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Cryptoverse and its Unflinching Cog of Fickleness

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C4, E5, F30, G1

Abstract: Investing in crypto currencies is highly risky and speculative because it is not backed by any economic fundamentals. This paper is an attempt to check if the volatility in cryptocurrency market is influenced by the volatile behaviour of three other markets, namely, Indian stock market, Volatility index and movement in the Oil prices. The time period of study ranges from February 28, 2017 to March 31, 2022 with daily frequency of data. A break point has also been identified to study the sub period movements. ARCH – GARCH family of models have been used to gauge the volatility transmissions. It is found that crude oil market and volatility index market spills the volatility in the cryptocurrency market but stock market does not play a significant role in transmitting the volatility. This is evident from the recent times when a huge fall in crypto currencies have been experienced with jig jag movements in the stock market behaviour.

1. Introduction

The concept of cryptocurrency was discovered by pseudonym researcher Satoshi Nakamoto long time ago in 2008. The whole market is outlined as the peer-to-peer cash system working on the advanced technology of block chains. The first cryptocurrency which emerged was Bitcoin (BTC) based on the SHA-256 algorithm. It is considered as the "gold standard" of all the crypto currencies since it is the oldest and most reputable one. The idea behind the introduction of the very first crypto, i.e., Bitcoin was to decentralise the digital currency and diverge it from the factors influencing fiat currency. Another coin in the evolutionary chain of cryptocurrency was Lite coin (released in the year 2011), also known as the "silver standard" of cryptocurrency, gained popularity and success making it receive a big chunk in market capitalisation after Bitcoin till 2014. Some of the other crypto currencies evolved over time include Ethereum, Cardano, Dogecoin and so on. It is indubitable that the emergence of crypto currencies will play an indispensable role in the future economic progress. Today, the market of crypto currencies is known for its volatile prices and speculative returns.

In the initial years after the launch, the purpose of isolating the cryptocurrency market from other markets was successful. However, this objective was defied after the growing popularity of various digital currencies among the return-seeking investors.

The concept of virtual currency is built upon the idea of supply and demand which altogether makes the market more volatile. The year 2017 marks as a landmark year for Bitcoin (BTC) as in this year, the value of BTC soared and leads to bubble burst ultimately hurting the investor sentiments at large. Followed by 2017; the coming years also contributed to the huge volatility showcased by the cryptocurrency market. The cryptocurrency investors can create their maximum return portfolio by not only looking at the crypto market but also the investors sentiments towards stock market and Crude oil prices in the backdrop of increasing interconnections between crypto market and other markets such as oil and stock market (Lopez-Cabarcos *et al.*, 2021). A wide research gap exists with regard to analysing the volatility of crypto market in developing countries with respect to interconnecting markets.

India is the most suitable country to study these volatility spillovers across the cryptocurrency market with the other markets such as stock market and Crude oil prices, as the first-time investors have increased their footprint in the crypto market over the years. Also, in the recent years, digital asset has proved to be the best asset class of 2021 may be because other asset classes were incapable of fulfilling the high aspirations of the smart investors who wish to grow their money in conjunction to the global growth rate. In India, the digital currency has still not got the legal tender due to the menace it may cause to the macroeconomic and financial stability. However, the union budget announcement on February 1, 2022 gave a ray of hope to many digital investors as the finance minister introduced the tax on the earnings from crypto market. Thus, due to the instability in the digital currency market, it loses the race to be called as a legal tender but is largely considered as a risk-diversifier by many investors. The extreme volatility of crypto market is higher than prominent exchange rates (Baur and Dimpfl, 2021).

The idiosyncrasy of crypto investors investing in large numbers in the digital asset despite of the high beta associated with it is of great interest. Thus, the objective of the paper is to detangle the association between different markets in Indian perspective. To elaborate, this research work aims to investigate the spill over effect from crude oil market, stock market and volatility index (VIX) to the cryptocurrency market in Indian perspective. It is important to understand the interrelation of volatility among different markets in order to let investors understand the association between fluctuations in digital market (cryptocurrency) and traditional markets (oil market and stock market). This study is novel in two ways, first, it is a unique attempt in the Indian context to find if the volatility in stock market and oil prices spills over to the volatility in cryptocurrency market, and secondly, the focus is on entire cryptocurrency market by taking S&P Cryptocurrency Broad Digital Market Index (SPCBDM) as a proxy to represent the entire crypto market rather than focussing only on the Bitcoin segment of the entire crypto market.

The rest of the paper is arranged in the following sequence - in the second section, we present a brief literature review with focus on research gaps. The third section contains the data sources used and the methodology adopted in the study. The fourth section talks about the empirical results obtained after applying several techniques. And lastly, the fifth section summarises the research findings.

2. Review of Literature

An extensive review of literature has been conducted to identify the research gaps in the existing literature. Over a period of time, cryptocurrency has gained attention of the investors globally. Due to the increased trading and awareness, the crypto market is presently strongly linked to other asset classes. This has been a point of discussion in the recent past across geographically dispersed areas among the researcher community. New fields of research have been coming up in an attempt to understand the behaviour of crypto market with respect to returns and volatility.

Brian (2015) and Corbet *et al.* (2019) points out that cryptocurrency, precisely Bitcoin acts as the asset and fails to qualify as traditional currency due to the lack of some vital fundamental values. Urquhart and Zhang (2019) further, re-confirms the status of Bitcoin as a safe haven asset. This is also supported by Shahzad *et al.* (2019). Ji *et al.* (2019a) finds that Bitcoin market is isolated from other asset classes; however, they found a significant association with some of the lagged asset classes. Further, Ji *et al.* (2019b) claimed that crypto market which used to be insulated from the shocks of other markets is turning to be interconnected over a period of time. Okorie and Lin (2020) investigated the relationship and connectedness between crude oil market and cryptocurrency market. The results suggest that there exists a bi- and unidirectional spillover effect from energy market (crude oil) to digital currency market and vice versa. Also, it has been observed that there exists a time-varying interconnectedness between financial stress and virtual asset market (Akyildirim *et al.*, 2019).

Bhullar and Bhatnagar (2020) analyses the relationship between stock exchange movements and price movement of Bitcoin in India and China and found that there is no causal relationship between these two. It further talks about the dependency of the casual relation between Indian bourses and crypto proxied by Bitcoin on economic policies.

Jeribi *et al.* (2021) studied the behaviour of five crypto currencies and five developing markets (BRICS Market). It was found that both the stock market returns as well as crypto returns are changing during the crisis period in a nonlinear and asymmetric framework. Ünvan (2021) analysed the impact of Bitcoin on USA, Japan, China and Turkey stock market indices. The findings suggested that Bitcoin had a two-way causality relation with Turkey stock market, and there is one way causality relation from China and Japan to Bitcoin.

Attarzadeh and Balcilar (2022) conducted a study to examine the interconnections between Bitcoin and other financial markets including clean energy, stock market and crude oil. The results suggest that Bitcoin and oil market transmits volatility to other financial markets. Moreover, they reported that the markets are weakly linked during non-crisis period and their linkage becomes strong during the crisis period. Katsiampa *et al.* (2019) proved that the shocks transmitted from Bitcoin market to other financial markets are largest among all the other crypto currencies but not yet dominant. This indicates that Bitcoin alone is not a good representation of the cryptocurrency market. Digging deeper, Aharon and Qadan (2018) reported that the anomaly of week of the day effect exists in the Bitcoin market as well which apparently leads to high returns and volatilities on the first day of the week, i.e., Monday.

While reviewing the literature, it has been observed that very few studies focus upon spillovers effect from different asset classes to cryptocurrency market and vice versa. Bouri *et al.* (2018) found that time and market conditions act as the major determinants in influencing the spillovers effect between Bitcoin and other asset classes. However, the paper considered only the stock market driven asset classes like stocks, commodities, currencies and bonds. A major market of Crude oil has been missed which is believed to significantly influence the stock market. Also, only a single crypto, i.e., Bitcoin has been focused upon. Various studies have used Bitcoin trading volume as a close approximation to the cryptocurrency market trade volume. However, Schinckus et al. (2019) finds that the trading volume of Bitcoin is important but fails to represent the trading volume of cryptocurrency market as whole.

2.1. Research Gaps

The present paper identifies the research gaps and attempts to fill the same. Firstly, the prior research work is largely based on the developed economies. India, being a fastest growing emerging nation and a hub for the largest number of crypto investors (close to 100 million) lags behind to be taken as the central point in any research. Secondly, the Bitcoin market is taken as a proxy for cryptocurrency market in previous research work. However, the BTC market is an inappropriate selection as a representation for the whole virtual asset market. Thus, the present work considers the SPCBDM Index as a close proxy to the cryptocurrency market. Thirdly, very few studies have considered the spillovers effect between different asset classes. The present research work is one of the few studies to undertake different asset classes for investigating the spillovers effect in two different time frames. The different periods are selected according to the Quandt-Andrews unknown breakpoint test and Chow Breakpoint test.

3. Objective and Hypothesis of the Study

The objective of present research work is to examine the volatility spill over effect from crude oil market, stock market and volatility index (VIX) to the cryptocurrency market in Indian perspective.

Accordingly, the Null Hypothesis (H_0) is that there is no volatility spill over effect from crude oil market, stock market and volatility index (VIX) to the cryptocurrency market in Indian perspective.

4. Data and Methodology

With the intention to examine the spillovers effect between four different markets, i.e., cryptocurrency market (SPCBDM), stock market, VIX (NSE Volatility Index) and crude oil market, the current study considers the period ranging from February 28, 2017 to March 31, 2022. Daily frequency of the variables has been focused upon as the linchpin of the study is to measure the flow of volatility and volatility is best measured when the frequency of the data is high. Further, the unavailability of SPCBDM prior to February 28, 2017 restrained our scope to exceed the timeline backwards in order to ensure uniformity of the variables.

The variables examined in the current study are - S&P cryptocurrency broad digital market index (SPCBDM) which is used as a close proxy to estimate the cryptocurrency market. The index considers the digital assets listed on selected open recognized exchanges that satisfies the minimum criteria of liquidity and market capitalization with an aim to track the performance of digital assets. Further, Nifty 50 is taken as a close approximation to Indian stock market; India VIX measures the volatility based on the prices of Nifty index options and has been taken to represent the volatility in Indian stock market; Brent crude oil prices to indicate the crude oil market in India. To elaborate, India has its own Indian Basket of Crude oil popularly known as IBC. The basket contains sour grade of oil imported from Oman and Dubai and sweet grade of oil imported from Brent. Petroleum Planning and Analysis Cell (PPAC), a government agency designed to monitor the crude oil prices in India reports the monthly data on IBC. Therefore, due to the non-availability of daily frequency of IBC data, the next best alternative was to represent the entire Indian crude oil market.

The variables have been extracted from reliable sources such as official website of Nifty for Nifty 50 and India VIX, S&P global ratings and yahoo finance.

The closing values of all the selected variables indicating different markets have been converted into logarithmic function. To point out, firstly, taking log values eliminates the fluctuations in the series and results in a liner form of data. Secondly, closing values of the selected variables have been considered as closing price is an outcome of post-noisy adjustments occurring during the trading period (Tripathi and Seth, 2019).

4.1. Tools Used

To measure the spillovers effect, advanced econometric tools have been used in the study, besides doing the preliminary checking of the stationarity of data using ADF and PP Unit root test. Unit root tests are commonly used to check the stationarity property of time series data. Stationary time series means when mean, variance and auto-covariance are time invariant.

ARCH Family of models are used to realize the objective of measuring the volatility spillovers. They are specifically designed to model and forecast conditional variances. Particularly, generalized autoregressive conditional heteroskedasticity (GARCH) has been used to measure the volatility and to check the asymmetry effect, exponential general autoregressive conditional heteroskedastic model (EGARCH) has been used.

Before applying models to check for Volatility clustering, the short run causality relationship between the said variables and the long run co-integration relationship has also been checked for using Granger Causality Test and Johansen Co-integration Test.

The study is also different as it examines the proposed model in two sub-periods based on the structural break. To find out the structural break, Quandt-Andrews unknown breakpoint test has been used. The date at which the time-series have a significant structural break is December 20, 2017. Further, this date has been verified by applying Chow breakpoint test. December 2017 witnesses the Great Crypto crash. Till December 17, 2017, the price of the dominant crypto, i.e., Bitcoin surged exorbitantly and soon after five days, the market crashed by 45 per cent. Further, in the early 2018, amidst the rumours of banning the Bitcoin in South Korea led to depreciation in Bitcoin prices.

Time series are time varying and highly volatile. However, all the instable movement in the series cannot be accounted for because of large number of resulting short periods. Moreover, the volatility in the crypto data is transitory and short-lived.

Hence, we have used Quandt-Andrews unknown breakpoint test to obtain a structural break and further verified it using Chow breakpoint test because the data range in the present study is already short due to paucity of crypto data. Had we use multiple breakpoint test, the data would have been divided into more shorter periods leading to inaccurate results. Moreover, the major bubble burst of utmost importance in December 2017 has been captured leading to enhanced results.

Table 1: Result for Chow Breakpoint Test

F-statistic	3.757567	Prob. F (4, 1226)	0.0048
Log Likelihood Ratio	15.03636	Prob. Chi-Square (4)	0.0046
Wald Statistic	15.03027	Prob. Chi-Square (4)	0.0046

Source: Authors' Computation

5. Data Analysis, Results and Discussion

5.1. Descriptive Analysis

To analyse the volatility effect in the selected markets using the proxies as identified above, it is important to look at the descriptive statistics of the variables used. These are reported in Table 2.

Table 2: Descriptive Statistics

	Nifty	*Oil Prices*	*SPBMI*	*VIX*
Mean	12153.29	62.73148	1521.875	18.11158
Median	11257.10	63.71000	747.2900	16.05250
Maximum	18477.05	133.1800	6215.990	83.60750
Minimum	7610.250	9.120000	98.74000	10.44750
Std. Dev.	2588.868	16.16535	1554.300	8.054081
Skewness	0.998938	0.216457	1.332152	3.604342
Kurtosis	2.789235	5.023915	3.343416	21.60932

Source: Authors' Computation

Table 2 shows that the mean values of NIFTY index, Oil prices, S&P cryptocurrency index and Volatility index as 12,153.29, $62.73148, 1521.875 and 18.11158. While the Nifty touched record height of more than 18000 points in October 2021 post pandemic, it also experienced a steep fall in the value touching around 7,600 points in January 2020 with Pandemic being anticipated to reach India. Skewness captures the asymmetry in the series distribution around its mean value. The skewness statistic is zero for a normal distribution. Here, the indices of all four markets are skewed to the right (has a right tail) or it can be said that they are positively skewed. Kurtosis values for all the series except Nifty index is more than 3, which signifies that the series distribution is leptokurtic relative to normal with fat tails. The same result is confirmed by JB statistics as well.

5.2. Correlation Analysis

Before estimating the volatility measures, it is vital to analyse the measure of association between the four markets. In other words, correlation analysis has been conducted to see the interconnectedness between the markets. Table 3 shows the result for Karl Pearson's coefficient of correlation.

From Table 3, it is found that the cryptocurrency index returns has positive correlation with the returns of stock market and the return series of oil prices. However, the volatility index is negatively correlated with crypto returns which imply that the high degree of volatility in the stock market reduces the returns from crypto currencies.

Table 3: Karl Pearson's Coefficient of Correlation

	DlogNifty	*DlogOil*	*DlogSPBMI*	*DlogVIX*
DlogNifty	1.000000	0.136391	0.100678	-0.531350
DlogOil	0.136391	1.000000	0.098222	-0.058489
DlogSPBMI	0.100678	0.098222	1.000000	-0.061343
DlogVIX	-0.531350	-0.058489	-0.061343	1.000000

Source: Authors' Computation

5.3. Unit Root Test

The result of Augmented Dickey Fuller (ADF) and Phillips Perron (PP) Unit Root test put forward that the time series of all the selected four markets in logarithm form are stationary at first difference.

Table 4: Results of ADF and PP Unit Root Test

Log of Index	*ADF (Trend and Intercept)*		*PP (Trend and Intercept)*	
	Level series	*First Differenced series*	*Level series*	*First Differenced series*
		(t – statistics)		
Nifty	-2.010471	-12.16876*	-1.768470	-37.24196*
Oil	-2.229630	-9.317459*	-1.773995	-38.10939*
SPBMI	-1.869879	-34.32016*	-1.986614	-34.46666*
VIX	-3.271056	-34.99545*	-3.443708	-34.99550*

*Significant at 1%

Source: Authors' Computation

5.4. Granger Causality Test

Granger causality test at two lags is applied on log differenced series to find out if there is presence of short run causal relationship between Nifty index stock returns, Oil price returns, Volatility index and Crypto market index.

Table 5: Results of Granger Causality

(Lags 2)	*Dlog Nifty*	*Dlog Oil*	*DlogSPBMI*	*Dlog VIX*
Dlog Nifty	-			
Dlog Oil	*	-		
Dlog SPBMI	*		-	***
Dlog VIX	**			-

* 1% level of significance
** 5% level of significance
*** 10% level of significant
Source: Authors' Computation

It is found that the Indian stock market returns are granger caused by all the remaining three variables considered in the study. This shows that the fluctuations in stock market are not only affected by the movements in other markets but also, some of the macroeconomic factors to an extent. The sub period results indicated that the causality running from Crypto market to stock market has intensified with the passage of time.

5.5. Johansen's Co-integration Test

Johansen Co-integration test is applied to check the long term relationship between the variables. It is based upon the premise that the two series may wander off in short run but they merge together in the long run. The said test is applied on the logarithm series of all the variables pair wise. All the possible models are applied based upon both Trace and Maximum Eigen value test statistics to provide robustness in the results.

As per the results presented in Table 6, Stock market series is found to have long run co-integration relationship with Oil prices and Volatility Index with at least one of the five models considered. Also, Oil market has long run co-integration relationship with Volatility Index. However, there is no indication of long run co-integration between stock market and crypto market. Even while doing sub period analysis, no long run co-integration relation is found between Nifty and crypto market

5.6. ARCH – GARCH Model

The application of Autoregressive Conditional Heteroskedasticity (ARCH) model needs the realization of two conditions:

Table 6: Results of Johansen Co-integration Test

Variables	*Type of Test*	*Co-integrating Relations reported under each Model*				
		Model 1 - No Intercept, No Trend	*Model 2 - Intercept, No Trend*	*Model 3 - Linear Intercept & No Trend*	*Model 4 - Linear Intercept & Trend*	*Model 5 - Quadratic Intercept & Trend*
Nifty – Oil	Trace test	1	0	0	0	1
	Max-Eigenvalue test	1	0	0	0	1
Nifty – SPBMI	Trace test	0	0	0	0	0
	Max-Eigenvalue test	0	0	0	0	0
Nifty – VIX	Trace test	1	0	0	0	1
	Max-Eigenvalue test	1	0	0	1	1
Oil – SPBMI	Trace test	0	0	0	0	0
	Max-Eigenvalue test	0	0	0	0	0
Oil – VIX	Trace test	0	0	0	0	2
	Max-Eigenvalue test	0	0	0	1	2
SPBMI – VIX	Trace test	0	0	0	0	0
	Max-Eigenvalue test	0	0	0	0	0

Source: Authors' Computation

(i) The presence of volatility clustering implying that the phases of high volatility are trailed by the phases of high volatility whereas phases of low volatility are followed by the phases of low volatility.

(ii) To check the presence of heteroskedasticity, the residual diagnostic ARCH test should be rejected.

The OLS regression run on log difference series of cryptocurrency market is found to have ARCH effect (the value of F-statistics is large enough with the p – value (probability value) of less than 0.05 that point towards the rejection of the null hypothesis stating there is no ARCH effect in time series residuals). Therefore, ARCH – GARCH model can be applied.

GARCH models comprises of estimation of 2 equations – Conditional Mean equation and Conditional Variance equation. The first part of the GARCH model i.e., Mean equation for Cryptocurrency market is given as:

$$DlogSPCBDM = C(1) + \varepsilon \quad \text{Equation 1}$$

The regression is run on constant. The above mean equation can be represented through ARCH-GARCH model because it satisfies both the above listed conditions. The second part of the model i.e., variance equation for checking the volatility in cryptocurrency market is given as:

$$H_t = C(2) + C(3) * \varepsilon_{(t-1)}^{\ 2} + C(4) * H_{t-1} \quad \text{Equation 2}$$

Where,

H_t = Residual error term's variance resulting from equation (1). It is volatility of Cryptocurrency returns.

$\varepsilon^2_{(t-1)}$ = Previous day's squared residual resulting from equation (1). It is also called as previous day's stock return information about volatility or ARCH term.

H_{t-1} = Variance of Previous day's residual series. It is also called as GARCH term.

DlogNifty, DlogOil and DlogVIX are the Exogenous variables or variance regressors to check if the volatility in Nifty Index, Oil Prices and Volatility Index affects the volatility of Cryptocurrency market. The results are summarized in Table 4.

Table 7: Results of ARCH-GARCH Model

Dependent Variable/ Coefficients		*Cryptocurrency Market Coefficients (Z- Statistics in parenthesis)*		
		Whole period	*Sub-period 1*	*Sub-period 2*
ARCH Term		0.046958*	0.136965*	0.041265*
		(7.314845)	(3.041437)	(6.531953)
GARCH Term		0.928279*	0.769324*	0.932084*
		(112.6383)	(11.74832)	(109.2626)
Volatility	Nifty	0.002964	-0.127021*	0.003763
		(1.053368)	(-2.184558)	(1.336145)
	Oil Prices	-0.003368*	-0.008077	-0.003153*
		(-4.965725)	(-0.876117)	(-4.463120)
	VIX	0.003734*	0.002397	0.003555*
		(5.858990)	(0.865570)	(5.717854)

*Significant at 5% level of significance

Source: Authors' computation

As per the results reported in Table 7, both the ARCH and GARCH term are significant for the return series of cryptocurrency market. As can be observed, ARCH term is significant which implies that the lagged information exerts a strong influence on the cryptocurrency market volatility whereas significant GARCH term implies that lagged volatility influences the current crypto market volatility. The cryptocurrency market has a persistent volatility as can be deduced by the higher GARCH coefficient than the ARCH coefficient. To elaborate, higher GARCH term indicates that the volatility in the cryptocurrency market is largely influenced by the previous period's volatility more than the previous period's information. This also demystifies that the digital asset market has a longer memory. Moreover, the sum of ARCH and GARCH coefficient is close to but less than 1 indicating that the model is stable. Lastly, the significant intercept term points out at the average long-term volatility in the cryptocurrency market.

The results further indicate that the volatility in cryptocurrency market is significantly affected by the volatility persisting in the oil prices and Volatility index. To our surprise, the volatility in cryptocurrency market is not getting affected by the volatile behaviour of stock market. The presence of breakpoint indicates that the volatility transmission in crypto market from Oil price market and Volatility Index has increased post major fall in December 2017. However, the volatile behaviour of Nifty stock returns has failed to cause volatility in cryptocurrency market even after accounting for the great crypto crash in 2017.

5.7. E-GARCH Model

Exponential Generalized Auto Regressive Conditional Heteroskedasticity Model (E-GARCH) has also been applied in order to check for the presence of asymmetric effect in the stock returns data of cryptocurrency market.

Table 8: Results of E-GARCH Model

Dependent Variable/ Coefficients	*Cryptocurrency Market Coefficients (Z- Statistics in parenthesis)*		
	Whole Period	*Sub-period 1*	*Sub-period 2*
ARCH Term	0.168658*	0.188246*	0.155341*
	(7.665742)	(2.369888)	(6.983235)
GARCH Term	0.906206*	0.887026*	0.899435*
	(51.60537)	(15.56316)	(41.70074)
E-GARCH Term	-0.017404	-0.030715	-0.026813*
	(-1.564382)	(-0.60597)	(-2.301108)

* Significant at 5% level of significance
Source: Authors' Computation

The coefficient for E-GARCH term point towards the presence of asymmetric effect and it is expected to be negative. The null hypothesis states that the "negative shocks create more volatility as compared to positive shocks of equal magnitude." Table 5 indicates that the coefficient of E-GARCH term is found to be negative for the cryptocurrency market but is not found to be significant at 5% level of significance which implies that the asymmetric effect is not significant for cryptocurrency index. When checked for sub-periods, it is found that the cryptocurrency market has become more sensitive to the flow of information post break point of 20th December 2017 when a steep fall was experienced in the Bitcoin digital currency. The significant E-GARCH term indicates the presence of asymmetric effect. In other words, the crypto index has become more sensitive to the negative information flow as compared to positive information of the equal magnitude.

6. Conclusion and Implications

The hype created around the cryptocurrency market over the period of time has motivated us to examine the volatility transmission between four different markets. The digital asset has been a volatile market in itself from the start. During December 2017, the market has witnessed the great crypto crash. Bitcoin, being the most popular virtual asset and holding the large market share significantly dictated the whole cryptocurrency market. Soon after a lot of digital assets has joined the cryptocurrency market which has made the strong footprint of Bitcoin on the cryptocurrency market slightly less (Schinckus *et al.*, 2020).

The cryptocurrency market moves in tandem with the stock market return which means that as stock return goes up, the returns in the cryptocurrency market also surges and vice versa. However, the volatility index bears a negative correlation with the cryptocurrency market which indicates that as the investors expect volatility to rise in the stock market, the risk aversion trait of the investors leads to falling returns in the cryptocurrency market. The revelations after empirically testing the volatility spillovers effect have knitted the story of cryptocurrency market in a different way. It is evident that crude oil market and volatility index market spills the volatility in the cryptocurrency market (Lopez-Carbarcos *et al.*, 2021). The crude oil market has deep connections with cryptocurrency market during economic turbulence (Jareno *et al.*, 2021). To put it differently, oil price shocks or news impact the macroeconomic indicators on a broader level mainly after the financialization of the crude oil market during mid-2000s and this might be the reason behind volatility transmission from oil market to volatility market (Yin *et al.*, 2021).

However, to our amaze, stock market does not take part in transmitting the volatility significantly. Further, even after introducing the breakpoint in the model, the results did not alter significantly. The incorporation of breakpoint, however, suggests that the cryptocurrency market has become more sensitive in the post-crash period, or, it can be said that the breakpoint just enhances the previously found results. The intensity of volatility transmission from oil market and volatility index has increased in the post-breakpoint period when compared to the pre-breakpoint period. Also, the sensitivity of the cryptocurrency market to the negative shocks has escalated when compared to the positive shocks of equal magnitude.

The reason explaining the insignificant effect of volatility transmission from stock market to cryptocurrency market may be arising from the blurred dissimilitude between the stock market volatility and volatility index. The stock market volatility signifies the actual movement in the prices and on the other hand, volatility index is the expectation of the investors' sentiments related to the stock market volatility. To put it differently, VIX can be interpreted as a measure indicating how the investors perceive the stock market volatility in the next 30 days.

Therefore, the sentiments of the investors captured in VIX have a ripple effect on the cryptocurrency market and hence, the effect of the actual movement in the stock prices (stock market volatility) does not substantiate significantly. This means that investors accurately foresee the stock market volatility. In other words, even before the volatility strikes the Indian bourses, the volatility index captures the stock market volatility and spills over its effect on the cryptocurrency market. This has been supported by previous study which revealed that VIX is an accurate indicator of the stock market volatility for one month period (Kothari and Bahadur, 2020). In addition, it has also been established that VIX has a negative correlation with Nifty returns which implies that VIX dictates the stock market return and crypto market return. Due to the disadvantage of crypto market not being regularised in India, the investors are recommended to invest cautiously to avoid high risks in their portfolio amid climate changes which may hamper the entire financial system (Gupta *et al.*, 2022). Though, crypto market yields high returns which are usually in tandem with the stock returns but the volatility in the market is unmatched. However, strong and growing interrelations between the stock market and crypto market do not spare the digital assets from the factors influencing the stock market returns. Thus, it is advisable that investors must scrutinize their sentiments and market conditions for avoiding irrational investment decisions (Yadav and Chaudhary, 2022).

7. Scope and Direction for Further Research

The scope of the current research work is confined to Indian stock market and Volatility Index. The future advancement in the study can include other countries where cryptocurrency is actively traded. Also, the same analysis can be performed on high frequency data, wherever applicable. Further, the study is exclusively reliant on secondary sources like official website of Nifty for Nifty 50 and India VIX, S&P global ratings and yahoo finance. Therefore, quality of the present research work is highly reliant on the precision and solidity of the secondary data sources. Moreover, it is observed that millennial footprints in the cryptocurrency market have risen over a period like stock markets (Sethi et al., 2021). Thus, efforts can be made by future researchers in comprehending the factors influencing the decision-making of largest group of stakeholders, i.e., millennials.

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