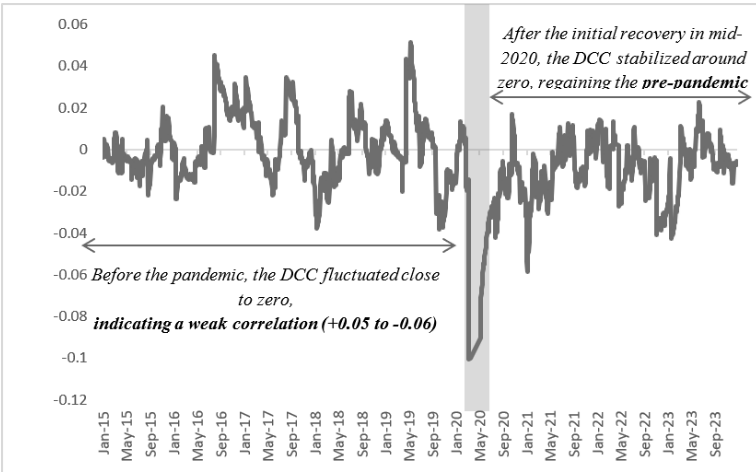
Estimation results show that the DCC model converged successfully after 29 iterations, confirming the adequacy of the optimization process. Moreover, the coefficient on parameter Theta 1 (α) which represents the short-term shocks of correlation dynamics, has a coefficient of -0.003763 with a p-value of 0.4235, indicating that it is not statistically significant. This would suggest that short-term fluctuations in correlation do not play a significant role in explaining the relationship between the ASPI and BTC/USD returns. On the other hand, the parameter Theta 2 (β), which captures persistence in the long-run, is highly significant with an estimate of 0.975743 and a p-value of 0.0000. This result indicates that the relationship between ASPI and BTC/USD returns are more dominated by long-term trends than by short-term, immediate changes. Based on the findings, the null hypothesis that there is no correlation between BNB and STI is thus disproved.

Discussion

The DCC matrix shows that the association between ASPI and Bitcoin returns is generally weak and consistent, with brief disruptions during world crises. The results demonstrate how robust their independent dynamics are, which is corroborated by the interaction of the DCC model's Theta 1 and Theta 2 parameters. Theta 1, which represents the short-term correlation response to shocks, is as important, even if Theta 2 predominates and emphasises the long-term persistence of correlation. While the correlation responds to short-term market fluctuations, the equilibrium between these parameters guarantees that it eventually returns to its long-term state. The potential of ASPI and Bitcoin as complementary investment possibilities in portfolio development is further supported by this dynamic. For risk management and strategic asset allocation, it is crucial to understand the impact of both short-term and long-term persistence variables, particularly in an era of increasing market integration and uncertainty. Together with Theta 2's stabilising impact, Theta 1's capacity to record instantaneous reactions guarantees the longevity of their historically shaky relationship.

Figure 2

Dynamic conditional correlation matrix



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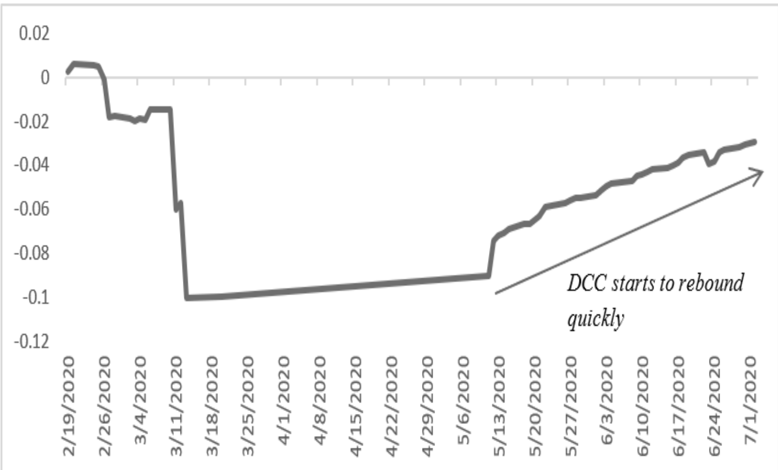

(Source: EViews 8)

Conclusion

This study examined the dynamic relationship between stock market returns, as measured by the ASPI of the CSE, and cryptocurrency returns, specifically represented by Bitcoin. The study employed the DCC-GARCH model to examine how the associations between these two asset classes evolved over time, particularly during various economic conditions, such as the COVID-19 pandemic. The results show a weak and time-varying link between cryptocurrency returns and ASPI returns. The association hangs near zero, according to the Dynamic Conditional Correlation (DCC) model, indicating a weak and erratic connection between these markets. Nonetheless, there are times when a noticeable difference is evident, especially during the early stages of the COVID-19 pandemic.

Extreme differences in investor behaviour and market dynamics brought on by global economic uncertainty were reflected in the correlation's brief decline to a negative value of -0.1 during this time. In this approach, the COVID-19 pandemic offered a special case study. Bitcoin demonstrated traits of a speculative asset during the period of exceptional volatility in global markets, responding quickly to shifts in investor mood and worldwide liquidity. Meanwhile, in a market with very little exposure to international financial trends, the ASPI's behaviour was influenced by regional economic upheavals, governmental regulations, and investor hesitancy. This period's brief negative correlation highlights how exogenous shocks can intensify the disparities across these asset types. The DCC-GARCH model proved resilient in capturing the changing relationship over time, despite these discrepancies. The correlation's ultimate recovery to almost zero values after the epidemic emphasises how fleeting these dramatic occurrences are in terms of their ability to affect long-term market behaviour. Notably, Theta 2's dominance in the DCC model was crucial in preventing the correlation from remaining negative for an extended period. The Central Bank of Sri Lanka's (CBSL) regulatory position is one element that may have contributed to the overall weak association observed throughout the time period in this study. Citing concerns about market volatility, a lack of regulatory protections, and the potential for abuse for illicit purposes, the CBSL has consistently discouraged investing in cryptocurrencies (Risks of Using and Investing in Cryptocurrency | CBSL, n.d.). It's possible that this legal framework reduced Sri Lankan investors' exposure to cryptocurrencies, which in turn decreased market interaction. The overall weak correlation between the ASPI and Bitcoin points to few prospects for diversification advantages in the Sri Lankan setting. The relationship may not be strong enough to offer substantial benefits to investors looking to utilise Bitcoin as a diversification asset or as a hedging tool for local equity portfolios. The DCC-GARCH model's capture of this correlation's dynamic character, however, suggests that the link is not totally static and may vary in response to shifts in investor behaviour, market structure, or regulatory regulations. In conclusion, the results indicate a relationship between cryptocurrency returns and CSE returns, although the Dynamic Conditional Correlation remains modest. The study's null hypothesis, which posited no association between the two asset classes, was rejected by the observed correlation, even though it was weak. This finding suggests that the weak and time-varying correlation between ASPI and BTC/USD returns presents only limited diversification opportunities for Sri Lankan investors, particularly during periods of market stability.

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