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MODELLING ASYMMETRIC VOLATILITY IN THE CRYPTO CURRENCY AND ITS DYNAMIC RELATIONSHIP WITH STOCK MARKET

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Abstract. The paper investigates the asymmetric volatility effect of five major cryptocurrencies and their bilateral linkages with major indices in the Indian stock market. To investigate the bilateral relationship of crypto currency with stock indices, researchers used two major stock indices in the Indian stock market namely, BSE Sensex and NSE Nifty. The study used GARCH, EGARCH and TGARCH models, asymmetric to model the asymmetric volatility effect in the conditional volatility of crypto currencies and stock indices. Johansen's cointegration and Vector Error Correction Model is used for examining the presence of cointegration between selected variables and to analyse the strength of causality among them. The study finds the evidence of cointegration between cryptocurrencies and stock market indices, implying that cryptocurrencies are related to stock indices. Further there is unidirectional relationship among stock and crypto market and crypto currencies having short-lived response to shocks in stock markets. Even with these currencies' explosive growth, there are still not many research examining their connection to stock markets. This study will help investor's those who making investment in currency market or in the stock market to evaluate the pattern of volatility, interconnection among them, so that they can make crucial investment decisions and diversification strategies. This will help them to gain knowledge about how these two markets move together so they may avoid underestimating risk when building portfolios that contain both kinds of assets.

1. Introduction

The ultimate objective of individual investors and portfolio fund managers during the 2000s was to create new financial products that maximised their return while taking reasonable amounts of risk. As a result, cryptocurrencies were developed in 2008 and experienced rapid growth as a new investment tool in the global financial system. A recently developed financial tool based on blockchain technology, the cryptocurrency market currently houses over 5,000 different currencies. Additionally, portfolio fund managers use cryptocurrencies as a reliable investment tool to minimise risk and make money by speculating on favourable circumstances Corbet et al., (2018) and Trimborn et al., (2019). Bitcoin, among many other cryptocurrencies such as Litecoin, Ethereum, Ripple, Peercoin, and Dogecoin, has risen to prominence in the cryptocurrency markets (Bouri et al. 2019).

Volatility clustering, leptokurtosis, asymmetric volatility and leverage effect are commonly observed in financial time series especially in stock returns. The approach to modelling conditional volatility has undergone numerous improvements since Engle (1982) introduced models of

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autoregressive conditional heteroskedasticity (ARCH) and Bollerslev (1986) generalised them. Because the fundamental GARCH model relies on a constant mean stock return, it is unable to account for the mechanism underlying volatility feedback. The "GARCH-in-mean" model Engle, Lilien, and Robins (1987) permits the conditional mean stock return to depend on the conditional variance of the return, but even when innovations are assumed to be conditionally normal, this model still imposes zero correlation between returns and future volatility, zero conditional skewness, and zero excess kurtosis. A significant positive relationship between the conditional mean and variance of stock returns is discovered by French, Schwert, and Stambaugh (1987) when they estimate a GARCH-M model with conditionally normal innovations. They assert that it would be desirable to account for the negative skewness from volatility feedback, but they make no attempt to do so. Some second-generation GARCH models include the EGARCH process developed by Nelson (1991), the quadratic GARCH process developed by Sentana (1991) and Engle (1990), and the TGARCH model developed by Zakoian (1991).

Intermarket connectedness is measured by return and volatility transmission, which offers new insights into global finance and has a big impact on portfolio and hedging decisions. The dynamic correlations between stock price movements and cryptocurrency movements have drawn the attention of academics and industry professionals. This problem has grown more urgent as the market integration between conventional financial assets and cryptocurrencies has increased. The relationship between cryptocurrencies and other financial assets has been studied from a wide range of angles. Bouri et al. looked into the relationships between Bitcoin and conventional financial asset classes (2018). Using a smooth transition VAR-GARCH-in-mean model, the results demonstrate that Bitcoin returns are closely related to most other assets, particularly commodities, demonstrating that the Bitcoin market is not entirely isolated. Utilizing LASSO-VAR analysis, Yi, Xu, and Wang (2018) looked into the relationship between volatility connectedness and the cryptocurrency market. They discovered that the relationship fluctuates cyclically and that volatility shocks spread from mega-caps to smaller companies. Additionally, Matkovskyy and Jalan (2019) investigated the contagion effect between five equity indices and Bitcoin markets using the regime-switching skew-normal model and discovered significant effects from financial to Bitcoin markets. Yang (2020) found a significant nonlinear relationship between Taiwan's stock market and Bitcoin.

To summarise, this study adds to the body of knowledge about crypto currency markets and their involvement in investment financing decisions. Our goal is to highlight the patterns of asymmetric volatility, return and long run connectedness among cryptocurrency markets and stock market indexes to guide investment decisions. We investigate the stochastic features of bilateral links between the main cryptocurrencies and major stock indices in the Indian stock market in particular. As a result, the study contributes to research on cryptocurrency markets' technical elements and stylized facts. This type of research is essential for making investment decisions since it identifies the patterns of information transmission across cryptocurrency markets and other financial assets.

The rest of the paper structured as follows; Section II summarise the relevant literature in this filed of the study, followed by description of methodology used in this study. Section IV reports the analysis and result. The final section presents some concluding remarks.

2. Literature Review

As a result of the introduction of various types of cryptocurrencies in recent years, the market size of cryptocurrency markets has rapidly increased. The recent sharp increase in Bitcoin trading volume has resulted in a comprehensive literature on cryptocurrency markets, which has attributed to the rise in cryptocurrencies and rapid development of cryptocurrency markets.

The literature in the crypto currency market has broadly classified in to two:

1. Studies focused on measuring volatility persistent, asymmetric volatility in crypto currencies.

2. Studies focused on relationship of crypto currencies with other financial assets.

The conditional variance's response of crypto currency market to previous positive and negative shocks is examined using asymmetric GARCH models by (Bouri et al., 2017), Baur and Dimpfl (2018), (Cheikh et al., 2019) and (Stavroyiannis, n.d.), who discover an inverted leverage effect. Further, (Liu & Serletis, 2019) investigate cryptocurrency market spillovers both within the market itself and to other financial markets using GARCH-in-mean models to analyse the correlation between volatility and returns of the top cryptocurrencies and (Katsiampa, 2019) analyses the volatility dynamics of five major cryptocurrencies: Bitcoin, Ether, Ripple, Litecoin, and Stellar Lumen using an asymmetric Diagonal BEKK model. It is demonstrated that both prior squared errors and prior conditional volatility have a significant impact on the conditional variances of each of the five cryptocurrencies. The conditional correlations of cryptocurrencies and financial market stress are shown to have time-varying positive interrelationship (Akyildirim et al., 2019) . Furthermore, these correlations significantly increase during times of high financial market stress, indicating that the spread of significant financial market fear affects these new financial products.

Using fractional integration techniques (Gil-Alana, Abakah, and Rojo 2020) investigated the stochastic properties of six major cryptocurrencies and their bilateral linkages with six stock market indices, and found the evidence in favour of mean reversion and proposed that there is no cointegration between the six cryptocurrencies. Similarly, when they test for cointegration between cryptocurrencies and stock market indices, they find no evidence of cointegration, implying that cryptocurrencies are unrelated to mainstream financial and economic assets. (Sami and Abdallah 2021) conducted a comparative analysis is extended to distinguish the impact of cryptocurrency market on the stock market performance in Middle East and North Africa (MENA) region and between Gulf countries and other economies in the region. They use the information of cryptocurrencies and the stock market indices of the Gulf countries for the period 2014–2018 on a daily basis. The results show that there is a significant relationship between the cryptocurrency market and the stock market performance in the MENA region. (Adebola, Gil-Alana, and Madigu 2019) use fractional integration and cointegration techniques to examine the degree of persistence of the series and the possibility of short and long run equilibrium relationships between cryptocurrencies and gold prices. The findings show that gold prices, as well as some cryptocurrencies, show evidence of mean reversion; however, cointegration is only found in a few cases, with a very low degree of cointegration in the long run relationship. By evaluating the price movements of a select sample of cryptocurrencies and examines whether they are cointegrated (Abraham 2020), (Göttfert 2019), suggests that the prices of crypto currencies have a long-term relationship.

Beyond the market discipline, researchers question the interaction between cryptocurrencies and macroeconomic variables, (Kostika and Laopodis 2020) investigated the short- and long-run dynamic linkages between selected cryptocurrencies, several major world currencies and major equity indices, show that, despite some similarities, cryptocurrencies do not exhibit any short- or long-term stochastic trends with exchange rates or equity returns. (Teker, Teker, and Ozyesil 2019) focused on how the changes in gold and oil prices effect the daily price movements of different cryptocurrencies, In the short and long run, crypto market-related factors such as market beta, trading volume, and volatility appear to be significant determinants of cryptocurrencies (yhlas sovbetov, 2018), (Teker, Teker, and Ozyesil 2020) investigated how the changes in gold and oil prices affect the daily price movements of various cryptocurrencies. By examining the Betas and Sharpe Ratios of cryptocurrencies, (White et al. 2020) were able to determine whether crypto currency is an asset class. they look at the diffusion patterns of cryptocurrencies to see if they are technology-based products or securities. Further, (Al-Khazali, Bouri, and Roubaud 2018), (Zhang et al. 2021), (Bouri et al., 2019), (Symitsi and Chalvatzis 2018),(Liu and Serletis 2019) , (Koutmos 2018)and (Yi, Xu, and Wang 2018) examined the volatility, performance and spillover effects of crypto currency.

This paper adds to the body of knowledge about cryptocurrency markets and their role in investment finance decisions. Our goal is to show the patterns of return and long run relationship among cryptocurrency markets and stock market indices in order to aid investment decisions. To our knowledge, this is the first study test the short and long run relationship between digital currency and stock indices using rigorous methodology cointegration and VECM to investigate the stochastic features of cryptocurrencies.

The following is the paper's structure: The second section gives a summary of studies in modelling asymmetric volatility of cryptocurrency and its relationship with other financial assets. Section 3 discusses the data and methodology, whereas Section 4 details with analysis and main findings. In Section 5, we make some last observations.

3. Data and Methodology

Data

In this study, we use a cryptocurrency dataset for the time period from 16-May-2017 to 16-May-2022, with 826 trading days in total. The researchers obtained data for cryptocurrencies from Yahoofinance.com and the data of SENSEX and NIFTY from official website of Bombay Stock Exchange (BSE) and National Stock Exchange (NSE) respectively. The study focused on the six cryptocurrencies with enough data available to achieve the objective of the study, these being Bitcoin, Ethereum, Ripple, Litecoin, Stellar and Tether.

Methodology

3.1 Unit root

To determine whether the series has a stochastic trend or not, tests such as the Augmented Dickey-Fuller (ADF), Kwiatkowski-Phillips-Schmidt-Shin (KPSS), Phillips-Perron (PP), and others were utilised. The stochastic trend indicates whether or not the series is non-stationary. The sequence of integration of the time series variables must be considered. The Augmented Dickey-Fuller (ADF) test was employed to examine if the time series data was stationary in this investigation (empirical verification of cointegration). At both the level and first order levels, this unit root test is run.

3.2 GARCH and Asymmetric GARCH models

The Autoregressive Conditional Heteroscedasticity (ARCH) model, put forth by Engle in 1982, calculates the variance of return as a straightforward quadratic function of the lagged values of innovations:

$$\sigma^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2$$

Bollerslev (1986) proposed the GARCH model to overcome the drawback of ARCH models (which frequently need numerous parameters and a high order q to capture the volatility process).

The standard GARCH (p, q) model expresses the variance at time t, σ_t^2 as:

$$\sigma_t^2 = \varpi + \sum_{i=1}^{q} \alpha_1 \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_1 \sigma_{t-j}^2$$

Both ARCH and GARCH models are fails to capture the leverage effect, as their distribution is symmetric. To address this, numerous non-linear extensions of GARCH were proposed, Nelson (1991) introduced the Exponential GARCH (EGARCH), Glosten et al. (1993) proposed the GJR-GARCH, and Ding (1993) put forth the Asymmetric Power ARCH (APARCH), and Threshold GARCH (TGARCH) by Zokian (1993).

Specification of non-linear models are:

EGARCH: $\ln \sigma^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_1 g(z_{t-i}) + \sum_{j=1}^{p} \beta_1 \ln(\sigma_{t-j}^2)$

TGARCH: $\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_1 \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_1 \sigma_{t-i}^2 + \sum_{i=1}^{q} \gamma_i \varepsilon_{t-i}^2 I_{t-1}$

3.3 Johansen cointegration

The long-run equilibrium link between variables is tested using Johansen's Cointegration (Johansen 1988), (Granger 1986) , (Robert F. ENGLE, 2012). Long-run equilibrium relationships between non-stationary variables are known as cointegration. There are two probability ratios that can be used to test Johansen cointegration: Trace statistics (λ_{trace}) and Max statistics ($\lambda_{\max}$):

$\lambda_{trace}(r) = -T\sum_{i=v+1}^{g} \ln\left[1-\lambda_i\right]$

$\lambda_{\max}(r, r+1) = -T\ln\left[1-\lambda_i\right]$

All of the variables must be I0 in order to use the Johansen technique. The Johansen technique cannot be utilised if there are I2 variables. In addition, if there are I_0 and I_1 combinations, the ARDL bound test process is employed. The trace statistics are more powerful than the max statistics (Johansen & Juselius 1990). The approach proposed by Johansen (1988) is used to conduct cointegration tests here (Johansen & Juselius 1990). As VAR (Vector Autoregression), the Johansen technique uses the highest likelihood procedure to assess the presence of cointegrating vectors in non-stationary time series (empirical verification of cointegration).

3.4 VECM

If the variables are non-stationary and cointegrated, the Vector Error Correction Model (VECM) is employed to investigate causation. In the first difference, it is a Vector Autoregression (VAR) model with the addition of a vector cointegrating residuals (1). Long-run equilibrium exists between the cointegrated variables, while short-run disequilibrium may exist (2). We used VECM in this study to capture both short-run dynamics and long-run equilibrium relationships between variables, as well as the speed of correction required to restore long-run equilibrium.

$\Delta Y_t = \alpha_0 + \delta_1[Y_{t-i} - \gamma X_{t-i}] + \sum_{i=1}^{k} \alpha_1 \Delta Y_{t=i} + \sum_{i=1}^{k} \alpha_2 \Delta X_{t=i} + \varepsilon_{1t}$

$\Delta Y_t = \beta_0 + \delta_2[Y_{t-i} - \gamma X_{t-i}] + \sum_{i=1}^{k} \beta_1 \Delta Y_{t=i} + \sum_{i=1}^{k} \beta_2 \Delta X_{t=i} + \varepsilon_{2t}$

3.5 Granger causality

The Granger causality test in our research estimates short-run causality between asset price series and decides whether one price series (X) is useful in the prediction of the other (Y). Causality in asset markets refers more to the efficiency of one market to predict the other. We employ the reasonably simple test procedure of causality suggested by Granger (1969) to look into the direction of causality between the price series. If the values of X carry statistically significant information content about the future values of Y, then we infer that the time series X Granger-cause Y.

$\Delta Y_t = \alpha_0 + \sum_{i=1}^{k} \alpha_1 \Delta Y_{t=i} + \sum_{i=1}^{k} \alpha_2 \Delta X_{t=i} + \varepsilon_{1t}$

$\Delta Y_t = \beta_0 + \sum_{i=1}^{k} \beta_1 \Delta Y_{t=i} + \sum_{i=1}^{k} \beta_2 \Delta X_{t=i} + \varepsilon_{2t}$

4. Results and Discussion

As a preliminary step, the descriptive statistics of the data are analysed. The mean, median, maximum, minimum, standard deviation, skewness, and kurtosis are given for all the variables for the entire study period. Table 1 explains the statistical moments price changes or return of five crypto currencies and two broad market indices. The average return is higher for broad market indices Nifty and Sensex, followed by Bitcoin. Return variance is higher for Bitcoin and Ethereum; while the same is lower in Tether and Ripple. Skewness is positive for all assets.

Our analysis checks the order of integration with Augmented Dickey-Fuller (ADF) test. The result of unit root test reported in Table 2, indicate that each of the series in their level form is non-stationary in two alternative models, with the presence of an Intercept and with the deterministic trend and an intercept. However, first differencing the series induce the stationarity in all asset, suggesting that all our price series are integrated of order 1. Thus, we reject the null hypothesis of non-stationary or the presence of a unit root at the 1% significance level, suggesting that all the price series of assets included in the sample are first-order integrated. Hence, we treat them as I (1) process and proceed with the causality and cointegration analysis.

Table 1. Descriptive statistics

Variable	Mean	Median	Minimum	Maximum	S.D.	Skewness	Ex. Kurtosis
Binance	3.633	3.0403	0.41235	6.5157	1.5664	0.60614	1.94022
Bitcoin	9.055	9.0949	7.4584	11.121	0.85932	0.61772	2.38262
Ethereum	6.304	5.9920	4.4345	8.4789	1.1766	0.42243	1.2648
Tether	0.001	1.0067	0.0339	0.0749	0.00599	1.8586	2.8720
Ripple	0.80	1.8457	1.9687	1.2172	0.61016	0.43777	2.67897
SENSEX	9.778	9.6513	9.1843	10.558	0.39681	0.51676	1.94210
NIFTY	9.069	8.9464	8.607	9.7386	0.32265	0.67521	2.83815

Our goal is to evaluate the four asset markets that make up our sample's cointegration and, consequently, long-run causation. Since the Johansen technique is lag length sensitive, we estimate the VAR system using two large stock index data sets and cryptocurrency prices for different lag lengths. The right lag duration for the cointegration analysis is determined by the values that compute for the pertinent Hannan–Quinn (HQC) and Akaike information criterion (AIC). During the sample period, we estimate six alternative VAR (p), p = 1, 2, 3,... The maximum values of the loglikelihood rise with p as predicted, and all three information requirements show that in each panel we have created, the ideal lag duration is one. For this reason, we use one lag in the VAR system to verify cointegration.

Table 2. Unit Root Test Result with Augmented Dickey Fuller

Variables	Level		First Difference	
	With Intercept	With Trend and Intercept	With Intercept	With Trend and Intercept
Binance	-1.3726	-2.309	-7.3457	-7.339
	(0.597)	(0.428)	(0.000)	(0.000)
Bitcoin	0.3219	-1.041	-8.376	-8.503
	(0.979)	(0.936)	(0.000)	(0.000)
Ethereum	-1.112	-1.849	-10.104	-10.10
	(0.713)	(0.680)	(0.000)	(0.000)
Tether	-5.038	-5.191	-14.319	-14.31
	(0.654)	(0.621)	(0.000)	(0.001)
Ripple	-3.791	-3.806	-8.532	-8.531
	(0.081)	(0.086)	(0.000)	(0.000)
SENSEX	-1.157	-1.371	-40.22	-40.24
	(0.694)	(0.869)	(0.000)	(0.000)
NIFTY	-1.119	-1.449	-40.392	-40.404
	(0.710)	(0.846)	(0.000)	(0.000)

We estimate the VAR system, which includes prices of six cryptocurrencies and two benchmark indices in the Indian stock market; S&P BSE Sensex and CNX Nifty, for various lag lengths because the Johansen technique is sensitive to lag length. The result of Lag length selection is presented in Table 3. The maximised values of the loglikelihood increase with p and all the three information criteria indicate that the optimal lag length is 1.

4.1 Cointegration and Causality

Since we are unable to rule out the null hypothesis of four cointegrating vectors in favour of the alternative hypothesis of five or more cointegrating vectors in panels, we have one cointegrating vector of eight asset prices. Table 4 displays the cointegration models' findings. These findings show that there is a good correlation between the stock index and cryptocurrency prices in India. The findings support the theory that there is a connection between the stock market and cryptocurrency once more. The models, which assess the cointegration for each

Table 3. Selection of Optimal Lag in the VAR System

Lags	Loglik	P(LR)	AIC	BIC	HQC
1	-36772.409		44.959*	45.196*	45.047*
2	-36691.293	0.00000	44.938	45.386	45.104
3	-36621.206	0.00000	44.931	45.590	45.104
4	-36568.908	0.00103	44.945	45.815	45.268
5	-36494.527	0.00000	44.932	46.013	45.333
6	-36425.532	0.00000	44.926	46.218	45.405
7	-36384.828	0.00703	44.955	46.458	45.512

Note: *Optimal lag length.

Note: The asterisks below indicate the best (that is, minimized) values of the respective information criteria, AIC = Akaike criterion, BIC = Schwarz Bayesian criterion and HQC = Hannan-Quinn criterion.

variable and reflect the market integration, appear to capture the majority of the implications of the underlying economic theory and are consistent with the results of earlier research. The existence of a cointegrating relationship between the markets implies that certain shared factors influence the values of stocks and cryptocurrencies in developing nations such as India.

Table 4. Johansen Cointegration

	Restricted Constant			Restricted Trend		
H0	Eigenvalue	λ max	λ trace	Eigenvalue	λ max	λ trace
r=0	0.69131	47.993*	32.811*	0.69131	46.991*	38.910*
r≤1	0.58164	22.821*	21.001*	0.58178	21.760*	22.010*
r≤2	0.54156	31.981*	32.802*	0.54163	32.971*	30.861*
r≤3	0.52051	26.321*	28.921*	0.52060	28.001*	26.116*
r≤4	0.49885	13.201*	12.280*	0.49969	16.621*	14.091*
r≤5	0.32183	13.001	10.222	0.32261	11.020	10.011

Since the variables bear a cointegrating relationship between assets during the sample period, we can employ the VECM model. Table 5 reports summary results from the VECM and the basic diagnostics about the residuals of each error correction equations. More specifically, we provide the coefficients and the corresponding t-statistics for the ECM components, which, in some cases, have the expected signs and are statistically significant. For long-run causality to exist, ECT should be negative and significant.

The long-run equilibrium relationship between the crypto currency and stock prices is shown by the VECM results. At a 5% level of significance, oil and stock market models are found to have long-run causality in the sample period, indicating that the crypto currencies have a long-run causality effect on benchmark indices value. All the variables are strongly exogenous to the models, as shown by the significance of the ECM component for all those variables. This result indicates that there is a long run relation among crypto market and stock market in India. It means that in the crypto currency market and broad market indices in the Indian stock market, there is an error correction mechanism in place that allows for the correction of previous period disequilibrium.

Impulse response function of each of crypto with two major stock indices in India has reported in figure 1. Shocks from S&P BSE Sensex initially positively affect the Bitcoin, Ripple and tether, but two, three days later they depress it before fully absorbing it in the fourth or fifth day. In case of Binance and Ethereum the initial response is negative and later two or three days it became positive. Same way, the response of crypto currencies to shock in Nifty is initially positive for all except Binance and Tether. For Binance and Tether, the initial response was negative, even though within two or three days they full depress it. Bitcoin's short-lived reaction

Table 5. Summary Results from the VECMs and Diagnostic Tests

	ecm (-1)	R^2	St. Error
Binance	-0.0075901	0.08100	0.00041
Bitcoin	-0.0119625	0.02096	0.03000
Ethereum	-0.0124388	0.02186	0.00259
Tether	-0.0260276	0.16730	0.00143
Ripple	-0.0041577	0.02770	0.01944
SENSEX	-0.02461263	0.06821	0.02498
NIFTY	-0.02146930	0.21017	0.01127

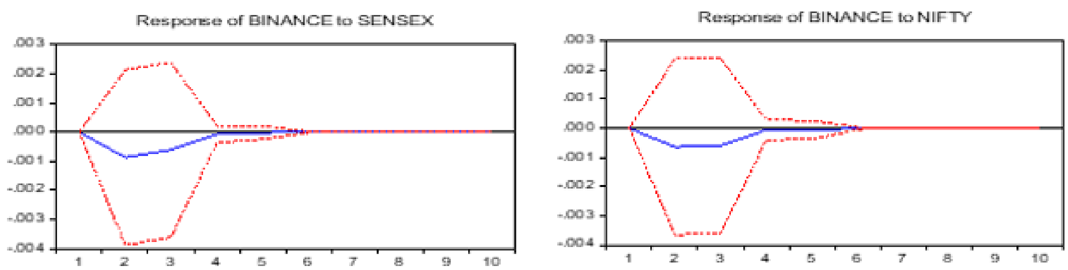

Figure 1. Impulse Response of Binance to Sensex and Nifty

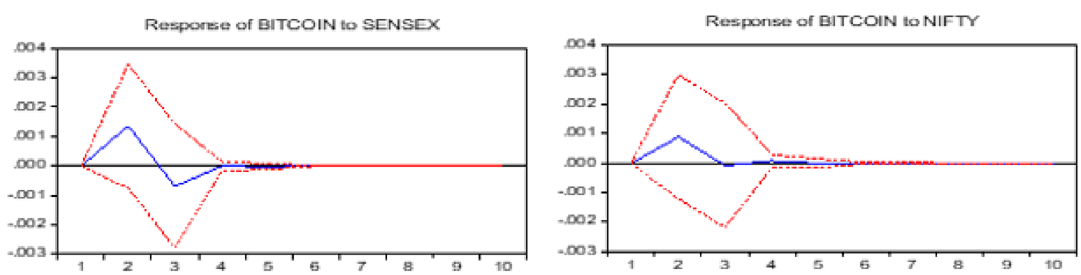

Figure 2. Impulse Response of Bitcoin to Sensex and Nifty

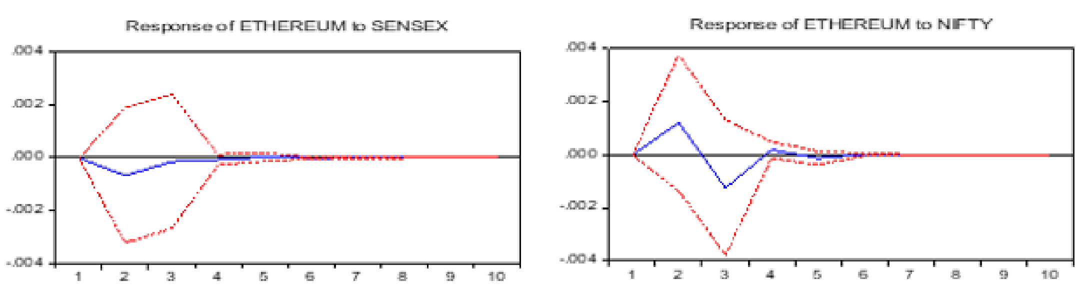

Figure 3. Impulse Response of Ethereum to Sensex and Nifty

to stock market shocks may be explained by the fact that, despite its sporadic volatility, the cryptocurrency has shown itself to be a dependable and safe investment vehicle in times of global economic instability, such as the global financial crisis of 2007, the sovereign debt crisis in Europe, and health crisis Covid-19.

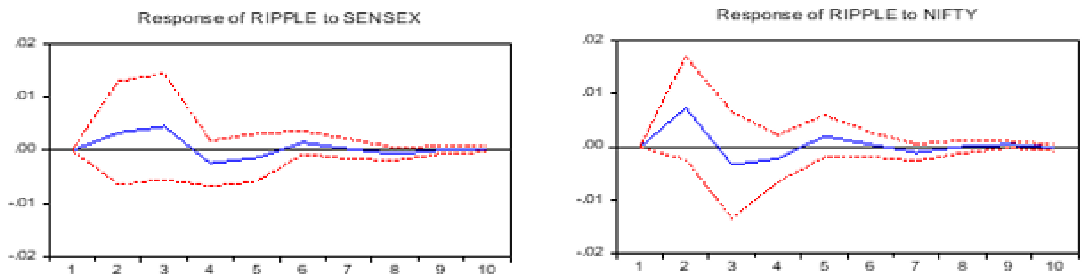

FIGURE 4. Impulse Response of Ripple to Sensex and Nifty

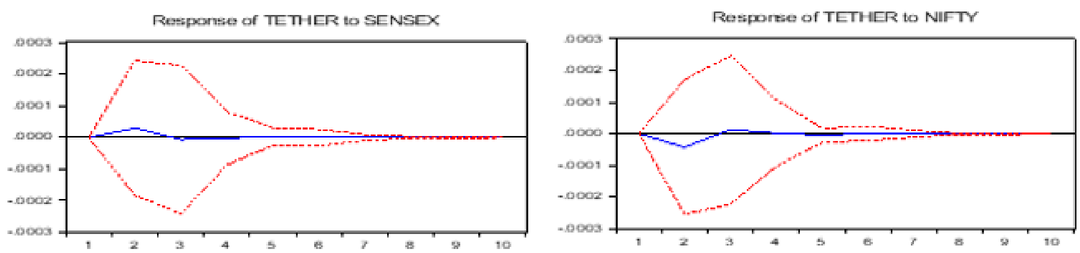

FIGURE 5. Impulse Response of Tether to Sensex and Nifty

Given that VECM provides proof of the long-term equilibrium relationship between the study's variables. It's time to identify the short-term causal relationship. Asset markets' integrative structure frequently presupposes that price series are causally related in both directions. The basic tenet of causation anticipates that price series across markets would always be interdependent. As a result, the study now looks at any proof of short-term causation between the price series. In the context of asset markets, causality mostly refers to how well one market predicts another. To investigate the direction of causation between the price series, we use Granger's (1969) pretty straightforward test procedure for causality.

It is visible from the result of Granger causality (Table 6) this table that, SENSEX is affected by crypto currencies and suggesting that crypto currencies can be used as a leading indicator for changing SENSEX return in the Indian stock market. No bidirectional effect is visible. Same way, it is visible from this Table 7 that, NIFTY is affected by crypto currencies and suggesting that crypto currencies can be used as a leading indicator for changing NIFTY index return in the Indian stock market. Only unidirectional causality is present in Granger causality test (no bidirectional effect is visible). Movements in the Indian stock market is a leading factor for movements in crypto currency market.

TABLE 6. Result of Granger Causality

Null hypothesis	Wald statistics	P-value
Binance does not granger cause to SENSEX	11.1102***	0.0000
Bitcoin does not granger cause to SENSEX	17.1000***	0.0000
Ethereum does not granger cause to SENSEX	22.2321***	0.0002
Tether does not granger cause to SENSEX	16.2010***	0.0001
Ripple does not granger cause to SENSEX	29.0120***	0.0001

4.2 Asymmetric volatility

Modelling asymmetric volatility effect in crypto currencies are presented in Table 8. By using EGARCH and TGARCH models, the study found significant effect of asymmetric effect

Table 7. Result of Granger Causality

Null hypothesis	Wald statistics	P-value
Binance does not granger cause to NIFTY	16.0012***	0.0000
Bitcoin does not granger cause to NIFTY	29.2110***	0.0001
Ethereum does not granger cause to NIFTY	12.0023***	0.0031
Tether does not granger cause to NIFTY	14.2010***	0.0000
Ripple does not granger cause to NIFTY	37.0102***	0.0010

Table 8. GARCH Estimation result

	GARCH (1,1)		EGARCH		TGARCH	
	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
Binance						
α_0	0.0017	0.0000	0.3549	0.0000	0.0010	0.0000
α_1	0.1506	0.0000	0.2745	0.0000	0.1390	0.0000
β	0.8378	0.0000	0.7721	0.0000	0.7361	0.0000
λ	-	-	-0.0234	0.0001	0.0298	0.0001
ARCH-LM	0.0666	0.7962	0.0916	0.7621	0.0447	0.8325
Bitcoin						
α_0	0.0061	0.0000	0.6382	0.0000	0.0012	0.0000
α_1	0.0240	0.0000	0.1146	0.0000	0.0848	0.0000
β	0.8271	0.0000	0.7226	0.0000	0.6126	0.0000
λ	-	-	-0.0479	0.0000	0.0976	0.0000
ARCH-LM	0.0246	0.8753	0.0312	0.8597	0.0022	0.9622
Ethereum						
α_0	0.0018	0.0000	0.4870	0.0000	0.0028	0.0000
α_1	0.0930	0.0000	0.1752	0.0000	0.0832	0.0000
β	0.8468	0.0000	0.6383	0.0000	0.7361	0.0000
λ	-	-	-0.0194	0.0002	0.0261	0.0003
ARCH-LM	0.1821	0.6696	0.0353	0.8508	0.0227	0.6334
Tether						
α_0	0.00011	0.0000	0.4763	0.0000	0.00015	0.0000
α_1	0.2474	0.0000	0.0076	0.0000	0.0851	0.0000
β	0.6174	0.0000	0.7896	0.0000	0.7194	0.0000
λ	-	-	-0.0076	0.0001	0.0834	0.0001
ARCH-LM	0.1513	0.6972	0.0023	0.9615	0.1842	0.6678
Ripple						
α_0	0.0023	0.0000	0.0741	0.0000	0.0024	0.0000
α_1	0.1434	0.0000	0.0470	0.0000	0.0813	0.0000
β	0.6978	0.0000	0.8215	0.0000	0.6929	0.0000
λ	-	-	-0.0495	0.0000	0.0679	0.0001
ARCH-LM	0.0750	0.7841	0.0077	0.9301	0.1008	0.7508

in the conditional variance of all crypto currencies with correct sign. It indicates that negative news/shocks create more volatility in conditional variance of crypto currencies than positive news/shocks of the same magnitude. As shown, the leverage effect coefficient γ is significant and negative for EGARCH model and positive for TGARCH model for all variables. It is possible to conclude that both crypto and stock market respond asymmetrically to negative and positive news or shocks. Negative news having more impact to crypto and stock index volatility than positive news of the same magnitude. For all the variables, the volatility persistence with the coefficient has likewise been high. All markets have experienced a substantial ARCH effect.

5. Conclusion

This research study, using the causality and cointegration tests, assessed cyclical effects of the short-run and long-run causality among crypto currencies and benchmark indices in the Indian stock market. For this study, data records from 2015 to 2021 were considered. One of the main goals of this research is to see if cryptocurrency prices are related to the variables in the long run. If two or more processes stay close to each other even if they drift as separate processes, they are said to be cointegrated. The Johansen cointegration method was used to test these processes. The maximum eigenvalue test and the trace test were used to determine the number of cointegrating vectors, and both tests use eigenvalues to compute the associated test statistics. Finally, to capture the long-run dynamics in the cryptocurrency price series, a vector error correction model (VECM) for the cointegrated series was estimated. The long-run and short-run dynamics of cryptocurrency prices and benchmark indices were investigated using an error correction model. The evidence from the error correction model estimates suggests that the prices of crypto currencies have a long-term relationship. Impulse response analysis and Granger causality suggests that the shocks in stock market is affecting the crypto market either positively or negatively, where the response is short-lived.

The next concern of the study is to model the asymmetric volatility effect in the crypto currency. By using Exponential GARCH (EGARCH) and Threshold GARCH (TGARCH) it is found that volatility of all crypto currencies behaves asymmetrically to positive and negative news/shocks. Negative news creates more volatility than positive news of the same magnitude. Both EGARCH and TGARCH models are accurately measures this asymmetric effect in the conditional variance. Like stock return, the response of crypto currencies to negative and positive shocks is also asymmetric. The result of the study supports the existing literature on the relation between crypto and stock market (Ghorbel, Frikha, and Manzli 2022), (Kostika and Laopodis 2020), (Corbet et al. 2018), (Canoz and Dirican 2017), who propose that there is interconnection among crypto and stock markets and same way it contradicts the findings of (Sajeev and Afjal 2022), (Gil-Alana, Abakah, and Rojo 2020) who propose that currency is a good hedge since there is little overall time-varying link between crypto and the stock markets, so that it can be used as an asset to protect against stock market risk.

Practical Implications and Limitations

Investors, market participants, and regulators may be benefited by the conclusions of this study. First, due to price independence, the low number of bilateral links between the cryptocurrency market and stock indexes observed in this study may have an impact on investors' choice of asset class to invest in. Because price swings in traditional asset classes have no direct impact on the cryptocurrency market, investors or market players can use their funds to invest in cryptocurrencies because to their inherent benefits. While constructing their portfolios, rational investors can use our findings as a reference on risk hedging and to prevent underestimating risk. Additionally, supervisory authorities can benefit from our insights. It will aid in the creation of appropriate policies by policymakers to spread the risk or uncertainty that spreads throughout these markets and to decrease their vulnerabilities. Besides these practical implications, there are some economic importance by studying the long-run connectedness among these markets; firstly, the emergence of cryptocurrencies is directly related to innovations in finance and technology. Examining the correlation between cryptocurrencies and stock markets can offer valuable perspectives on the wider effects of technological advancements on the financial industry. Secondly, as the regulatory landscape surrounding cryptocurrencies is still developing and relatively new. Given the relationship between the stock and cryptocurrency markets, authorities may need to work together to maintain the integrity and stability of both.

The study's conclusions are not free from its limitations. Even while the current findings can be a useful tool for identifying short- and long-term relationships among crypto currency and stock indices, we cannot guarantee that the pattern will continue in the future. Another apparent shortcoming of this research is that the degree of stock market interdependence with the rest of the markets is often sector-specific.

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