Cryptocurrency Market Spillovers to Stock Indexes: A Co-Integration Analysis in the Context of Global and Asian Markets

Ali Nawaz[1], Wajid Alim[2], Sammar Abbas[3] and Shahid Manzoor Shah[4]

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Abstract

The study investigates the co-movement relationships between cryptocurrencies and South Asian stock markets, focusing on five leading cryptocurrencies: Bitcoin, Ethereum, Tether, Binance Coin, and Ripple, and five South Asian stock indices: BSE, PSX 100, DSE 30, NEPSE, and Sri Lanka's All Share Index, and also used five major global indices for the accuracy of analysis. The study aims to understand their integration and causal dynamics. The analysis uses 357 weekly observations of historical prices from November 6, 2017, to September 2, 2024, applying econometric tools such as the Augmented Dickey-Fuller and Phillips-Perron tests, Johansen's Cointegration Test, Vector Auto-Regression, Vector Error Correction Model, and Granger causality to examine statistical properties, integration, and causality among the variables. Results show significant cointegration and causality between cryptocurrencies and South Asian stock indices, with cryptocurrency prices exhibiting higher volatility and faster adjustments than stock indices. These findings provide actionable insights for investors, policy-makers, and researchers regarding regulation and cross-market investment strategies. This study uniquely explores the interplay between emerging digital assets and traditional finance in a South Asian context, offering novel evidence on volatility dynamics and causal relationships that inform coupled regulatory frameworks and cross-market investment planning.

Keywords: Cryptocurrency, South Asian Stock Indices, Multivariate Cointegration.

Introduction

Cryptocurrencies, beginning with Bitcoin in 2009, operate on decentralised blockchain technology, enabling secure, transparent transactions without central authorities. Their rise has introduced a new asset class, with major players like Ethereum and Ripple contributing to a market that exceeded $2 trillion by 2022. While cryptocurrencies offer benefits such as lower costs and faster transactions, they face challenges including regulatory uncertainty, security risks, and price volatility. Governments worldwide have adopted diverse regulatory stances, shaping the evolving landscape. The relationship between cryptocurrencies and traditional financial assets is a growing

[1]*PhD Scholar, Lahore School of Accountancy and Finance, The University of Lahore.*
[2]*Assistant Professor, Lahore School of Accountancy and Finance, The University of Lahore.*
Corresponding Author Email: wajid@uolcc.edu.pk
[3]*Associate Professor, College of Business and Entrepreneurship, Abdullah Al Salem University, Kuwait.*
Email: sammar.abbas@aasu.edu.kw
[4] *Assistant Professor, Lahore School of Accountancy and Finance, The University of Lahore. Email: shahidmanzoorphd@gmail.com*

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research area. Bitcoin is often regarded as "digital gold" due to its limited supply, and studies suggest that cryptocurrencies generally exhibit low or negative correlations with traditional markets, making them attractive for portfolio diversification. However, their integration with traditional finance is increasing, as seen with Bitcoin futures on major exchanges. Despite this, cryptocurrencies can experience periods of correlation with traditional assets due to economic and geopolitical factors.

Stock markets, driven by economic indicators, corporate earnings, and investor sentiment, remain crucial for global finance. Unlike equities, cryptocurrencies derive their value from market perception and innovation, rather than tangible backing or centralised regulation. The rise of cryptocurrencies complicates financial markets, particularly in South Asia, where stock indices such as India's BSE Sensex and Pakistan's KSE-100 react to both local and global influences. Research into their correlation with cryptocurrencies presents mixed results, highlighting the complexities of integrating digital assets into conventional finance and the need for careful risk assessment.

Contemporary research highlights intensifying linkages among cryptocurrencies, stock markets, commodities, and macro-financial risks. Political and institutional conditions have been shown to influence market behaviour, including stock returns, volatility, and corporate governance outcomes (Alim et al., 2024). Research on cross-market dynamics documents strong connectivity between cryptocurrencies, commodities, gold, and BRICS indices, as well as the transmission of global financial stress to cryptocurrency markets through long-run cointegration and causality channels (Bouzguenda & Jarboui, 2025; Colombage et al., 2025). Cryptocurrency-implied volatility emerges as a key driver of inter-asset return spillovers (Dangi, 2025), and cryptocurrencies significantly affect stock markets across both emerging and advanced economies (Ebenezer, 2025; Fernando, 2025). Long-run relationships between global indexes, commodities, and major cryptocurrencies have also been established (Erdas & Yagcilar, 2025), while crypto and commodity price movements correlate with broad market indices such as the S&P 500 (Heydarpour & Mohammadi, 2025). Additional evidence shows that cryptocurrency volatility shapes stock and exchange rate dynamics (Jimoh & Oluwasegun, 2020), that external shocks, such as terrorism, alter market behaviour (Khan et al., 2022), and that major cryptocurrencies exhibit causal linkages with stock and foreign exchange markets in BRICS-T countries (Sarp & Anbar, 2025). Overall, the literature underscores the growing interconnectedness of global financial systems.

Literature Review

The relationship between cryptocurrencies and traditional stock indices has garnered significant attention in recent years, particularly as cryptocurrencies have emerged as alternative investment assets. Studies have explored the cointegration, causality, and volatility spillovers between these asset classes, often focusing on developed markets such as the U.S., Europe, and Australia. However, research on emerging markets, particularly South Asia, remains limited, creating a critical gap in understanding the financial dynamics of these regions.

Dirican and Canoz (2017) investigated the relationship between Bitcoin and major global stock indices, including the Dow30 and Nasdaq100, using the Auto Regressive Distributed Lag (ARDL) model. Their findings revealed a cointegrating relationship between Bitcoin and specific indices, such as the Dow30 and China-A30, but not others, such as the Nikkei225 and FTSE100. Similarly, Caporale et al. (2024) employed a DCC-GARCH model to analyse Bitcoin's correlation with stock indices across continents, finding positive correlations with U.S. and European indices but

negative correlations with Asian markets. These studies highlight varying degrees of integration between cryptocurrencies and stock markets, which are often influenced by regional economic conditions. In emerging markets, studies such as Malhotra and Gupta (2019) examined volatility transmission between cryptocurrencies and Asian stock indices, including India's NSE and Singapore's SES. Their findings indicated short-term volatility spillovers from Bitcoin to stock markets, suggesting limited long-term cointegration. Similarly, Chang et al. (2021) examined a significant relationship between Bitcoin and India's Sensex but no causality with China's SSIC, emphasising the potential for diversification benefits in emerging markets.
Recent studies have also explored the impact of external shocks, such as the COVID-19 pandemic, on crypto-equity linkages. Kostika and Laopodis (2019) used wavelet coherence to analyse the relationships among Bitcoin, Ethereum, and stock indices during the pandemic, revealing financial contagion effects. Similarly, Mand and Thaker (2020).analysed that cryptocurrencies and stock markets exhibited higher correlations during crises, challenging the notion of cryptocurrencies as safe-haven assets. Despite these advancements, the literature lacks comprehensive studies of South Asian stock indices, particularly those that employ robust methodologies to capture nonlinear dynamics. Addressing this gap is crucial for understanding the long-run and short-run cointegration (H1A and H1B) and causality (H1C) between cryptocurrencies and stock indices in emerging markets.

Methodology

This study analyses long-term relationships among 11 cryptocurrencies using time-series analysis and cointegration methods, including ADF and PP tests for stationarity. Johansen's approach identifies long-run associations, while the Vector Error Correction Model evaluates short-run correlations. The Granger Causality test examines lead-lag relationships among five cryptocurrencies. This research analyses the co-integration between five cryptocurrencies and South Asian stock indices using weekly closing prices from Investing.com, Nepsealpha.com, and Yahoo Finance, covering the period from November 2017 to September 2024. The study focuses on Bitcoin, Ethereum, Tether, Binance Coin, Ripple, and five major South Asian stock indices.

$X_t = bY_t + u_t \dots\dots\dots\dots\dots\dots\dots.$

The analysis involves two main steps: first, applying the unit-root test to identify non-stationarity; second, conducting the co-integration test if the first-differenced variables are stationary. Traditional methods, like least squares, are inadequate for non-stationary time series, making co-integration a necessary approach for accurate analysis. Co-integration testing finds long-term linkages between variable sets. Three of the most commonly used measurements are: ADF tests for unit roots in time series to check stationarity. Used here to ensure reliable regression analysis. Phillips-Ouliaris tests cointegration in time series. Used to detect long-term relationships through the equation. Johansen tests multiple cointegrating relationships. Used to check cointegration among variables. VECM models cointegrated variables and corrects short-term deviations. Used to detect cointegration individually between all variables. Granger Causality tests if one variable predicts another. Used to identify the relationships of all variables

$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum \delta_i \Delta y_{t-i} + \varepsilon_t.$

$y_t = \alpha + \beta x_t + \varepsilon_t,$

$\Delta Y_t = \Pi Y_{t-1} + \sum \Gamma_i \Delta Y_{t-i} + \varepsilon_t$, where $\Pi = \alpha\beta'$.

$\Delta Y_t = \alpha\beta' Y_{t-1} + \sum \Gamma_i \Delta Y_{t-i} + \varepsilon_t.$

$y_t = \alpha + \sum \beta_i x_{t-i} + \sum \gamma_j y_{t-j} + \varepsilon_t.$

Table 1: Cryptocurrency, South Asian, and Global Stock Indices Variables

Cryptocurrency			
Name	**Symbol**	**Market Capitalization**	**Sample Period**
Bitcoin	BTC	$1300 billion	2017 to 2024
Ethereum	ETH	$369 billion	2017 to 2024
Tether	USDT	$111 billion	2017 to 2024
Binance Coin	BNB	$87.4 billion	2017 to 2024
Ripple	XRP	$29.6 billion	2017 to 2024
South Asian Stock Indices			
Name	**Symbol**	**Market Capitalization**	**Sample Period**
Bombay Stock Exchange Index	BSE SENSEX	30 stocks with a total market of 14,499.07 billion	2017 to 2024
Pakistan Stock Exchange Index	PSX 100	9,062.903 billion	2017 to 2024
Dhaka Stock Exchange Index	DSE 30	$ 72.1 billion	2017 to 2024
Nepal Stock Exchange Index	NEPSE	$24 billion	2017 to 2024
All Share Price Index (Sri Lanka).	ASPI	4,534.65	2017 to 2024
Global Stock Indices			
Name	Symbol	Market Capitalization	Sample Period
Cotation Assistée en Continu 40	CAC 40	€1.9 trillion	2017 to 2024
Deutscher Aktienindex	DAX	€1.5 trillion	2017 to 2024
Nikkei Stock Average	Nikkei 225	¥6.3 trillion	2017 to 2024
Standard & Poor's 500	S&P 500	$40 trillion	2017 to 2024
Tokyo Stock Exchange	TSE	¥6.5 trillion	2017 to 2024

Figure 1: Crypto Market Capitalization

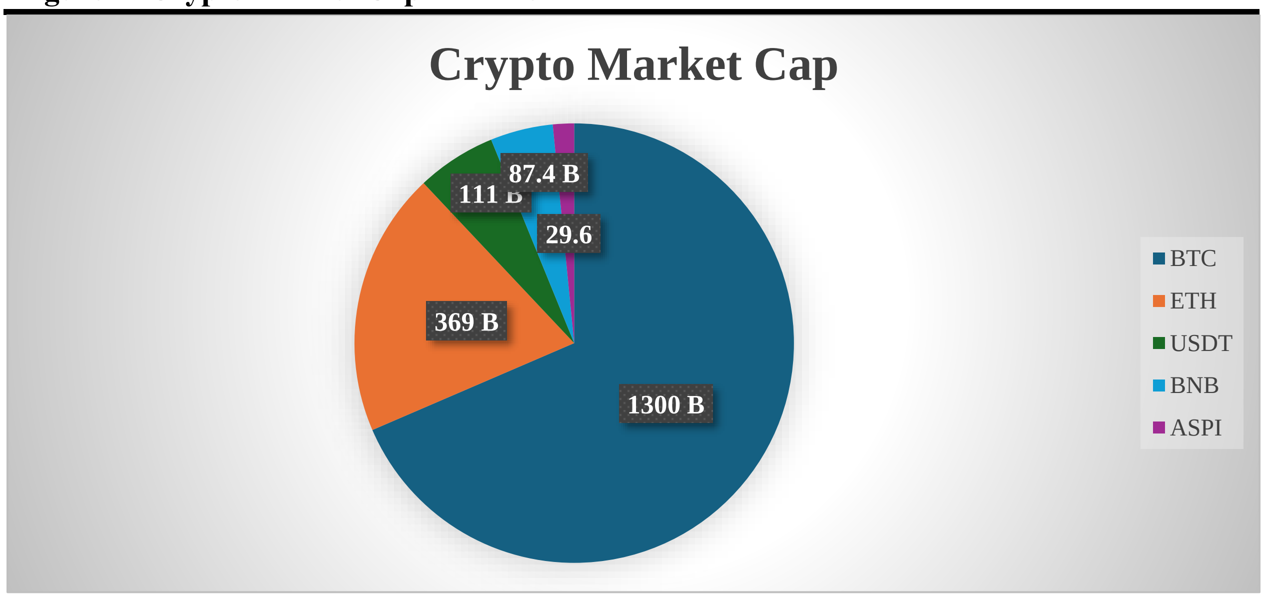

Figure 2: Stock Market Capitalization

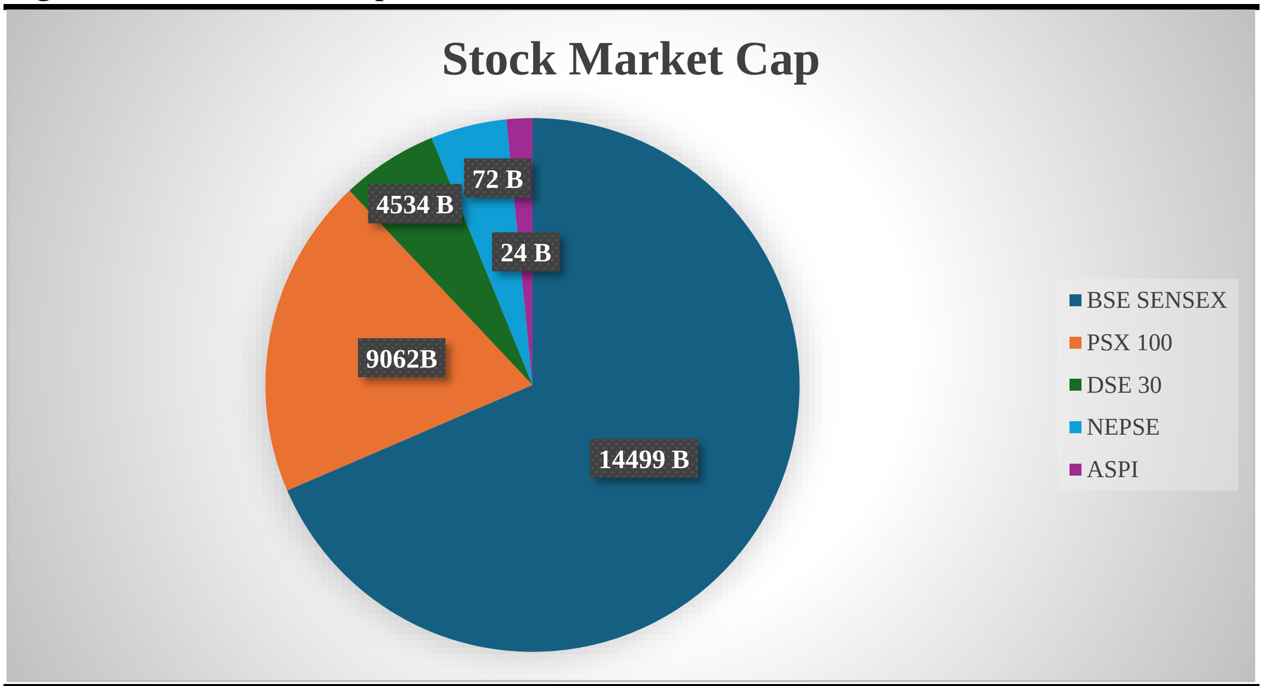

Figure 3: Global Stock Market Capitalization

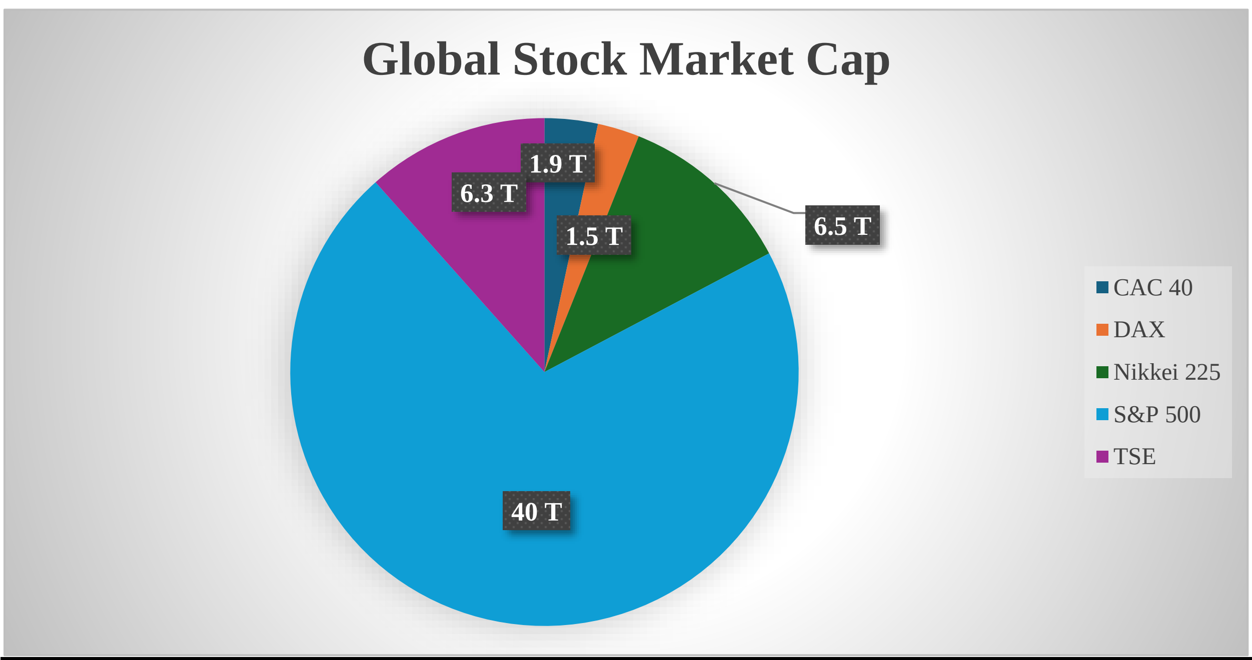

Table 2: Descriptions of variables

Variable	Measurement Unit	Data Source	Time Period	Frequency	Symbol
Bitcoin Price	USD	Yahoo Finance	2017 to 2024	Weekly	BTC
Ethereum Price	USD	Yahoo Finance	2017 to 2024	Weekly	ETH
Tether Price	USD	Yahoo Finance	2017 to 2024	Weekly	USDT
Binance Coin Price	USD	Yahoo Finance	2017 to 2024	Weekly	BNB
Ripple Price	USD	Yahoo Finance	2017 to 2024	Weekly	XRP
Bombay Stock Exchange Index Price	USD	Yahoo Finance	2017 to 2024	Weekly	BSE SENSEX
Pakistan Stock Exchange Index Price	USD	Yahoo Finance	2017 to 2024	Weekly	PSX 100
Dhaka Stock Exchange Index Price	USD	www.investing.com	2017 to 2024	Weekly	DSE 30
Nepal Stock Exchange Index Price	USD	www.nepsealpha.com	2017 to 2024	Weekly	NEPSE
All Share Price Index Price (Sri Lanka)	USD	www.tradingeconomics.com	2017 to 2024	Weekly	ASPI

Results and Discussion

Table 3: Descriptive Statistics

Table: Descriptive Statistics (South Asia)

	BTC	ETH	USDT	BNB	XRP	BSE	PSX 100	DSE 30	NEPSE	ASPI
Mean	25418.07	1425.774	1.001300	201.3716	0.526191	20563.74	1828.652	2027.949	1438.037	7834.397
Median	20049.76	1280.257	1.000309	216.4658	0.466867	19866.86	1851.138	2108.320	1874.600	7333.420
Maximum	73083.50	4626.359	1.023578	673.3153	3.377810	37496.80	3488.358	2767.380	3180.860	13371.61
Minimum	3413.768	85.26210	0.980969	1.519690	0.150214	10527.29	849.9515	0.000000	0.000000	0.000000
Std. Dev.	19256.11	1207.157	0.004443	198.3002	0.330614	6442.204	480.3459	376.2029	1055.672	2494.023
Skewness	0.747902	0.652553	1.436434	0.584785	3.081143	0.696309	0.312094	-1.816670	-0.335012	0.011276
Kurtosis	2.342123	2.333713	11.04174	2.097161	20.77121	2.623958	3.257537	10.86515	1.623924	3.150674
Jarque-Bera	39.71968	31.94017	1084.728	32.47233	5262.620	30.95176	6.782056	1116.545	34.84496	0.345268
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.033674	0.000000	0.000000	0.841445
Sum	9074251.	509001.2	357.4641	71889.65	187.8504	7341254.	652828.9	723977.9	513379.3	2796880.
Sum Sq. Dev.	1.32E+11	5.19E+08	0.007026	13998975	38.91278	1.48E+10	82140674	50384198	3.97E+08	2.21E+09
Observations	357	357	357	357	357	357	357	357	357	357

Source: Author's Estimation

The analysis presents descriptive statistics for five cryptocurrencies Bitcoin, Ethereum, Tether, Binance Coin, and Ripple and five South Asian stock indices, including the Bombay Stock Exchange and Pakistan Stock Exchange, based on 357 observations. Bitcoin shows a mean of

Table 4: Descriptive Statistics (Global)

	BTC	ETH	USDT	BNB	XRP	CAC40	DAX	NIKKEI	S_P500	TSE
Mean	25421.54	1421.341	0.999801	201.5184	0.527521	6153.975	14007.02	25821.73	3742.229	18370.09
Median	19710.00	1268.940	1.000200	216.5779	0.466278	6035.390	13526.13	23360.30	3839.500	18480.98
Maximum	69946.00	4652.400	1.029700	673.8413	3.359538	8219.140	18930.85	41190.68	5648.400	23346.18
Minimum	3186.000	83.44000	0.963300	1.541336	0.148313	4048.800	8928.950	16552.83	2304.920	11851.81
Std. Dev.	19272.26	1203.290	0.004488	198.5009	0.335671	979.6703	2074.374	5360.278	818.5392	2422.707
Skewness	0.746055	0.643306	-2.238428	0.585243	3.088281	0.205819	0.382815	1.203814	0.299424	-0.019298
Kurtosis	2.326121	2.305809	28.25989	2.096722	20.17520	2.012230	2.549104	3.655206	2.052905	1.819660
Jarque-Bera	39.87255	31.79195	9789.298	32.51600	4955.421	17.03389	11.74374	92.61131	18.67717	20.74604
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000200	0.002818	0.000000	0.000088	0.000031
Sum	9075489.	507418.7	356.9289	71942.05	188.3249	2196969.	5000506.	9218357.	1335976.	6558122.
Sum Sq. Dev.	1.32E+11	5.15E+08	0.007172	14027330	40.11234	3.42E+08	1.53E+09	1.02E+10	2.39E+08	2.09E+09
Observations	357	357	357	357	357	357	357	357	357	357

Source: Author's Estimation

$25,418.07 and a high standard deviation of $19,256.11, indicating significant volatility. Ethereum has a mean of $1,425.77 and a standard deviation of $1,207.16. Tether, a stablecoin, maintains a mean of $1.0013 with minimal fluctuations. Binance Coin and Ripple exhibit means of $201.37 and $0.53, respectively, with substantial standard deviations, reflecting high volatility. The stock indices, particularly the BSE, have a mean of $20,563.74 and a standard deviation of $6,442.20, indicating moderate volatility. Skewness and kurtosis analyses reveal that cryptocurrencies have right-skewed distributions and high kurtosis, suggesting the presence of extreme price movements. The Jarque-Bera test confirms that most assets are not normally distributed, except for the ASPI index, which shows normality. Maximum and minimum values indicate significant price fluctuations for cryptocurrencies and stock indices, with BSE ranging from $10,527.29 to $37,496.80. Overall, cryptocurrencies exhibit greater volatility and risk compared to traditional stock indices, influencing investment strategies and portfolio management.

Table 5: Augmented Dickey-Fuller Test Results

At Level l(0)			At First Difference l(1)	
Variables	t-statistics	Probability	t-statistics	Probability
BTC	-1.050855	0.7357	-19.92929	0.0000
ETH	-1.397952	0.5837	15.45739	0.0000
USDT	-6.928904	0.0000	-19.64441	0.0000
BNB	-1.388569	0.5883	-18.13929	0.0000
XRP	-4.718275	0.0001	-17.21740	0.0000
BSE SENSEX	1.831507	0.9998	-17.29925	0.0000
PSX-100	-2.256384	0.1870	-21.16913	0.0000
DSE 30	-0.575582	0.8726	-8.554090	0.0000
NEPSE	-1.516561	0.5242	-18.32566	0.0000
ASPI	-1.383504	0.5908	-18.08130	0.0000

Source: Author's Estimation

The Augmented Dickey-Fuller (ADF) test was conducted on cryptocurrencies (BTC, ETH, USDT, BNB, XRP) and South Asian stock indices (BSE SENSEX, PSX-100, DSE-30, NEPSE, ASPI) to assess stationarity. Most variables were found to be non-stationary at level form, with BTC showing a t-statistic of -1.050844 and a p-value of 0.7346, indicating a unit root. Similar results were observed for Ethereum, Binance Coin, and the stock indices. However, Tether and Ripple were exceptions, with USDT and XRP exhibiting significant t-statistics of -6.928902 and -4.718277, respectively, and p-values below 0.05, confirming their stationarity at a level. All variables became stationary after first differencing, with BTC showing a t-statistic of -19.92919 and a p-value of 0.0002. This indicates that while most variables are I(1), USDT and XRP remain stationary at the level, allowing them to be included in further analyses without differencing.

Table 6: Augmented Dickey-Fuller Test (Global)

At Level l(0)			At First Difference l(1)	
Variables	t-statistics	Probability	t-statistics	Probability
BTC	-1.021229	0.7467	-17.89784	0.0000
ETH	-1.607186	0.4778	-18.12355	0.0000
USDT	-6.047976	0.0000	-14.00208	0.0000
BNB	-1.312843	0.6246	-18.14142	0.0000
XRP	-4.400624	0.0003	-15.76978	0.0000
CAC40	-1.234093	0.6606	-19.12920	0.0000
DAX	-0.803140	0.8166	-18.77801	0.0000
NIKKEI	-0.379791	0.9095	-19.09156	0.0000
S_P500	-0.347785	0.9147	-19.64879	0.0000
TSE	-0.846006	0.8042	-17.49939	0.0000

Table 7: Phillips-Perron Unit Root Test

Phillips-Perron Unit Root Test				
At Level l(0)			At First Difference l(1)	
Variables	t-statistics	Probability	t-statistics	Probability
BTC	-1.124080	0.7073	-19.91228	0.0000
ETH	-1.635512	0.4633	-17.26955	0.0000
USDT	-10.97720	0.0000	-55.03638	0.0001
BNB	-1.351331	0.6064	-18.14349	0.0000
XRP	-4.677088	0.0001	-21.35861	0.0000
BSE SENSEX	1.611441	0.9995	-17.37987	0.0000
PSX-100	-2.256384	0.1870	-21.26335	0.0000
DSE 30	-0.676085	0.8498	-18.36924	0.0000
NEPSE	-1.539825	0.5124	-18.35832	0.0000
ASPI	-1.823695	0.3687	-18.14666	0.0000

Source: Author's Estimation

The Phillips-Perron unit root test results indicate that most cryptocurrencies and South Asian stock indices are non-stationary at the level but become stationary after first differencing. At the level, high p-values suggest that Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), and stock indices like BSE SENSEX, PSX-100, and DSE 30 do not reject the null hypothesis of a unit root. For instance, BTC has a t-statistic of -1.124080 with a p-value of 0.7073. However, after first differencing, all variables exhibit strong stationarity, with significantly lower t-statistics and p-values close to zero. For example, BTC's t-statistic drops to -19.91228 (p-value 0.0000). This pattern is consistent across all examined cryptocurrencies and indices. These findings highlight the importance of first differencing in econometric modeling to ensure stationarity and avoid spurious regressions, making the variables suitable for further analysis.

Table 8: VAR Lag Order Selection Criteria

VAR Lag Order Selection Criteria						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-21197.39	NA	2.86e+40	121.5323	121.6428	121.5763
1	-17221.79	7700.601	6.47e+30	99.32256	100.5376*	99.80625
2	-17068.84	287.4901	4.78e+30	99.01913	101.3388	99.94254
3	-16785.24	516.8111	1.67e+30*	97.96700*	101.3913	99.33013*
4	-16710.78	131.4256	1.95e+30	98.11336	102.6422	99.91621
5	-16623.95	148.2845	2.12e+30	98.18883	103.8223	100.4314
6	-16543.51	132.7574	2.41e+30	98.30093	105.0390	100.9832
7	-16439.04	166.4432	2.40e+30	98.27528	106.1180	101.3973
8	-16354.06	130.5098*	2.69e+30	98.36137	107.3087	101.9231

* *Indicates lag order selected by the criterion*

The table presents the results of a lag order selection criterion for a Vector Autoregressive (VAR) model. Several statistical measures, including the Log-Likelihood (LogL), Likelihood Ratio (LR) test, Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Criterion (HQ), are used to determine the optimal lag length. Among the criteria, the lowest values indicate the preferred model. The FPE, AIC, and HQ suggest an optimal lag of 3, as they reach their minimum values at this lag (FPE = 1.67e+30, AIC = 97.96700, HQ = 99.33013). Meanwhile, the SC criterion selects a lag of 1 (100.5376). Given that AIC and FPE generally perform better in large samples and are widely used in time-series analysis, a lag of 3 appears to be the most appropriate choice for this model. Using an optimal lag length ensures that the model captures relevant past information while avoiding overfitting or inefficiency. Therefore, for further analysis, a VAR model with lag 3 should be considered as it balances model complexity and predictive accuracy effectively.

Table 9: Multivariate Cointegration Analysis - Trace Statistic

Hypothesized No. of CE(s)	**Eigenvalue**	**Trace Statistic**	**0.05 Critical Value**	**Prob.****
None *	0.223240	305.6474	239.2354	0.0000
At most 1 *	0.144763	216.4710	197.3709	0.0038
At most 2 *	0.126250	161.2700	159.5297	0.0401
At most 3	0.105880	113.6288	125.6154	0.2126
At most 4	0.083395	74.12265	95.75366	0.5760
At most 5	0.050309	43.38399	69.81889	0.8780
At most 6	0.041603	25.16251	47.85613	0.9143
At most 7	0.016028	10.16256	29.79707	0.9778
At most 8	0.011457	4.458886	15.49471	0.8632
At most 9	0.001108	0.391345	3.841466	0.5316

Source: Author's Estimation

The Johansen cointegration test was conducted to determine the number of cointegrating relationships among the variables. This test is crucial for non-stationary time series data, identifying long-run equilibrium relationships. The trace statistic results show that the null hypothesis of no cointegration is rejected, with the first three trace statistics exceeding their critical values at the 5% level. The test indicates three cointegrating equations, as the null hypothesis is rejected up to "At most 2," but not beyond "At most 3." The eigenvalues decrease progressively, suggesting the strongest relationships in the first few vectors. These findings have significant implications for modeling, supporting the use of a Vector Error Correction Model (VECM) with three cointegrating equations. This approach ensures a comprehensive analysis of both short-run and long-run dynamics, providing valuable insights for economic modeling, policy decisions, and future research.

Table 10: Multivariate Cointegration Rank Test (Global)

Multivariate Cointegration Rank Test (Global)				
Hypothesized		Trace	0.05	
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**
None *	0.210311	295.7413	239.2354	0.0000
At most 1 *	0.141992	212.6283	197.3709	0.0069
At most 2 *	0.126373	158.7224	159.5297	0.0553
At most 3	0.094183	111.1665	125.6154	0.2693
At most 4	0.074146	76.34751	95.75366	0.4937
At most 5	0.053947	49.22995	69.81889	0.6709
At most 6	0.040233	29.70911	47.85613	0.7337
At most 7	0.027612	15.25428	29.79707	0.7634
At most 8	0.014231	5.397977	15.49471	0.7652
At most 9	0.014231	0.352532	3.841466	0.5527

Source: Author's Estimation

The Multivariate Cointegration Rank Test (Global) assesses the presence of long-run relationships among variables using the Johansen cointegration test. The trace statistic compares against the critical value at a 5% significance level to determine the number of cointegrating equations (CEs). The results indicate at least two cointegrating relationships, as the trace statistics for "None" (295.7413) and "At most 1" (212.6283) exceed their critical values, with p-values < 0.05. However, for "At most 2," the p-value (0.0553) is marginally above 0.05, suggesting weak evidence of a third cointegration relationship. Beyond "At most 3," all p-values exceed 0.05, indicating no additional significant cointegration. Overall, the presence of two strong and one marginal cointegrating vectors suggests long-run equilibrium relationships among the variables, supporting the use of vector error correction models (VECM) for further analysis.

Table 11: Multivariate Cointegration Analysis – Maximum Eigenvalue

Multivariate Cointegration Rank Test (South Asia)

Hypothesized		**Max-Eigen**	**0.05**	
No. of CE(s)	**Eigenvalue**	**Statistic**	**Critical Value**	**Prob.****
None *	0.223240	89.17640	64.50472	0.0001
At most 1	0.144763	55.20098	58.43354	0.1008
At most 2	0.126250	47.64128	52.36261	0.1407
At most 3	0.105880	39.50611	46.23142	0.2192
At most 4	0.083395	30.73866	40.07757	0.3767
At most 5	0.050309	18.22148	33.87687	0.8662
At most 6	0.041603	14.99995	27.58434	0.7482
At most 7	0.016028	5.703678	21.13162	0.9881
At most 8	0.011457	4.067541	14.26460	0.8521
At most 9	0.001108	0.391345	3.841466	0.5316

Source: Author's Estimation

The Johansen Maximum Eigenvalue test was conducted to determine the number of cointegrating relationships among the variables. This test identifies long-run equilibrium relationships between non-stationary time series. The Maximum Eigenvalue statistic sequentially tests (r) cointegrating vectors against (r + 1). The first test (r = 0) yields a statistic of 89.17640, exceeding the 5% critical value of 64.50472, with a p-value of 0.0001, leading to the rejection of no cointegration. However, at (r = 1), the statistic falls below the critical value, and p-values remain above 0.05 for further tests, indicating only one cointegrating equation. This suggests a single long-run equilibrium relationship among variables. The result supports using an error correction model (ECM) to account for short-run and long-run dynamics while preserving long-run information. The findings enhance model reliability and provide valuable insights for economic modeling, policy implications, and future research.

Table 12: Multivariate Cointegration Rank Test (Global)

Hypothesized		Max-Eigen	0.05	
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**
None *	0.210311	53.90590	64.50472	0.0004
At most 1	0.141992	47.55588	58.43354	0.1308
At most 2	0.126373	47.64128	52.36261	0.1431
At most 3	0.094183	34.81900	46.23142	0.4715
At most 4	0.074146	27.11756	40.07757	0.6247
At most 5	0.053947	19.52083	33.87687	0.7890
At most 6	0.040233	14.99995	27.58434	0.7900
At most 7	0.027612	14.45484	21.13162	0.7580
At most 8	0.014231	9.856299	14.26460	0.7361
At most 9	0.001001	5.045444	3.841466	0.5527

Source: Author's Estimation

The Multivariate Cointegration Rank Test (Global) assesses the presence of cointegrating relationships among variables using the Max-Eigen statistic. The null hypothesis tests whether there are no cointegrating equations (CEs) or at most a certain number of them. The first row, "None", shows a statistically significant result (p = 0.0004), indicating at least one cointegrating relationship exists. However, for higher ranks (at most 1 to at most 9), the test statistics fall below the critical values, and the p-values are above 0.05, suggesting no additional significant cointegrating vectors. Thus, the findings imply a single long-run equilibrium relationship among the variables. This result is crucial for economic and financial modelling, as it confirms that despite short-term fluctuations, the system exhibits long-run stability. However, further analysis, such as vector error correction modelling (VECM), is necessary to explore the dynamics of this equilibrium.

Table 13: Vector Error Correction Model Analysis

Vector Error Correction Estimates

Error Correction:	**D(BTC)**	**D(BSE)**	**D(ETH)**	**D(PSX_100)**	**D(USDT)**	**D(DSE_30)**	**D(BNB)**	**D(NEPSE)**	**D(XRP)**	**D(ASPI)**
CointEq1	0.016917	0.002506	-4.49E-05	-0.000757	7.64E-09	0.000115	0.000203	-0.000509	2.84E-06	-0.009985
	(0.01069)	(0.00176)	(0.00082)	(0.00047)	(1.4E-08)	(0.00024)	(0.00013)	(0.00069)	(6.0E-07)	(0.00254)
	[1.58327]	[1.42336]	[-0.05504]	[-1.62475]	[0.53001]	[0.47875]	[1.51125]	[-0.73604]	[4.73272]	[-3.93345]
CointEq2	0.107616	0.002439	0.002385	0.000243	-1.39E-07	0.000385	0.000730	0.001205	3.72E-06	0.008113
	(0.02211)	(0.00364)	(0.00169)	(0.00096)	(3.0E-08)	(0.00050)	(0.00028)	(0.00143)	(1.2E-06)	(0.00525)
	[4.86622]	[0.66947]	[1.41229]	[0.25162]	[-4.67160]	[0.77224]	[2.62767]	[0.84225]	[2.99946]	[1.54415]
CointEq3	1.957629	0.033995	-0.001390	0.000947	3.83E-07	-0.002033	0.008859	0.060820	4.51E-05	0.279923
	(0.35932)	(0.05920)	(0.02744)	(0.01567)	(4.8E-07)	(0.00811)	(0.00451)	(0.02324)	(2.0E-05)	(0.08536)
	[5.44809]	[0.57421]	[-0.05065]	[0.06042]	[0.78989]	[-0.25082]	[1.96353]	[2.61648]	[2.23450]	[3.27919]
D(BTC(-1))	-0.329829	-0.018053	0.007833	0.000504	1.37E-08	0.003457	0.001286	0.000922	-3.86E-06	-0.029394
	(0.06583)	(0.01085)	(0.00503)	(0.00287)	(8.9E-08)	(0.00149)	(0.00083)	(0.00426)	(3.7E-06)	(0.01564)
	[-5.01050]	[-1.66449]	[1.55815]	[0.17541]	[0.15455]	[2.32753]	[1.55577]	[0.21662]	[-1.04581]	[-1.87962]
D(BSE(-1))	0.468539	0.084868	-0.002625	0.047329	-5.71E-08	0.005163	-0.003860	0.015358	1.94E-05	-0.158197
	(0.36091)	(0.05946)	(0.02756)	(0.01574)	(4.9E-07)	(0.00814)	(0.00453)	(0.02335)	(2.0E-05)	(0.08574)
	[1.29820]	[1.42722]	[-0.09525]	[3.00669]	[-0.11742]	[0.63405]	[-0.85173]	[0.65777]	[0.95785]	[-1.84506]
D(ETH(-1))	1.366988	0.242668	0.102824	-0.078518	1.66E-06	-0.030653	0.009834	-0.293785	-1.87E-05	0.314124
	(1.16946)	(0.19268)	(0.08931)	(0.05101)	(1.6E-06)	(0.02638)	(0.01468)	(0.07565)	(6.6E-05)	(0.27782)
	[1.16891]	[1.25944]	[1.15132]	[-1.53941]	[1.05196]	[-1.16178]	[0.66972]	[-3.88332]	[-0.28511]	[1.13066]
D(PSX_100(-1))	0.730075	-0.049536	-0.116675	-0.105178	2.50E-06	-0.031436	0.000687	-0.090244	-0.000208	-0.031721
	(1.31122)	(0.21604)	(0.10014)	(0.05719)	(1.8E-06)	(0.02958)	(0.01646)	(0.08482)	(7.4E-05)	(0.31150)
	[0.55679]	[-0.22929]	[-1.16517]	[-1.83914]	[1.41591]	[-1.06263]	[0.04172]	[-1.06389]	[-2.81935]	[-0.10183]
D(USDT(-1))	-74283.02	-2027.240	-1884.729	2650.011	-0.220189	-970.3870	-559.2076	2773.225	3.647160	16175.59
	(48816.1)	(8042.92)	(3728.02)	(2129.09)	(0.06582)	(1101.37)	(612.953)	(3157.95)	(2.74033)	(11597.1)
	[-1.52169]	[-0.25205]	[-0.50556]	[1.24467]	[-3.34517]	[-0.88108]	[-0.91232]	[0.87817]	[1.33092]	[1.39480]
D(DSE_30(-1))	-6.019682	-0.908929	-0.018496	-0.047834	-1.85E-06	0.110692	0.036512	-0.265684	-1.09E-05	0.316025
	(2.56249)	(0.42220)	(0.19569)	(0.11176)	(3.5E-06)	(0.05781)	(0.03218)	(0.16577)	(0.00014)	(0.60876)
	[-2.34915]	[-2.15286]	[-0.09451]	[-0.42800]	[-0.53582]	[1.91463]	[1.13478]	[-1.60273]	[-0.07551]	[0.51913]
D(BNB(-1))	28.97842	-0.726779	-1.072532	-0.130935	-1.01E-05	0.011924	-0.033695	1.488410	-5.10E-05	1.816787
	(6.87616)	(1.13291)	(0.52512)	(0.29990)	(9.3E-06)	(0.15514)	(0.08634)	(0.44482)	(0.00039)	(1.63354)
	[4.21433]	[-0.64151]	[-2.04244]	[-0.43660]	[-1.09274]	[0.07686]	[-0.39026]	[3.34607]	[-0.13205]	[1.11217]
D(NEPSE(-1))	-1.539095	-0.195311	-0.023176	-0.023261	-1.38E-07	-0.015042	-0.023989	-0.015171	5.47E-05	-0.173909
	(0.87854)	(0.14475)	(0.06709)	(0.03832)	(1.2E-06)	(0.01982)	(0.01103)	(0.05683)	(4.9E-05)	(0.20871)
	[-1.75189]	[-1.34933]	[-0.34544]	[-0.60707]	[-0.11682]	[-0.75888]	[-2.17462]	[-0.26693]	[1.10933]	[-0.83325]

D(XRP(-1))	2776.628	260.3824	196.9765	111.9569	0.002325	25.64322	7.422361	84.19559	0.286857	-182.9440
	(1118.62)	(184.304)	(85.4276)	(48.7882)	(0.00151)	(25.2378)	(14.0458)	(72.3645)	(0.06279)	(265.747)
	[2.48219]	[1.41279]	[2.30577]	[2.29475]	[1.54134]	[1.01606]	[0.52844]	[1.16349]	[4.56818]	[-0.68841]
D(ASPI(-1))	0.478753	0.067816	0.034331	-0.005705	9.54E-08	-0.002435	0.003614	-0.006107	1.17E-05	-0.016528
	(0.23709)	(0.03906)	(0.01811)	(0.01034)	(3.2E-07)	(0.00535)	(0.00298)	(0.01534)	(1.3E-05)	(0.05632)
	[2.01929]	[1.73606]	[1.89606]	[-0.55167]	[0.29836]	[-0.45523]	[1.21384]	[-0.39819]	[0.87989]	[-0.29344]
C	115.4797	60.60259	9.461187	0.175706	-8.68E-05	-1.803323	2.124379	-2.677395	0.005235	-33.56533
	(143.871)	(23.7042)	(10.9872)	(6.27488)	(0.00019)	(3.24596)	(1.80650)	(9.30714)	(0.00808)	(34.1790)
	[0.80266]	[2.55662]	[0.86111]	[0.02800]	[-0.44758]	[-0.55556]	[1.17596]	[-0.28767]	[0.64816]	[-0.98205]

Source: Author's Estimation

The Vector Error Correction Model (VECM) analysis examines the dynamic interrelationships between major cryptocurrencies (Bitcoin, Ethereum, Binance Coin, Tether, Ripple) and South Asian stock market indices (BSE, PSX 100, DSE 30, NEPSE, ASPI). The model identifies three cointegrating equations that capture long-run equilibrium relationships among the variables. Key findings reveal that Bitcoin (BTC) adjusts slowly towards equilibrium, while Ripple (XRP) shows a rapid adjustment. The analysis indicates significant short-run dynamics, with BTC negatively affecting itself and other indices, suggesting momentum effects and spillovers. For instance, the first lag of BSE positively influences PSX 100, indicating shock transmission between Indian and Pakistani markets. Additionally, Ethereum exhibits mean-reverting behavior, while Tether's negative adjustment suggests its role in correcting market disequilibria. The interconnectedness between cryptocurrencies and stock markets is evident, with declines in the DSE 30 impacting BTC and BSE. The study highlights the complex dynamics and spillover effects among these financial assets, providing insights for investors, policymakers, and researchers regarding the integration of cryptocurrency and traditional financial markets in South Asia.

Table 14: Granger Causality Test Results

Granger Causality Test

Null Hypothesis:	**Obs**	**F-Statistic**	**Prob.**
BSE does not Granger Cause BTC	356	3.79509	0.0522
BTC does not Granger Cause BSE		0.24092	0.6238
ETH does not Granger Cause BTC	356	0.00017	0.9896
BTC does not Granger Cause ETH		13.4419	0.0003
PSX_100 does not Granger Cause BTC	356	0.02308	0.8793
BTC does not Granger Cause PSX_100		2.12927	0.1454
USDT does not Granger Cause BTC	356	0.17473	0.6762
BTC does not Granger Cause USDT		4.71689	0.0305
DSE_30 does not Granger Cause BTC	356	0.04205	0.8376
BTC does not Granger Cause DSE_30		1.31543	0.2522
BNB does not Granger Cause BTC	356	2.55521	0.1108
BTC does not Granger Cause BNB		31.1511	5.E-08
NEPSE does not Granger Cause BTC	356	3.41249	0.0655
BTC does not Granger Cause NEPSE		2.21767	0.1373
XRP does not Granger Cause BTC	356	2.11875	0.1464
BTC does not Granger Cause XRP		4.70869	0.0307

ASPI does not Granger Cause BTC	356	3.48051	0.0629
BTC does not Granger Cause ASPI		1.56098	0.2123
ETH does not Granger Cause BSE	356	0.00035	0.9851
BSE does not Granger Cause ETH		2.14669	0.1438
PSX_100 does not Granger Cause BSE	356	0.04359	0.8347
BSE does not Granger Cause PSX_100		0.82550	0.3642
USDT does not Granger Cause BSE	356	0.02768	0.8680
BSE does not Granger Cause USDT		5.92378	0.0154
DSE_30 does not Granger Cause BSE	356	1.02484	0.3121
BSE does not Granger Cause DSE_30		4.96065	0.0266
BNB does not Granger Cause BSE	356	0.01908	0.8902
BSE does not Granger Cause BNB		7.68427	0.0059
NEPSE does not Granger Cause BSE	356	0.26860	0.6046
BSE does not Granger Cause NEPSE		3.11883	0.0783
XRP does not Granger Cause BSE	356	0.03013	0.8623
BSE does not Granger Cause XRP		0.57946	0.4470
ASPI does not Granger Cause BSE	356	0.33180	0.5650
BSE does not Granger Cause ASPI		3.98378	0.0467
PSX_100 does not Granger Cause ETH	356	0.01438	0.9046
ETH does not Granger Cause PSX_100		1.68217	0.1955
USDT does not Granger Cause ETH	356	0.16010	0.6893
ETH does not Granger Cause USDT		5.10789	0.0244
DSE_30 does not Granger Cause ETH	356	1.42684	0.2331
ETH does not Granger Cause DSE_30		0.42907	0.5129
BNB does not Granger Cause ETH	356	0.03113	0.8600
ETH does not Granger Cause BNB		4.53710	0.0339
NEPSE does not Granger Cause ETH	356	8.61186	0.0036
ETH does not Granger Cause NEPSE		3.55706	0.0601
XRP does not Granger Cause ETH	356	0.55707	0.4559
ETH does not Granger Cause XRP		2.35768	0.1256
ASPI does not Granger Cause ETH	356	3.58311	0.0592
ETH does not Granger Cause ASPI		0.11419	0.7356
USDT does not Granger Cause PSX_100	356	1.07674	0.3001
PSX_100 does not Granger Cause USDT		5.23895	0.0227
DSE_30 does not Granger Cause PSX_100	356	3.56581	0.0598
PSX_100 does not Granger Cause DSE_30		1.62893	0.2027
BNB does not Granger Cause PSX_100	356	0.96709	0.3261
PSX_100 does not Granger Cause BNB		0.53908	0.4633
NEPSE does not Granger Cause PSX_100	356	0.20145	0.6538
PSX_100 does not Granger Cause NEPSE		2.82277	0.0938
XRP does not Granger Cause PSX_100	356	1.12417	0.2897
PSX_100 does not Granger Cause XRP		1.66230	0.1981
ASPI does not Granger Cause PSX_100	356	1.23548	0.2671
PSX_100 does not Granger Cause ASPI		1.06909	0.3019
DSE_30 does not Granger Cause USDT	356	1.00449	0.3169
USDT does not Granger Cause DSE_30		0.19615	0.6581

BNB does not Granger Cause USDT	356	5.53796	0.0192
USDT does not Granger Cause BNB		0.01982	0.8881
NEPSE does not Granger Cause USDT	356	3.98283	0.0467
USDT does not Granger Cause NEPSE		0.16932	0.6810
XRP does not Granger Cause USDT	356	0.18549	0.6670
USDT does not Granger Cause XRP		14.5930	0.0002
ASPI does not Granger Cause USDT	356	3.85993	0.0502
USDT does not Granger Cause ASPI		0.02766	0.8680
BNB does not Granger Cause DSE_30	356	1.55172	0.2137
DSE_30 does not Granger Cause BNB		0.71060	0.3998
NEPSE does not Granger Cause DSE_30	356	4.63847	0.0319
DSE_30 does not Granger Cause NEPSE		0.02356	0.8781
XRP does not Granger Cause DSE_30	356	0.01611	0.8991
DSE_30 does not Granger Cause XRP		5.98674	0.0149
ASPI does not Granger Cause DSE_30	356	19.6777	1.E-05
DSE_30 does not Granger Cause ASPI		1.21380	0.2713
NEPSE does not Granger Cause BNB	356	4.89486	0.0276
BNB does not Granger Cause NEPSE		3.03273	0.0825
XRP does not Granger Cause BNB	356	0.33054	0.5657
BNB does not Granger Cause XRP		1.30649	0.2538
ASPI does not Granger Cause BNB	356	1.72786	0.1895
BNB does not Granger Cause ASPI		0.84980	0.3572
XRP does not Granger Cause NEPSE	356	0.25522	0.6137
NEPSE does not Granger Cause XRP		0.81554	0.3671
ASPI does not Granger Cause NEPSE	356	1.48648	0.2236
NEPSE does not Granger Cause ASPI		10.7339	0.0012
ASPI does not Granger Cause XRP	356	0.93475	0.3343
XRP does not Granger Cause ASPI		0.61737	0.4326

Source: Author's Estimation

The Granger causality test analyses the predictive relationships between major cryptocurrencies (Bitcoin, Ethereum, Binance Coin, Tether, Ripple) and South Asian stock market indices (BSE, PSX 100, DSE 30, NEPSE) using 356 observations. Key findings indicate that Bitcoin (BTC) Granger-causes Ethereum (ETH), Binance Coin (BNB), Tether (USDT), and Ripple (XRP), highlighting BTC's dominance in the cryptocurrency market. The BSE also influences USDT, DSE 30, BNB, and ASPI, suggesting interconnections among regional markets—Ethereum Granger-causes USDT and BNB, reinforcing its significance within the crypto ecosystem. Notably, the NEPSE impacts ETH, BNB, and ASPI, indicating cross-border investment effects and regional linkages. Additionally, USDT Granger-causes XRP and PSX 100, demonstrating its role in liquidity and price discovery. The analysis reveals that cryptocurrency behaviours are influenced by traditional equity markets, with BTC's dominance affecting other cryptocurrencies and stock indices. The findings underscore the interconnectedness of cryptocurrency and stock markets in South Asia, as well as the pivotal role of stablecoins like USDT in shaping market dynamics. Overall, the study suggests that economic factors and investor sentiment drive these complex relationships across markets.

Discussion

The study explores the cointegration between cryptocurrencies and South Asian stock indices, revealing a long-run equilibrium relationship, particularly during economic crises, that contradicts earlier claims that cryptocurrencies operate independently. This finding aligns with Rijanto (2023) and Tibay (2018) who emphasise the impact of external shocks, such as geopolitical events, on interactions between the cryptocurrency and stock markets, reinforcing their potential as hedging instruments. However, the results contrast with Soltani et al. (2023) who argue that cryptocurrencies remain distinct from traditional assets, with only partial integration observed. Regional factors, such as unique investor behaviours in emerging markets like Nepal, may explain these divergences, as highlighted by Kartal & Can (2022) who note the stabilising role of stablecoins like USDT in bridging the digital and traditional markets.

Supporting the study's findings, Dirican and Canoz (2017) found a positive relationship between Bitcoin and major indices such as the Dow30 and China-A30. However, no such relationship was observed with other indices, such as the Nikkei 225. Similarly, Kumah & Odei-Mensah (2021) demonstrated that Bitcoin and exchange rates influenced the PSEi index, suggesting time-variant effects. Conversely, Ebenezer, (2025) reported varying correlations: Bitcoin was positively correlated with US and European indices but negatively correlated with Asian markets, indicating regional disparities. Erdas et al. (2025) further noted that cryptocurrencies do not serve as a shield against systemic economic risks, aligning with the study's acknowledgement of conflicting perspectives. On the other hand Jaroenwiriyakul and Tanomchat (2020) found that cryptocurrencies react strongly to macro-financial variables, suggesting closer ties to traditional financial assets. Kang et al. (2019) also observed low co-movements between cryptocurrencies and the S&P 500, supporting the argument for their diversification potential. However, Gil-Alana, (2020) highlighted the autonomous relationship of cryptocurrencies, with low co-efficiency and market autarky, contradicting the study's findings of increasing integration. Similarly, Khan et al. (2020) concluded that cryptocurrencies function as distinct assets, unconnected to traditional markets, further complicating the debate.

In conclusion, while the study affirms increasing crypto-market integration in South Asia, the literature reveals a complex landscape. Institutional investment and evolving financial structures may drive further alignment, but regional disparities and conflicting findings underscore the need for continued research. Investors, policymakers, and researchers must consider these dynamics when integrating digital assets into traditional markets.

Conclusion

This study investigates the correlation between cryptocurrencies and South Asian stock indices, addressing a research gap. It analyses Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Binance Coin (BNB), and Ripple (XRP) against major stock markets (BSE, PSX 100, DSE 30, NEPSE, ASPI) using 357 observations. Findings reveal that cryptocurrencies exhibit higher volatility and non-normal distributions compared to traditional stock indices, with BTC and ETH showing significant price swings. Stationarity tests indicate that most variables are non-stationary at levels but stationary in first differences. Cointegration analysis confirms long-run relationships among the variables, with the VECM highlighting that cryptocurrencies adjust more rapidly to equilibrium than stock indices. The Granger causality test indicates that BTC is a market leader, influencing other cryptocurrencies and stock indices. Overall, the research demonstrates significant co-movement between cryptocurrencies and South Asian stock markets, emphasising implications for investor diversification and portfolio management.

This study's findings suggest several policy and research directions for integrating cryptocurrencies into traditional financial markets. Comprehensive regional analyses are needed to explore interactions across diverse market contexts, particularly in emerging economies such as South Asia, and to determine whether the observed integration is part of a broader global trend. The role of stablecoins, such as USDT, should be examined further to understand their impact on liquidity and market stability. Additionally, the influence of institutional investors on the integration process warrants investigation, especially during market turbulence. Policymakers should develop adaptive regulatory frameworks that balance innovation with financial stability, while investors should tailor strategies to account for the dynamic relationships between cryptocurrencies and traditional assets. Finally, further interdisciplinary research is essential to enhance understanding of cryptocurrency market dynamics, contributing valuable insights for investors, regulators, and financial institutions navigating this complex landscape.

Implications and Future Research

This study highlights important implications for practice and theory regarding the interdependence between cryptocurrencies and stock indices. Investors and portfolio managers must adjust diversification strategies to account for cross-hauling effects across these markets, as these relationships can lead to significant shocks. Policymakers should closely monitor these interactions and develop measures to foster market stability, especially in emerging markets with weaker legal frameworks. The research contributes to the literature by providing empirical evidence on the dynamics between cryptocurrencies and stock markets in South Asia, an underexplored region. Future research could expand the model to include macroeconomic factors, investor sentiment, and regulatory changes, and could also investigate nonlinearity and high-frequency data. Additionally, examining the impact of global events, such as pandemics or geopolitical crises, on the interdependence of these markets could provide valuable insights. Overall, the findings underscore the need for further exploration in this emerging field to support financial stakeholders.

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