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MODELLING VOLATILITY SPIILLOVER BETWEEN THE CRYPTO MARKET AND THE INDIAN STOCK MARKET

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ABSTRACT

The crypto market is growing rapidly in the post pandemic era. It is expected to grow at a rate 12% compounding per annum in the near future. There is a shift in investors' interest towards crypto currencies has gained greater significance, Young India investors are keen in exploring newer investment avenues such as Bitcoin, Ethereum, Polygon, etc., which can provide them diversified returns. In India more than 15 million retail investors are currently trading with these digital currencies. The present study aims at examining the volatility in the crypto currencies market with the help of GARCH family models. The most powerful currency the Bitcoin is considered as a sample to understand the volatility in the crypto market.

KEYWORDS: *Crypto Market, Volatility, Significance, Analytics, Operating.*

INTRODUCTION

According to study conducted by NASSCOM on 'Crypto Industry in India' during September, 2021 there is a shift in investors' interest towards crypto currencies has gained greater significance as a result of which the Indian and the Global crypto market is expected to reach USD 241 Million and USD 2.6 Billion by 2026 respectively. Young India investors are keen in exploring newer investment avenues such as Bitcoin, Ethereum, Polygon, etc., which can provide them diversified returns. The Global crypto market is expected to grow with a CAGR of 12%. In India more than 15 million retail investors are currently trading with these digital currencies and more than 230 start-ups are already operating in the Crypto Tech space. This market has also started to create employment opportunities across trading, software development, analytics, and other practices. Therefore the Indian crypto market is expected to grow 2 times faster and shall provide around 8 lakh job opportunities by 2030. There are around 4000 digital currencies available in the global market. Out of which 25 have gained greeter significance which make up 90% of the total market.

Almansour (2020) Investors' choices of digital currencies are affected by other investors' choices which significantly affect their investment decisions. Similarly herding theory, prospect theory, and heuristic theory significantly effect on investors' investment decisions in digital currencies. Chowdhury &Mendelson, (2013) the turbulence in financial markets has led most investors to search for new investment opportunities. The cryptocurrency market is a new investment platform for investors to invest their capital in addition to common financial equity markets. Kristoufek, (2015); Khan et al., (2020) Individuals, as well as institutional investors, pay attention to the development of the cryptocurrency market, Where Bitcoin is gaining more attention from investors On several occasions, Bitcoin prices have been showing a bubble behavior. Garcia et al. (2014) suggested that Bitcoin is considered as a financial bubble because there is a difference between the fundamental value of Bitcoin and its exchange rate. It takes only a few investors to overreact to any news which can then trigger a flow of aggregate information. Since the cryptocurrency market comprises unsophisticated traders, their reactions can trigger a bubble behaviour in the prices of Bitcoin.

Among the digital currencies Bitcoin (BTC) is the first and remains as the most powerful and preferred currency in the crypto market. In Indian Rupee, the cost of one Bitcoin has never come down below Rs 35 lakhs and during the fiscal year 2020-21 it even hit Rs 56 lakh during the same year. The trading volume of BTC is approximately 7 billion and the market capitalization of BTC amounts to USD 1 Trillion. The volume of trade in the crypto markets indicate that the market is highly speculative and the instruments as well. In the recent years, significant studies have been undertaken in understanding the volatility in these markets. This study examines the volatility of the digital currency, namely the Bitcoin, the Ethereum (ETH) and the Cardano (ADA). And the Indian stock market index the 'Nifty'. The study models the volatility of the selected variables and also investigates the volatility spill over between the variables

LITERATURE REVIEW

Digital currencies that make use of encryption for verification of a transaction are called as cryptocurrencies which has been widely recognized in the past few years. Malladi and Dheeriya (2021), has examined the linkage between the returns and volatility of 2 major Crypto currencies namely Bitcoin and Ripple by employing GARCH and VAR models. The return and volatility spiller effects on other variables such as Gold prices and VIX were also analysed. The study concludes that the magnitude of BTC volatility are more, returns of global stock markets and gold do not have a causal effect on BTC returns. XRP's are more sensitive to gold prices and general stock market volatility.

Kyriazis, Daskalou, Arampatzis, Prassa, &Papaioannou, E. (2019), employed GARCH models to model the volatility in crypto currencies considering 12 currencies and found that almost all cryptocurrencies are complementary to the three key coins which are mainly responsible for the herding behaviour in the markets of digital currencies. Geuder, Kinateder, and Wagner (2019) investigated the behavior of Bitcoin prices over the period 2016 – 2018. They employed two methods: namely PSYmethodology and the log-periodic power law. The PSY method was employed to find multiple bubble periods as well as to show explosive behavior. The log-periodic power law identified bubble growth and potential critical bubble termination times. The results indicated that the bubble behavior was common and re-occurring haracteristic of Bitcoin prices.

Feng, Wang and Zhang, Z. (2018), investigated whether investments in crypto currencies are safe considering 7 major currencies and concluded that cryptocurrencies are very good diversification assets for stocks, as their left tails are uncorrelated with the left tails of selected indices. Zhang et al. (2018) studied the relationship between the cryptocurrency market and Dow Jones industrial average. The authors concentrated on the largest 20 cryptocurrencies, and the data was gathered from the 28th April 2013 to the 4th January 2018. Based on their analysis, they constructed a Cryptocurrency Composite Index (CCI). The results indicated that the cryptocurrency composite index and Dow Jones industrial average were cross-correlated

Barots (2015) conducted a study to test whether Bitcoin follows efficient market hypothesis or not. In his study, the characters as well as features of Bitcoin were introduced and analyzed. The results showed that Bitcoin's prices followed an efficient market hypothesis; this indicates that the price of Bitcoin will react directly to new public information. It is argued by Madhavan (2000) that the structure and efficiency of information in financial markets are vital for understanding investor's behavior. In other words, the vast amount of published information guarantees that investors have a good deal of information for decision making.

RESEARCH DESIGN AND METHODOLOGY

OBJECTIVES OF THE STUDY

- To examine the relationship between crypto prices and its impact on the Indian stock market with special reference to Nifty.
- To investigate the effect of volatility spill over between the crypto market and the Indian stock market.

SAMPLING

The current study investigates the relationship between the crypto market returns and the Indian stock market returns. Bitcoin (BTC) is the first and remains as the most powerful and preferred currency is considered a s a proxy to represent the crypto market and the NIFTY 50 comprising of 50 stocks spread across 23 sectors is considered as a proxy to represent the Indian stock market. The daily closing prices for the period 01 January, 2019 to 30 September, 2021 were considered for the study.

HYPOTHESIS OF THE STUDY

H_o: There is no significant relationship between the crypto market volatility and stock market volatility.

METHODOLOGY

First, descriptive statistics have been run to understand the mean reactions, standard deviation, other applicable insights to find out the outliers and to better comprehend the information. Second, the collected data has been tested for unit root by applying ADF test. Third, a robust regression has been run and residual diagnostics test like Serial Correlation and Hetroskedasticity Test have been conducted. Fourth, to investigate the causes of volatility GARCH (1, 1), EGARCH (1,) and DCC GARCH (1, 1) model have been run.

RESULTS AND DISCUSSIONS

The data obtained has been represented through a graph which indicates that both variables demonstrate a random walk with drift that an upward trend prevails over time. The Augmented Dickey Fuller Test to test the Stationarity of the variables was conducted at 99% and 95% levels of significance. The presence of unit root is confirmed in both variables. In order obtain Stationarity and make the data fit for father analysis the log returns have been ascertained. The ADF test results of RBTC and RNIFTY indicate that the unit root was not present as the p value is less than 0.05 and significant at 1% at level. The graphs of the return series indicate symbols of volatility clustering and mean reversion. The series also demonstrate the nature of volatility in the data.

$RBTC = In (BTC_1) - In (BTC_0)$

$RNIFTY = In (NIFTY_1) - In (NIFTY_0)$

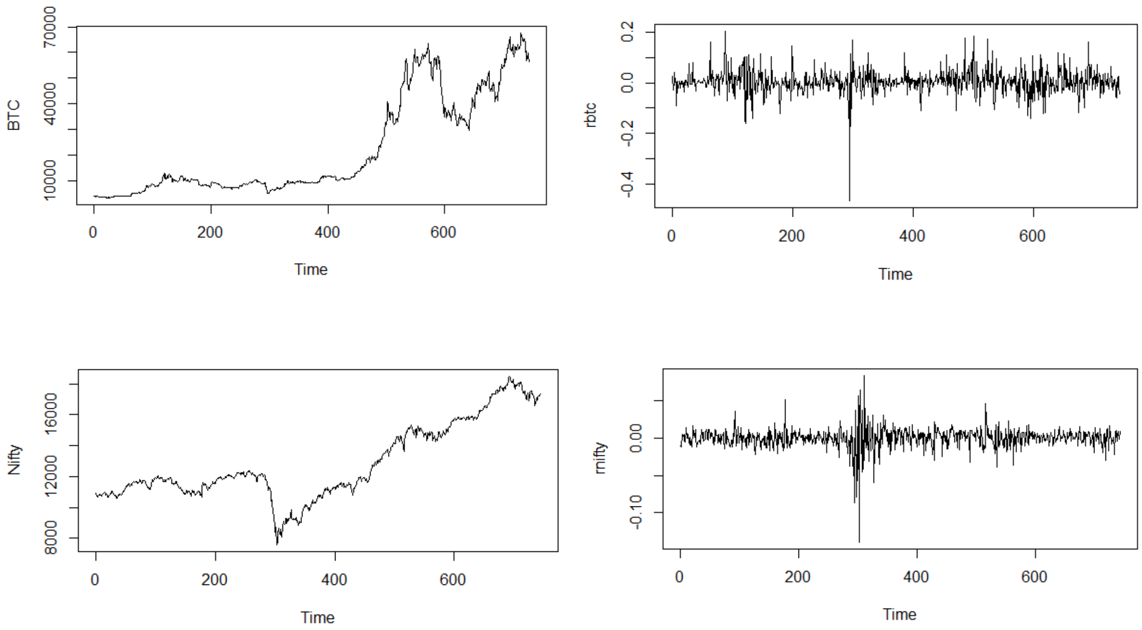

TABLE 01: UNIT ROOT TEST

Null Hypothesis: The series has a unit root		
Series	**ADF**	**Prob.***
BTC	-2.1288	0.5238
Nifty	-1.4949	0.7921
RBTC	-7.6869	0.00
RNifty	-7.438	0.00

Regression model was executed and residuals were tested for serial correlation and hetroskedasticity. The ARCH LM test was executed to understand whether the presence of hetroskedasticity and the results presented in the table below indicate that the return series of both the variables are hetroskedasticity as their p values are less than 0.05.

Table 04: Hetroskedasticity (ARCH LM) Test		
RBTC	Chi-Square	19.539
	p-value	0.07632
RNIFTY	Chi-Square	225.75
	p-value	0.000002

Further to the confirmation of ARCH effect in the variables, GARCH (1, 1) model was executed to understand the relationship between past errors, variance and volatility. From the below table it is inferred that past errors (alpha1: 0.16991) and variance (beta1: 0.663215) are significant and alpha plus beta is less than 1. This indicates that past errors and variance significantly contribute to present volatility in the returns of the variable. Similarly GARCH (1, 1) model on Nifty returns also indicate that past errors (alpha1: 0.139115) and variance (beta1: 0.833856) are significant and alpha plus beta is less than 1. This indicates that past errors and variance significantly contribute to present volatility in Nifty returns.

Standard GARCH (1, 1) for RBTC

Parameters	Estimate	Std. Error	t value	Prob.*
mu	0.003722	0.000041	90.1849	0
ar1	0.991962	0.004327	229.2628	0
ma1	-1	0.000035	-28984.8235	0
omega	0.000399	0.000107	3.743	0.000182
alpha1	0.16991	0.041538	4.0905	0.000043
beta1	0.663215	0.068742	9.6478	0

Standard GARCH (1, 1) for RNIFTY

Parameters	Estimate	Std. Error	t value	Prob.*
mu	0.000926	0.000272	3.40633	0.000658
ar1	-0.114983	0.342535	-0.33568	0.737111
ma1	0.162701	0.338227	0.48104	0.630487
omega	0.000005	0.00001	0.44162	0.658764
alpha1	0.139115	0.007208	19.30147	0
beta1	0.833856	0.052975	15.74056	0

Further to the GARCH (1, 1) model, EGARCH model was run to understand the leverage and feedback effect between return and volatility in the variables. The EGARCH coefficient (gamma: 0.385477 and 0.165549) are positive and significant. The results indicate that negative news creates more volatility in the returns than positive news. Alpha + beta – (gamma /2) is less than 1, this again confirms that negative news shocks create more volatility than positive news shocks of the same magnitude.

EGARCH (1, 1) for RBTC

Parameters	Estimate	Std. Error	t value	Prob.*
mu	0.001453	0.001574	0.92334	0.355832
ar1	-0.457583	0.054957	-8.32627	0
ma1	0.446078	0.055475	8.0411	0
omega	-1.281278	0.282774	-4.53111	0.000006
alpha1	-0.122578	0.040476	-3.02837	0.002459
beta1	0.784969	0.045826	17.12943	0
gamma1	0.385477	0.063211	6.09822	0

EGARCH (1, 1) for RNIFTY

Parameters	Estimate	Std. Error	t value	Prob.*
mu	0.000319	0.000309	1.0324	0.301894
ar1	-0.081614	0.081065	-1.0068	0.314049
ma1	0.156345	0.08182	1.9108	0.056024
omega	-0.249299	0.005239	-47.5832	0
alpha1	-0.132864	0.016018	-8.2944	0

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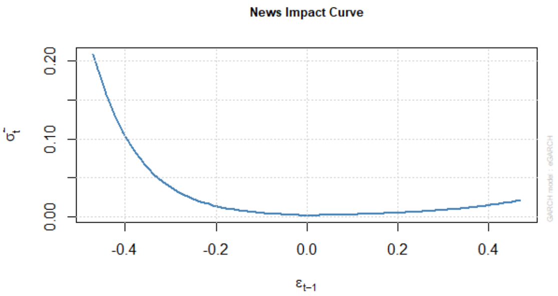
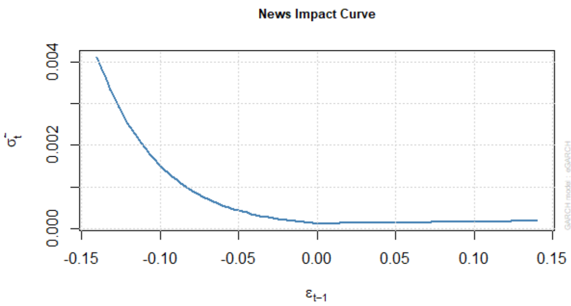
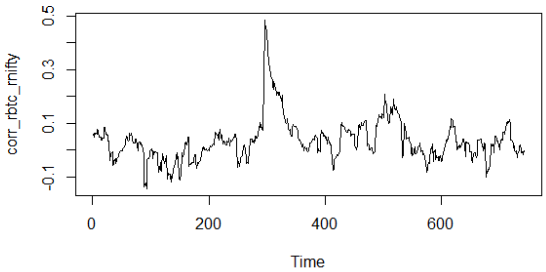
beta1	0.971821	0.000629	1544.621	0
gamma1	0.165549	0.006723	24.6246	0

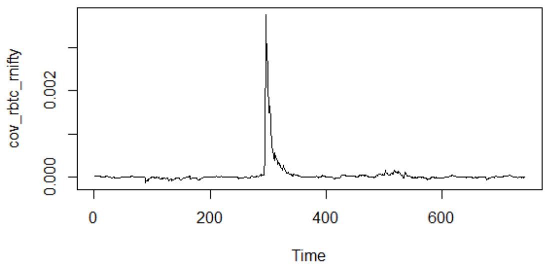


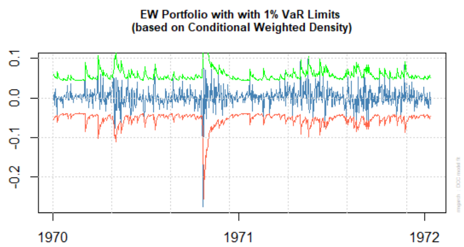


Robert F. Engle (1999) Dynamic Conditional Correlation GARCH is a simple class of Multivariate GARCH Models. Time varying correlations are often estimated with Multivariate GARCH models that are linear in squares and cross products of returns. A new class of multivariate models called dynamic conditional correlation (DCC) models is proposed.These have the flexibility of unilabiate GARCH models coupled1 withparsimonious parametric models for the correlations. They are not linear but canoften be estimated very simply with unilabiate or two step methods based on thelikelihood function. It is shown that they perform well in a variety of situations and give sensible empirical results.

The DCC GARCH (1, 1) results in the below table indicate that the crypto met and the Indian stock market are integrated I the long run as a result of which a shock in one market affects another market in the long run. In the short run, one market does not influence another. The joint beta coefficient 0.92279 is significant and less than one. This represents that volatility spill over effect from the crypto market to the Indian stock market is confirmed. Any shock in the crypto market shall create an impact in the stock market.







DCC GARCH (1, 1)

Parameters	Estimate	Std. Error	t value	Prob.*
RBTC.mu	0.003856	0.001583	2.4362	0.014843
RBTC.omega	0.000402	0.000169	2.38721	0.016977
RBTC.alpha1	0.172898	0.135209	1.27874	0.0200988
RBTC.beta1	0.660241	0.122026	5.41066	0
RNIFTY.mu	0.000922	0.000792	1.16304	0.244815
RNIFTY.omega	0.000005	0.000028	0.16438	0.869432
RNIFTY.alpha1	0.138635	0.061721	2.24614	0.024695
RNIFTY.beta1	0.833072	0.169011	4.92908	0.000001
DCC Alpha1	0.021494	0.023497	0.91476	0.360319
DCC Beta 1	0.92279	0.121514	7.59409	0

CONCLUSION

The crypto market is a highly volatile market. Several past literature indicate that is market is not influenced by macroeconomic aggregates and can be considered as an asset in the investment portfolio which shall help in diversifying the risk. But since 2020 there a huge rise in the number of investors and also a higher shift in prices of crypto currencies which indicates that more studies shall be conducted to understand the factors that create volatility in this market. The present study is an attempt to understand the relationship between past and the present conditional variance with the help of the lagged values. Similar studies including larger time period can be conducted and also considering several other variables. Advance technique shall also be used to obtain better results.

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