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Analysis of Returns and Volatility Spillover of Cryptocurrencies in Select sectoral indices of National Stock Exchange

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ABSTRACT

Cryptocurrencies have established themselves as a distinct and noteworthy asset class, characterized by their innovation and marked price volatility. This research undertakes a comprehensive investigation into the returns and volatility spillover between four leading cryptocurrencies: Bitcoin, Ethereum, Tether, and XRP on selected Indian Sectoral indices namely, Nifty Bank and Nifty IT. Exponential GARCH (EGARCH) is employed to effectively capture the leverage effect of time-varying nature of volatility inherent to these crypto currencies. The study encompasses daily return data spanning from January 1, 2018, to October 31, 2023. From the findings it is revealed thatXRP and Ethereum indicates the decreasing volatility spillover among Nifty IT and Bank returns.Lower spillover effect from Nifty Bank and Nifty IT are observed among selected cryptocurrencies. The practical applicability of this study extends to investors, facilitating the formulation of effective trading strategies and the implementation of effective risk management approaches.

Keywords: Cryptocurrency, Nifty Bank, EGARCH, Volatility Spillover.

1. Introduction

Cryptocurrencies have witnessed a surge in popularity among consumers across the globe, spanning both developed and developing nations. Functioning as digital and virtual currencies, they enable users to engage in online transactions, store assets, and conduct sales via digital wallets. Not subject to governmental or banking control, these currencies aim to replace traditional fiat currencies(Che et al., 2023). The inception of the first cryptocurrency, Bitcoin, occurred in 2008, introduced by Nakamoto (2008) and has since been followed by the emergence of over 10,000 variants. Bitcoin, beyond being a virtual currency, relies on a decentralized peer-to-peer network to maintain a transparent ledger of all transactions. Online platforms such as Coinbase, Coinswitch Kuber, Bitget,Mudrex, WazirX and Binance facilitate bitcoin trading, offering services that encompass wallet management and streamlined conversion of bitcoins into traditional fiat currencies.The dynamic and evolving landscape of financial markets has witnessed a paradigm shift with the emergence of cryptocurrencies. With $1.39 Trillion Dollars market capitalisation, the interactions of cryptocurrency marketwith traditional financial markets have given rise to extensive study of volatility spill over to forecast the market movements. As one of the major growing markets in the world, the Indian stock market took the attention of the researchers to study the impact of these digital currency markets. The present study aims to evaluate the significant impact of cryptocurrencies on selected sectors of National Stock Exchange of India.

2. Literature review

In recent years, the volatility in digital currency market has attracted the attention of financial and economic researchers. There is substantial evidence of existence of volatility among the cryptocurrencies(Salisu & Ogbonna, 2022). The asymmetric effect of volatility has been observed in Bitcoin and Ethereum(Gupta et al., 2022). Both unidirectional and bidirectional volatility spillover supports the presence of time varying conditional correlations among cryptocurrencies(Katsiampa et al., 2019). Higher amount of variation in returns are observed from higher liquidity in cryptocurrency market.(Leirvik, 2022). Moreover, it is also found that the traditional crypto currencies display higher level of risk resonance compared to stable coins(X. Wang et al., 2024).

It is evident from the past literature that as a crypto as a parallel currency has a substantial impact over global stock market.Unidirectional and bidirectional spillover of returns from digital currency market are observed among E7 and G7 countries.(Aydoğan et al., 2022). Besides Developed economies, aconsiderable increase in volatility is noticed MSCI emerging marketsduring covid pandemic(Iyer, n.d.).In addition, the cryptocurrency has amplified financial risk in less developed economies(Office for the Americas, 2023). In the context of risk management, the stable coins are considered as effective hedge against the risk of macro-economic activities(Murakami & Viswanath-Natraj, 2022). Asian markets also effected by the pas t innovations in the Bitcoins(Malhotra & Gupta, 2019). To understand the impact of volatility researchers, have employed different econometric techniques. Simultaneous Equation Method (Bouteska et al., 2023),Dynamic Conditional Correlation GARCH with Wavelet analysis(Özdemir, 2022), BEKK GARCH(Katsiampa et al., 2019), Exponential GARCH(Jebran & Iqbal, 2016), Granger Causality Test with Value At Risk(VAR) model (Luu & Huynh, 2019) are the few in this area.

The sign of variation in cryptocurrency also significantly effects the volatility in Stock market returns. With this approach, further studies in crypto volatility in sectoral indices will be helpful in portfolio management. The present study aimsto explore the volatility impact of cryptocurrencies on sectoral indicesof Indian Stock Market. The study will support the existing literature of digital currency volatility in emerging economies.

3. Methodology

A. Data

TABLE 3.1 Market capitalization as on 31 October 2023.

Cryptocurrency	Market Capitalisation (in $)
Bitcoin	$672 billion
Ethereum	$216 billion
Tether	$84 billion
XRP	$31 billion

SOURCE: https://www.forbes.com/advisor/in/investing/cryptocurrency/why-is-crypto-going-up/

In this paper, our focus has centered on the examination of four prominent cryptocurrencies—Bitcoin, Ether, Tether, and XRP. Despite the existence of over ten thousand cryptocurrencies in the market, a majority of them exhibit thin trading volumes and are in the early stages of market development. The selection of these four currencies stems from their status as having the highest market capitalization, as outlined in Table 1 as of October 31, 2023. To understand the volatility spillover of cryptocurrencies within the Indian stock market context, returns of two key NSE sectoral indices: Nifty Bank and Nifty IT are considered. These sectoral indices were chosen to provide insights into the potential impact of cryptocurrency fluctuations on specific segments of the Indian stock market. The dataset used for this study spans from January 1, 2018, to October 31, 2023. Daily closing prices of the selected cryptocurrencies in USD were sourced from Yahoo Finance (https://finance.yahoo.com/) as of November 1, 2023. The daily log returns, a crucial metric for volatility analysis, were computed using the following formula:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \quad (1)$$

Where R_t=Daily Returns, P_t=price of the current period and $P_{(t-1)}$ = price at the previous period.

B. ADF Test

To assess the stationarity of the data series, the Augmented Dickey-Fuller (ADF) unit root test has been employed(Dickey et al., 1981).The null hypothesis of the test states that the data are not stationary.

$$\Delta y_t = \alpha + \beta Y_{t-1} + \sum_{i=1}^{n} \mu \Delta Y_{t-i} + \varepsilon_t \quad (2)$$

In this context of the unit root test, Y_t represents the time series under examination. The parameters include, α, which denotes the intercept term, β, representing the coefficient of the variable in the unit root test, μ, serving as the parameter for the augmented lagged first difference of to characterize the n^{th} order autoregressive process, and, ε_t which signifies the white noise error term.

C. ARCH effect

To test for the presence of heteroscedasticity in the residuals, the ARCH-LM test i.e., Autoregressive Conditional Heteroscedasticity–Lagrange Multiplier test(Ljung & Box, 1978)is applied. The ARCH-LM test is formulated as follows:

$$u_t^2 = p_0 + p_1 u_{t-1}^2 + p_2 u_{t-2}^2 + p_3 u_{t-3}^2 \ldots p_n u_{t-n}^2 + v_t \quad (3)$$

D. GRANGER CAUSALITY TEST

The Granger causality test has been employed to investigate potential relationships in the returns among selected cryptocurrencies and NSE indices. The test is conducted using the following equations:

$$y_t = a_0 + a_1 y_{t-1} + a_2 y_{t-2} \ldots a_p y_{t-p} + b_1 x_{t-1} + b_2 x_{t-2} + \cdots b_p x_{t-p} + \epsilon_t \quad (4)$$

$$x_t = c_0 + c_1 x_{t-1} + c_2 x_{t-2} \ldots c_p x_{t-p} + d y_{t-1} + d_2 y_{t-2} + \cdots d_p y_{t-p} + u_t \quad (5)$$

In Equation (4), the null hypothesis asserts that in series X, there is no Grangercausality for Y, which implies that all the coefficients of X are zero. A rejection of this null hypothesis indicates that series X significantly influences the returns of series Y.

Similarly, in Equation (5), the null hypothesis posits that in series Y, there is no Granger causality for X. This null hypothesis holds true if all the coefficients of Y are zero. A rejection of this null hypothesis signifies that series Y significantly impacts the returns of series X.The Granger causality test aids in discerning the directional influence between two time series and is instrumental in understanding potential causal relationships in the context of financial returns.

E. EGARCH

The study of asymmetric behavior of volatility of cryptocurrencies in Indian Stock market employs the E-GARCHmodel developed by (Nelson, 1991). The E-GARCH model is specifically designed to capture the impact of both low and high volatility regimes of cryptocurrencies in Indian Stock Market. It offers a comprehensive framework for modelling the intricate dynamics of volatility.

The E-GARCH model is recognized for its effectiveness in capturing the leverage effect of shocks, a phenomenon where negative news tends to induce more significant volatility compared to positive news. This observation has been supported by researchers(Gupta et al., 2022; C. Wang, 2021).The leverage effect, as revealed by these studies, suggests that adverse events or negative news have a more pronounced influence on volatility than positive events. This asymmetry is a key characteristic observed in financial markets and can be attributed to the way firms are leveraged, causing volatility to respond more sensitively to unfavourable developments.

In the context of cryptocurrencies, where market sentiment and information play crucial roles, the application of the E-GARCH model allows for a detailed examination of volatility, accounting for the leverage effect and providing insights into the impact of different types of news on the overalldynamics of Indian stock market.

$$\ln(h_t) = \alpha_0 + \alpha_1 \left| \frac{u_t - 1}{\sqrt{h_t - 1}} \right| + \lambda \frac{u_t - 1}{\sqrt{h_t - 1}} + \ln(h_{t-1}) \quad (6)$$

$\log(h_t)$ is the logarithmic of the variance of dependent variable. α_0 is constant.

α_1 indicatescoefficient of the ARCH effect, capturing the influence of past news and incorporating the size effect of the news. λ represents the presence of the asymmetric effect or sign effect of the news. If $\lambda<0$, it implies that negative shocks (bad news) in the cryptocurrency markets generate larger volatility than positive shocks (good news). **β**Coefficient of the GARCH term is indicating the persistency of the volatility.

4. Results and Discussion.

TABLE 4.1 Descriptive Statistics

	BITCOIN	ETHEREUM	TETHER	XRP	NIFTY BANK	NIFTY IT
Mean	0.001148	0.001119	0.000000134	0.000131	0.000409	0.000635
Median	0.000970	0.000502	-0.000011	-0.000591	0.000868	0.000916
Maximum	0.203046	0.353652	0.053393	0.626741	0.099951	0.086404
Minimum	-0.464730	-0.550732	-0.052570	-0.550503	-0.183130	-0.100650
Std. Dev.	0.043869	0.057606	0.003757	0.068048	0.016011	0.014371
Skewness	-1.076882	-0.875742	0.354198	0.914542	-1.236365	-0.553602
Kurtosis	15.46972	13.47034	66.97376	21.77899	20.88450	9.249194
Jarque-Bera	9227.642	6494.091	235867.4	20514.27	18784.01	2321.038
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	1383	1383	1383	1383	1383	1383

Table 4.1 provides the summary statistics of returns of cryptocurrency and Nifty sectoral indices. Bitcoin, and Ethereum, Nifty Bank and Nifty IT demonstrate positive mean values, reflecting positive average returns. Bitcoin and Ethereum are having higher mean return in comparison other selected cryptocurrencies and Nifty indices. In comparison to Indian stock market, cryptocurrencies exhibit higher variation in terms of standard deviation. Notably, Tether is having lowest mean returns and standard deviation among the cryptocurrencies.The skewness among the cryptocurrencies varies significantly from asset to asset. Despite of higher market capitalisation Bitcoin&Ethereum, are negatively skewed whereasTether and XRP are positively skewed. The results of the kurtosis of all the variable returns are leptokurtic in nature. The Jarque-Bera coefficients with 0 probability value confirms that the datasets are normally distributed for the sample period.

TABLE 4.2 CORRELATION MATRIX

VARIABLES	BITCOIN	ETHEREUM	TETHER	XRP	NIFTY BANK	NIFTY IT
BITCOIN	1					
	-					
ETHEREUM	0.82835	1				
	0.0000	-				
TETHER	-0.0162	-0.053898521	1			
	0.5471	0.0451	-			
XRP	0.58221	0.653872722	-0.0381	1		
	0.0000	0.0000	0.1564	-		
NIFTY BANK	0.09062	0.117838799	-0.0782	0.0409	1	
	0.0007	0.0000	0.0036	0.1285	-	
NIFTY IT	0.13469	0.141869799	-0.0959	0.07558	0.422590042	1
	0.0000	0.0000	0.0004	0.0049	0.0000	-

The Table 4.2 reports the correlation between selected NSE indices and cryptocurrencies. Majority of the selected cryptos had a slight positive correlation with Nifty and and Nifty IT. Tether has a negative correlation with the Indian stock market. There is higher correlation between Bitcoin and Ethereum. Among the NSE indices, Nifty IT has marginally better correlation. XRP has no correlation between XRP and Nifty Bank

.

TABLE 4.3 ADF AND PP test RESULTS

VARIABLES	ADF		PP	
	t stat	Probability	t stat	Probability
BITCOIN	-37.9661	0.0000	-37.9618	0.0000
ETHEREUM	-38.6857	0.0000	-38.6599	0.0000

TETHER	-25.2003	0.0000	-25.1875	0.0000
XRP	-38.8045	0.0000	-38.7678	0.0000
NIFTY_BANK	-36.1032	0.0000	-36.1666	0.0000
NIFTY_IT	-38.2637	0.0000	-38.2546	0.0000

The ADF and PP test results shown in Table 4.3 clearly indicates the stationarity of the datasets. Since the p value is lesser than 0.05 in for all the variables in both the tests, the time series considered for the study is stationary. In Fig,1, the clustering nature of returns are also indicating the suitability for EGARCH analysis.

Fig.1: Volatility Clustering

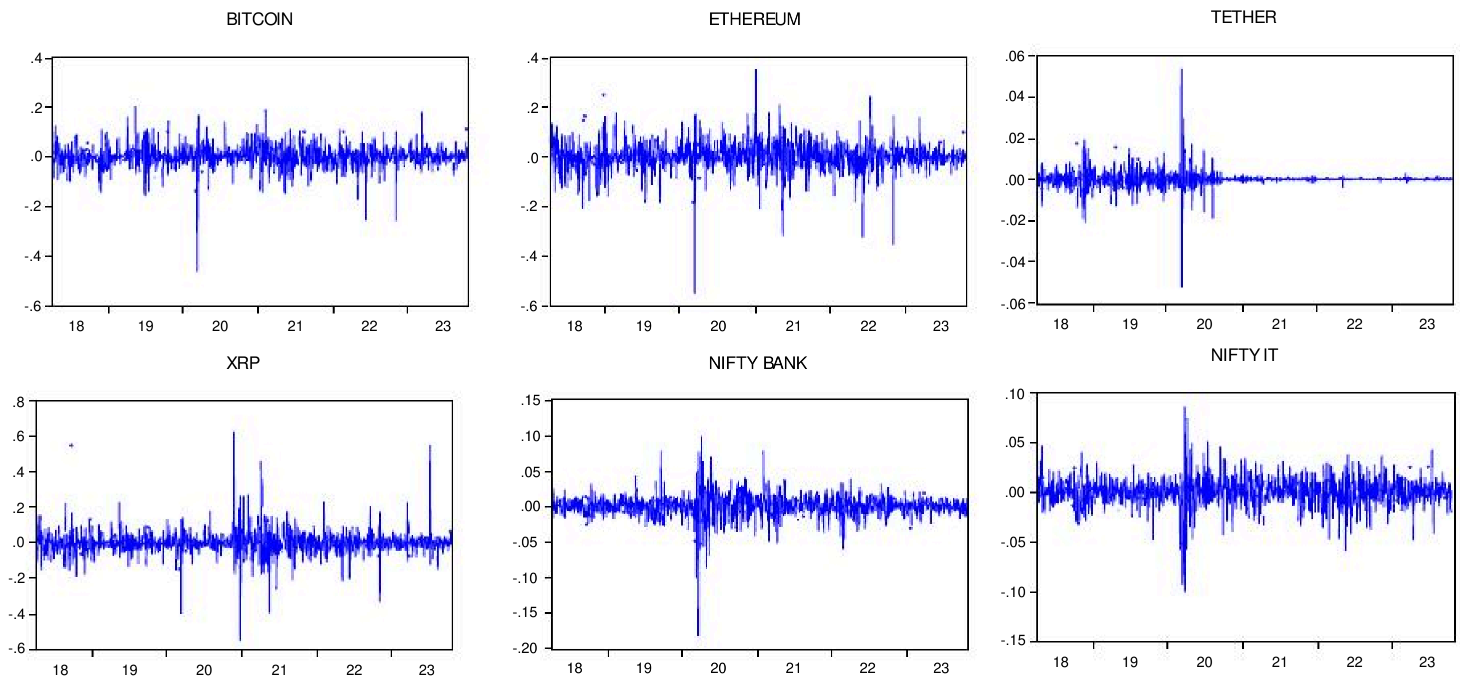

TABLE 4.4Heteroskedasticity Test

Variables	F statistic	p value
BTC	7.529023	0.0006
Ethereum	13.19346	0.0000
TETHER	72.26114	0.0000
XRP	13.6076	0.0002
Nifty IT	126.2254	0.0000
Nifty Bank	9.127043	0.0000

The null hypothesis of ARCH-LM test indicates that there is no conditional heteroskedasticity in the residuals of the model. As per the observation from the table 4.4, it is evident that there is ARCH effect in the return series and the residuals.It also supports the application of appropriate GARCH model for the study.

TABLE 4.5 Granger Causality Results

Relation (from-to)	F statistic	p value	Null hypothesis	Type of causality
BTC*-Nifty Bank	1.03862	0.3542	Accepted	No Causality
Nifty Bank-BTC	1.55755	0.211	Accepted	No Causality
BTC--Nifty IT	9.38117	0.00009	Rejected	Unidirectional
Nifty IT- BTC-	0.38343	0.6816	Accepted	No Causality
ETH*-Nifty Bank	3.01455	0.0494	Rejected	Unidirectional
Nifty Bank- ETH	1.88119	0.1528	Accepted	No Causality
ETH -Nifty IT	11.3807	0.00001	Rejected	Unidirectional
Nifty IT- ETH	0.82183	0.4398	Accepted	No Causality
TET*-Nifty Bank	11.1257	0.00002	Rejected	Bidirectional
Nifty Bank- TET	7.56913	0.0005	Rejected	
TET -Nifty IT	14.731	0.0000005	Rejected	Bidirectional
Nifty IT- TET	4.65084	0.0097	Rejected	
XRP-Nifty IT	12.063	0.000006	Rejected	Unidirectional
Nifty IT- XRP	0.2383	0.788	Accepted	No Causality
XRP-Nifty Bank	3.48142	0.031	Rejected	Unidirectional
Nifty Bank-XRP	2.45486	0.0863	Accepted	No Causality

*BTC-Bitcoin; ETH-Ethereum; TET-Tether.

The Granger Causality output shown in Table 4.5, indicate the bidirectional Causality of Tether with Nifty Bank and Nifty IT.Causality of univariate nature is found among Bitcoin and Nifty IT, Ethereum and Nifty Bank, Ethereum and Nifty ITand from XRP to Nifty IT & Nifty Bank. It is also evident from the test that there is no influence of Bitcoin on Nifty Bank returns and vice versa.

TABLE 4.6Volatility from Cryptocurrency to NIFTY IT and NIFTY bank indices

Variables	NIFTY IT			NIFTY BANK		
	ARCH	LEVERAGE	GARCH	ARCH	LEVERAGE	GARCH
BITCOIN	0.179071	-0.072416	0.949581	0.185769	-0.097021	0.982018
	0.00000	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*
ETHEREUM	0.178041	-0.07193	0.950602	0.183356	-0.09756	0.981803
	0.00000	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*
TETHER	0.181805	-0.072764	0.952356	0.184997	-0.096633	0.981992
	0.00000	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*
XRP	0.181514	-0.074106	0.951189	0.187224	-0.096915	0.9819
	0.00000	*0.00000*	*0.00000*	*0.00000*	*0.00000*	*0.00000*

The results of EGARCH model shown in table 4.6 indicate the volatility spillover from selectcryptocurrencies to the NIFTY IT and BANK sector indices. Nifty ITshows the marginally higher of magnitude of the shock(ARCH) from Tether in comparison to other 3 cryptocurrencies. Whereas, XRP has significant impact ion NIFTY Bank returns. It is evident that there is significant persistence in Nifty IT and NIFTY bank indices from its past volatility (GARCH). There is significant effect of volatility spillover from Cryptocurrencies to Indian Stock market. XRP (-0.074106) and Ethereum(0.09756)indicates the decreasing volatility spillover among Nifty IT and Bank returns.

TABLE 4.7 Volatility from NIFTY IT and NIFTY bank indices to Cryptocurrencies

Variables	NIFTY IT			NIFTY BANK		
	ARCH	LEVERAGE	GARCH	ARCH	LEVERAGE	GARCH
BITCOIN	0.336547	-0.083924	0.804537	0.346404	-0.09230	0.788470
	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
ETHEREUM	0.230514	-0.009461	0.941275	0.238064	-0.014592	0.934738
	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
TETHER	0.391616	-0.061234	0.99095	0.381169	-0.06534	0.99077
	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
XRP	0.380217	0.108648	0.813473	0.375589	0.102274	0.80597
	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

As shown in Tables 4.7, Tether exhibits a slightly higher magnitude of shock from Nifty IT (0.391616) and Nifty Bank (0.381169) compared to the other three cryptocurrencies. This suggests that Tether is more sensitive to shocks from the Nifty IT and Bank indices. Notably, Tether demonstrates a noticeably higher persistence of volatility impact from its historical movements. The analysis indicates a substantial and significant effect of volatility spillover from Nifty IT and Bank indices to the selected cryptocurrencies, excluding XRP. This observation suggests that the volatility in Tether, Bitcoin, Ethereum, and XRP is influenced by the past movements in the Nifty IT and Bank indices. However, XRP stands out by exhibiting a decreasing trend in volatility spillover among cryptocurrencies, implying a unique pattern of reduced influence from other digital assets.

5. Discussion and Conclusion

In this paper an attempt has been made to investigate the spillover effect among crypto currencies and Indian stock market returns. To understand the sign of impact, EGARCH model has been employed. Despite having comparativelylower market capitalisation, Tether and XRP are depicting marginally higher impact on Nifty IT and Nifty Bank. In case of volatility spillover from Indian stock market to digital currency market, there is higher magnitude of impact of Nifty Bank and IT sector returns on Tether.

From the study it is observed that the higher amount of GARCH coefficients proves the existence of higher amount of volatility incryptocurrencies.Though the impact of volatility of cryptocurrencies on Indian stock market is marginally less, there exists the asymmetric effect of cryptocurrency on Nifty indices. Based on the lower magnitude of the effect of cryptocurrency volatility and unorganised nature of digital currency market it is opined that the volatility of crypto currencies may not have enough forecasting power to predict Indian Stock market volatility. The study supports to the existing literature and useful for the investors with higher risk appetite and policy makers. Investors also need to carefully consider the potential impact of cryptocurrencies on their investment portfolios. The increase of participation from institutional investors in the digital currency market may reflect in increase of volatility to equity market. (Che et al., 2023)Hence, the understanding the volatility spillover and return co-movement between cryptocurrencies and traditional assets is essential for making informed investment decisions and managing risk. As the cryptocurrency market continues to evolve and its adoption increases, further research is needed to fully understand the complex relationship between cryptocurrencies and traditional financial markets, particularly in emerging economies like India.

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