Asian Journal of Research in Banking and Finance
ISSN: 2249-7323 Vol. 12, Issue 4, April 2022 SJIF 2022 = 8.558
A peer reviewed journal

ESTIMATING THE VOLATILITY OF CRYPTOCURRENCIES BY EMPLOYING GARCH MODELS

Mrs. P. B. Saranya*

*Assistant Professor,
GRG School of Management Studies,
PSGR Krishnammal College for Women,
Coimbatore, INDIA
Email id: pbsaranya@grgsms.ac.in

DOI: 10.5958/2249-7323.2022.00022.0

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 and other currencies like Ethereum and Cardano were considered as samples to understand the volatility in the markets.

KEYWORDS: *diversified, volatility, significance, currency, compounding.*

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 CryptoTech 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 market.This study examines the volatility of the digital currency, namely the Bitcoin, the Ethereum (ETH) and the Cardano (ADA). The study models the volatilityof the selected currencies and also investigates the short and long run association between the variables. Daily data for the period January 01, 2019 to September 30, 2021 has been obtained to model the volatility. The impact is examined with the help of GARCH family models.

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 whetherBitcoin follows efficient market hypothesis or not. Inhis study, the characters as well as features of Bitcoinwere introduced and analyzed. The results showed thatBitcoin's prices followed an efficient market hypothesis;this indicates that the price of Bitcoin will react directly tonew public information. It is argued by Madhavan (2000)that the structure and efficiency of information in financialmarkets are vital for understanding investor's behavior.In other words, the vast amount of published informationguarantees that investors have a good deal of informationfor decision making.

DATA AND METHODOLOGY

Three digital currencies, namely the Bitcoin (BTC) , the Ethereum (ETH) and the Cardano (ADA) were identified based on their market capitalization (BTC – USD 1 T, ETH – USD 420 B, ADA – USD 70 B) as samples representing the crypto market. The daily closing prices of these variables have been obtained for the period 01 January, 2019 to 30 September, 2021 from the Yahoo Finance website. Various Tools such as ADF, Granger Causality, ARCH, GARCH, and TARCH& EGARCH were used to test and obtain the results for the following objectives:

- To examine the causal relationship between the variables
- To model the volatility in the variables.
- To analyse the impact of positive and negative news shocks on volatility of the variables
- To understand the asymmetric relationship between the return and volatility of the variables

RESULTS AND DISCUSSIONS

To investigate the volatility of the crypto market the sample variables have been analysed and tested. The daily closing prices of the variables demonstrate a random walk pattern which indicated that there is no mean reversion. Generally any time series data shall be non-stationary in nature that is, the mean and the variance shall vary over a period of time. Constant mean and variance indicate that the data is stationary and suitable for modelling. In the process of modelling volatility, it's highly essential to test the data for Stationarity with the help of the Augmented Dickey Filler Test. The results are presented in the table 01. The results indicate that the closing prices of BTC, ETH and ADA has a unit root. Therefore the log returns were calculated for the closing prices and was found that the return series of the variables do not have a unit root. Now the return series can be used for further analysis as majority of the econometric models can be applied on a data which is stationary.

TABLE 01: ADF TEST

Null Hypothesis: There is a unit root					
Series	**1% level**	**5% level**	**10% level**	**t-Statistic**	**Prob.***
BTC	-3.967289	-3.414332	-3.129289	-1.795958	0.7063
RBTC	-3.967326	-3.41435	-3.129299	-34.00391	0.0000
ETH	-3.96744	-3.414406	-3.129332	-1.896544	0.6555
RETH	-3.967326	-3.41435	-3.129299	-34.54302	0.0000
ADA	-3.967587	-3.414477	-3.129375	-1.89163	0.6581

RADA	-3.967326	-3.41435	-3.129299	-34.19114	0.0000

To understand the short run causal relationship between the variables, Granger causality test has been applied and the results have been presented in table 02. The causality test reveals that a short run causation exist between variables that is a unidirectional causation is found between RBTC to RADA, RETH to RADA and RETH to RBTC. In the short run the changes or volatility in RADA is influenced by the volatility inn RBTC and RADA and similarly volatility in RBTC is influenced by the changes in RETH.

Table 02: Granger Causality Test with Lag 2

Null Hypothesis:	**F-Statistic**	**Prob.**
RBTC does not Granger Cause RADA	4.62864	0.01
RADA does not Granger Cause RBTC	1.50416	0.2227
RETH does not Granger Cause RADA	4.14285	0.0162
RADA does not Granger Cause RETH	0.14543	0.8647
RETH does not Granger Cause RBTC	3.70651	0.0249
RBTC does not Granger Cause RETH	0.43059	0.6502

Based on the results of Granger causality, RADA has been considered as a dependent variable as the volatility of ADA is influenced by BTC and ETH. A regression equation considering RBTC and RETH as independent variables has been run to understand the independent variables ability to explain the changes in the dependent variable. The results presented in table 03 indicate that both RBTC and RETH coefficients are significantly influencing the RADA. The R square also indicates that the changes in the dependent variable are explained by the independent variable to an extent of 58%. To accept the existing regression models it's essential to test the residuals for auto correlation and hetroskedasticity. The residual were tested and results given in table 04 indicate that the residuals are hetroskedastic which means that the errors are dependent of time or the volatility varies from one time to another time. The graph also demonstrates clustering volatility in residuals.

Table 03: Least Squares

Dependent Variable: RADA

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	0.001073	0.001208	0.888263	0.3746
RBTC	0.247725	0.053158	4.660193	0
RETH	0.716121	0.041116	17.41701	0
R-squared	0.583425	Akaike info criterion		-3.688619
Adjusted R-squared	0.582592	Schwarz criterion		-3.673942
Prob(F-statistic)	0	Durbin-Watson stat		1.983353

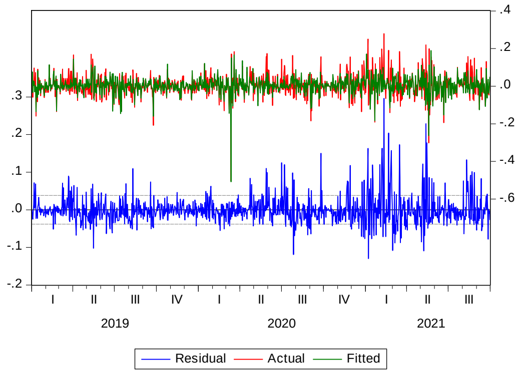

Table 04: Heteroskedasticity Test	
F-statistic	10.76721
Obs*R-squared	10.67391
Prob. F(1,1001)	0.0011
Prob. Chi-Square(1)	0.0011

Since the residuals are hetroskedastic its becomes essential to understand the impact of past variance and errors on present and future volatility and smartly the impact of good and bad news on volatility of the variable. The GARCH model allows the conditional variance to be dependent upon previous own lags apart from the past innovation. The GARCH family models help us in estimating the extent of volatility caused by the past variance in a variable and the results have been presented in the table 05, 06 & 07. Based on the results obtained it evident that past variance (GARCH) and past errors (ARCH) have a significant relationship with present volatility that is they significantly contribute to the volatility of all the selected variables. The bad news creates more volatility in the variable than the good news of the same magnitude. The positive and significant TGARCH coefficient indicates the significant relationship between bad news and volatility. The result also indicates that the volatility created by a bad news is significantly high (0.169) in BTC that ETH and ADA. But an asymmetry between the returns and volatility is found in all three variables.

TABLE 05: GARCH FAMILY MODEL RESULTS FOR RBTC

RBTC	GARCH	TARCH	EGARCH
Variable	Coefficient (p value)	Coefficient (p value)	Coefficient (p value)
C	0.000137 0.000	0.000187 0.000	(-0.695082) 0.000
ARCH (Past Error)	0.104187 0.000	0.046466 0.0005	0.171348 0.000
GARCH (Past Variance)	0.821727 0.000	0.769257 0.000	0.91079 0.000
Bad News Shocks	-	0.16939 0.000	-
Leverage Effect (Asymmetry)	-	-	(-0.068993) 0.000

Akaike info criterion	-3.680193	-3.696731	-3.693619
Schwarz criterion	-3.660624	-3.672271	-3.669158

TABLE 06: GARCH FAMILY MODEL RESULTS FOR RETH

RETH	GARCH	TARCH	EGARCH
Variable	Coefficient (p value)	Coefficient (p value)	Coefficient (p value)
C	0.000176 0.000	0.000237 0.000	(-0.561226) 0.000
ARCH (Past Error)	0.114371 0.000	0.081017 0.0002	0.20829 0.000
GARCH (Past Variance)	0.828972 0.000	0.798956 0.000	0.930785 0.000
Bad News Shocks	-	0.076107 0.000	-
Leverage Effect (Asymmetry)	-	-	(-0.039341) 0.0002
Akaike info criterion	-3.201267	-3.203349	-3.693619
Schwarz criterion	-3.181699	-3.178888	-3.669158

TABLE 07: GARCH FAMILY MODEL RESULTS FOR RADA

RADA	GARCH	TARCH	EGARCH
Variable	Coefficient (p value)	Coefficient (p value)	Coefficient (p value)
C	0.000321 0.000	0.000329 0.000	(-0.790309) 0.000
ARCH (Past Error)	0.148555 0.000	0.130729 0.000	0.298286 0.000
GARCH (Past Variance)	0.771951 0.000	0.755846 0.000	0.89945 0.000
Bad News Shocks	-	0.077581 0.0002	-
Leverage Effect (Asymmetry)	-	-	(-0.0387910) 0.001
Akaike info criterion	-2.913709	-2.914979	-2.918766
Schwarz criterion	-2.89414	-2.890518	-2.894305

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.

REFERENCES

- AL-MANSOUR, B. Y. (2020). Cryptocurrency market: Behavioral finance perspective. The Journal of Asian Finance, Economics, and Business, 7(12), 159-168.
- Malladi, R. K., & Dheeriya, P. L. (2021). Time series analysis of Cryptocurrency returns and volatilities. *Journal of Economics and Finance*, *45*(1), 75-94.
- Kyriazis, N. A., Daskalou, K., Arampatzis, M., Prassa, P., & Papaioannou, E. (2019). Estimating the volatility of cryptocurrencies during bearish markets by employing GARCH models. *Heliyon*, *5*(8), e02239.
- Feng, W., Wang, Y., & Zhang, Z. (2018). Can cryptocurrencies be a safe haven: a tail risk perspective analysis. *Applied Economics*, *50*(44), 4745-4762.
- Qayyum, A., & Kemal, A. R. (2014). Volatility spillover between the stock market and the foreign exchange market in Pakistan. *Research Journal Social Sciences*, *3*(2).
- Morales, L. (2008). Volatility spillovers between stock returns and foreign exchange rates: evidence from four eastern European countries.
- Mishra, A. K., Swain, N., & Malhotra, D. K. (2007). Volatility Spillover between Stock and Foreign Exchange Markets: Indian Evidence. *International journal of business*, *12*(3).