Asymmetric Volatility Modelling Using Threshold-GARCH Approach Of Various Cryptocurrencies, Financial Markets, And Investment Alternatives

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ABSTRACT

Asymmetric volatility often acknowledged as the leverage effect is described as an indicator of investment decision-making by various financial investors. Simple ARCH/GARCH models are incapable of dealing with the impact of leverage effect on financial markets. Hence, this paper is an attempt to capture the impact of asymmetric news, happenings, and events causing volatility in various Cryptocurrencies, Financial Markets, and Investment Alternatives using "the T-GARCH model", an extension of the simple "GARCH" model. The study undertakes the dataset of daily close prices from FY 2015 to FY 2020 of financial markets and investment alternatives namely; NYSE DJ, NIFTY, SENSEX, Crude Oil, Gold, and USD along with 10 cryptocurrencies namely, Binance coin, Bitcoin cash, Bitcoin SV, Bitcoin, EOS, Ethereum, Litecoin, Monero, Tether, and Ripple, from emerging cryptocurrency market extracted from yahoo finance and coin market cap. The empirical results provide a viewpoint of the reaction of leverage effect on selected time series of financial markets and alternatives. We observe that some of the time series are showing the inverted asymmetric effect on the market prices, that is, the positive news or events have a more significant impact on the price volatility than the bad ones. These findings will benefit largely the investors in making an essential financial decision in times of uncertainty and turmoil.

JEL Codes: C580, C220, C180, C120, C150, C210

Keywords: Threshold GARCH, ARCH, ARMA, Asymmetric Volatility, Cryptocurrencies, Financial Markets.

1. INTRODUCTION

Individual investors' decisions are generally influenced by their age, investment portfolio, education, income, and other demographic characteristics. To create efficient investment plans for individual investors, investment advisers, and finance experts must include behavioral difficulties as risk factors. In foreign exchange markets, traders, arbitrageurs, speculators, and hedgers. When compared to certain other types of investments, the forex trading market is the largest globally. There are various traders in India who trade commodities based on the link between the exchange rate and the commodity price. Government policies, such as the budget, inflation, and the country's economic and political situation, all have an impact on gold and crude oil prices (Joshi, 2011). The development of international commerce necessitated the ability to evaluate the relative worth of currencies based on their buying power disparities. Foreign exchange risk arose as a result of the necessity to convert one currency to another to deal in goods and services, resulting in a thriving forex market.

Sebi's board of directors has been tasked with protecting investors' interests since its inception in 1992. Minimum investment thresholds for high-risk goods, including portfolio management services, are part of the path to safeguard investor interests. Many international investors engage in India through portfolio investments.

While gold, crude oil, and financial markets are seen to be good hedges in times of economic depression, more young Indians appear to be changing their minds. As things stand, digital coin investments make up a small portion of bullion market holdings, but younger Indians prefer cryptocurrencies to gold. Cryptocurrency is emerging and being used more swiftly than predicted in India, but the country is falling behind in developing appropriate financial literacy about the commodity at the same time, owing to legal and legislative ambiguities. This poses a risk because the crypto business is still in its early stages, with a plethora of currencies and tokens, many of which will eventually perish, putting the money of major investors at risk. Bhattacharjee & Kaur (2015), explored the emergence of Bitcoin as a currency, the events before and following it, as well as its ramifications and impacts on the current economy. The authors talked about its growth, transaction volumes, currency acceptance, and other considerations.

India's cryptocurrency investment volumes have been quickly increasing, putting it in the lead globally. Since March 2020, when the Supreme Court overturned a Reserve Bank of India prohibition on crypto trading, cryptocurrency has made a remarkable comeback in India. According to industry estimates, more than $1 billion equivalent has been invested by around 15 million Indians (Kaul, 2021). Hence, investing in cryptos is expected to grow in the next few days, necessitating a greater emphasis on educating investors about the current financial landscape. “At least 1.5 crore Indians have invested in cryptocurrencies, according to different reports, indicating significant cryptocurrency proliferation in a nation where households are known to prefer gold and other safer investments. As seen by the growing number of cryptocurrency users, the country's younger generation is forcing a shift in the investment paradigm.", Das, 2021.

Scientists, researchers, and technocrats have for years been engaged in the quest of discovering the reason for volatility in the financial markets (Berggren & Folkelid (2015) in turn trying to help investors around the world to make wise investments. The latest studies by various researchers and authors have signaled a crucial issue of vulnerability in investing, especially in cryptocurrency markets (Liu & Serletis, 2019). These markets have been continuously considered volatile (Costa, 2017). A higher volatility means high risk on investment resulting in higher returns (Phillip, et al. 2019). Despite of decentralized nature (Sovbetov, 2018), investors are using it as a speculative tool instead of using it as a payment method. Furthermore, this has led to the popularity and growth in terms of volume and market capitalization of some leading cryptocurrencies such as bitcoin (Cheikh, et al., 2020), and is proven to be the favorite investment alternatives of investors (Balcilar, et al, 2017; Katsiampa, 2017; Katsiampa, 2019) that is being accepted globally (Vo & Xu, 2017).

However, the recent emergence of the pandemic has led investors and researchers to re-examine the coordinated action plans to mitigate the impact of news events and take suitable measures to minimize the risk caused by them. To achieve this goal of risk and return planning for the financial markets. The accurate forecasting process is a critical step in the decision-making process for investors, as it improves and guarantees that risk and return analyses can be carried out efficiently in the ever-changing globalized economy.

Price movements are inevitable phenomena of the financial market (Goudarzi & Ramanaraynan, 2011) and are further accelerated by events, incidents, and news such as mergers and acquisitions, takeovers, launches of newly discovered products or services, international relations, etc have a very powerful and strong impact on the decision making of the financial investors. Consequently, having an asymmetric impact on the financial markets (Wajdi, et al., 2020; Cheikh, et al., 2020). Asymmetric volatility is a phenomenon that refers to the fact that equity market volatility is higher in sinking markets than in rising markets. When the broader market is performing badly, the fluctuation of security is greater than when it is performing well. Although experts dispute what causes asymmetric volatility, variables like leverage and panic are frequently mentioned. Hedging techniques and option pricing models benefit from the existence of asymmetric volatility (Financial Glossary, 2011).

Models such as ARCH (Auto-regressive conditional heteroskedasticity) and GARCH (Generalised auto-regressive conditional heteroskedasticity) are the most abundantly used forecasting models and tools but they rarely work in the market with a condition of asymmetric volatility (Engle & Ng, 1982; Wajdi, et al., 2020). Hence, they are incapable of capturing the leverage effect in the financial markets, and in reality, the market never remains unimpacted by social, political, technological, or environmental happenings. Furthermore, if asymmetric volatility is ignored then it will lead to a significant underestimation of risk that will add up to unbearable losses to the investors and stakeholders of financial markets and other investment alternatives (Cheikh, et al., 2020).

To compute asymmetries an asymmetric GARCH model will help better than a simple GARCH model (Grinberg, 2012; Gronwald, 2014; Katsiampa, 2017; Teräsvirta, 2009). T-GARCH (Threshold GARCH) (Bouoiyour & Selmi, 2015; Bouoiyour & Selmi, 2016; Bouri, et al. 2017; Vo & Xu, 2017), an extension of simple GARCH model developed by Zakoian (1990) and Glosten, Jaganathan and Runkle (1993) also acknowledged as GJR model was developed to capture the leverage effect in the financial markets. It is so far considered “the best model to capture the leverage effect” (Engle & Ng, 1993).

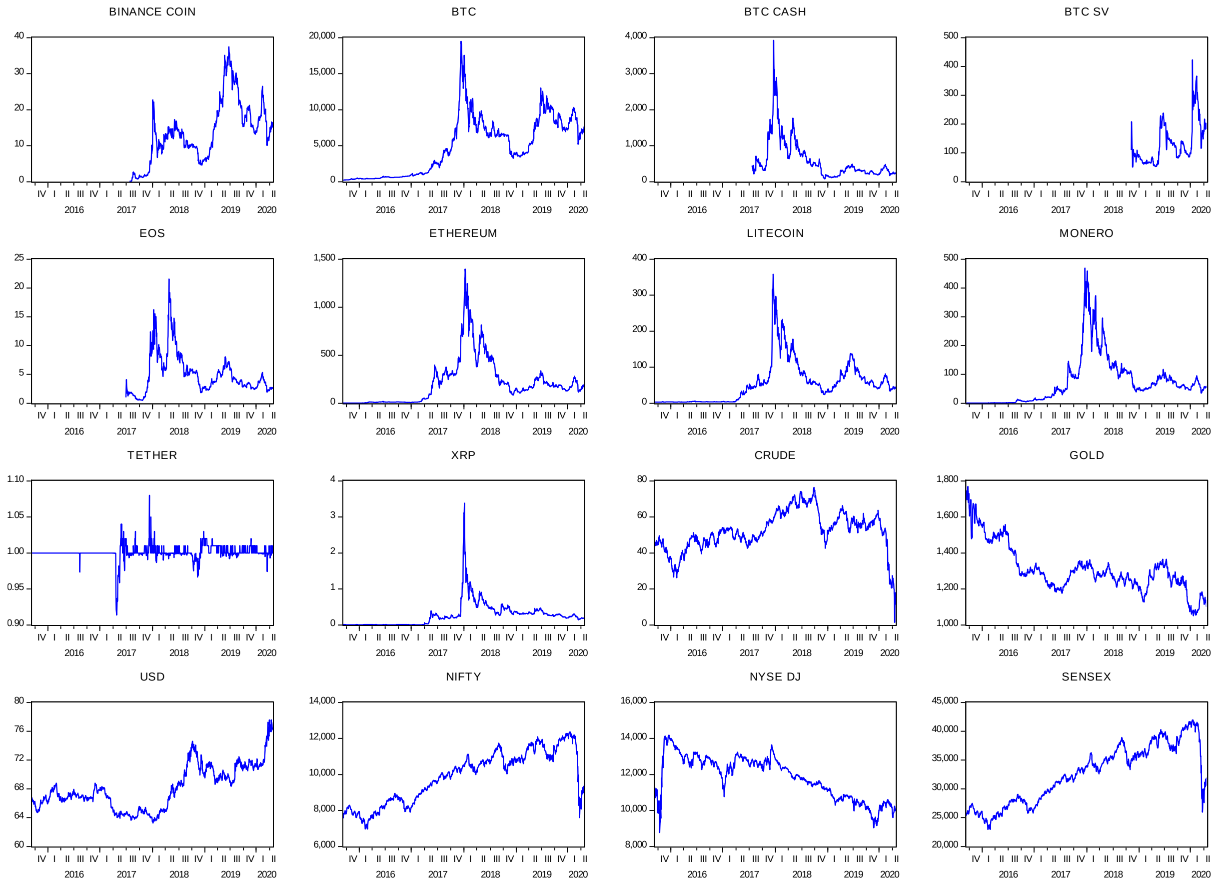

Figure 1: The Daily Closing Price of Selected Time Series Data (Source: The Author)

For this reason, this paper is an attempt to assess the impact of news, happenings, and events causing asymmetric volatility in the financial markets using the “T-GARCH” model, an extension of the simple “GARCH” model. The study undertakes the dataset of daily close prices from FY2015 to FY 2020 of financial markets and investment alternatives are NYSE DJ, NIFTY, SENSEX, Crude Oil, Gold, and USD along with 10 cryptocurrencies namely, Binance coin, Bitcoin cash, Bitcoin SV, Bitcoin, EOS, Ethereum, Litecoin, Monero, Tether, and Ripple, from the emerging financial market.

We have investigated the asymmetric volatility using ARMA-TGARCH (1,1,1) model. We found that the selected time series dataset consists of the leverage effect and is beneficial in providing useful insights to the investors of financial markets.

2. LITERATURE REVIEW

For a long, many researchers have contributed to huge literature and addressed the problems in the financial markets. Such as Sotomayor & Cadenillas, A. (2009) addressed the problem of consumption and investment by an investor in the financial market with different regimes. Other authors, Narayanaswamy, & Karthika (2018) shredded some light on the use of cryptocurrency, Bitcoin, as an investment instrument by comparing their characteristics of the investment and its international acceptance. Whereas, Vishwanath & Kaufmann (2001) emphasized the need for transparency through implementing disclosure policies and regulations in the financial markets (Brunnermeier, et al., 2009; Jansen, 2011). Furthermore, many authors have tried to identify and study the volatility in the financial markets (Green & Pearson, 1995; Lillo & Mantegna, 2000; Poon & Granger, 2003; Tsantekidis, et al, 2017).

The problem of volatility has increased, for a decade, with the introduction of cryptocurrencies. Greater volatility will increase the risk and stability in the markets (Valenti, et al., 2018; Catania, et al., 2018). There have been studies that focused on the impact on economies due to a flutter in asset prices. Sudden changes in the price of assets have resulted in considerable changes in the financial markets around the globe (Akyildirim, et al., 2020). Liu & Serletis (2019) studied return and volatility spillover between cryptocurrencies and other financial markets and found a significant spillover of return and volatility from the cryptocurrency market to various financial markets. Othman, et al (2019) compared the volatility of three forms of cryptocurrencies to fiat currency and gold to determine whether they can be used as investment assets against various market risks associated with financial markets. Bishnoi & Ved. (2018) captured the roles of macroeconomic variables in explaining the volatility of the Indian stock market using the MIDAS GARCH approach.

The importance of understanding the financial market volatility is increasing among investors as they their return on money invested and the risk associated with it (Mamtha & Srinivasan, 2016). Some studies have examined the volatility of time series data of the cryptocurrency market and financial market through GARCH models (Bollerslev, 1986; Engle, 2001; Williams, 2011; Ruppert, 2011). Engle, (2001) applied a simple GARCH model to the time series and gave the usefulness of the model in examining risk in the optimizing portfolio and analyzing risk in asset pricing.

In the latest study, Chopra & Saldi (2022) examined Bitcoin's persistence and hedging features in the pre-COVID period to show its efficiency and safety by examining essential data. The authors utilized daily and weekly data and used the GPH estimator and ARFIMA to map the changing efficiency of the Bitcoin price, and the Threshold GARCH (TGARCH) was used to analyze the trade connection between Bitcoin prices and four key indexes, namely the S & P 500, FTSE, Hang Seng, and Nikkei.

However, the simple GARCH model is only ideal when there is symmetry in the price volatility. They are incapable of addressing the problem of asymmetric volatility or the leverage effect (Jiang, 2012; Hassan, et al, 2018). In practicality, the market does not react equally or uniformly to both positive and negative news. Researchers have concluded that financial market reaction toward positive and negative news is different (Katsiampa, 2019). Katsiampa, et al, (2019) investigated volatility co-movements and conditional volatility dynamics of major cryptocurrencies and concluded that there are significant asymmetric effects of good and bad news in the time series.

There are many authors focused on capturing the leverage effect or asymmetric volatility through various models. Rabemananjara & Zakoian, (1993) in their study evidenced the presence of asymmetries in the volatility in the French stock series and applied the TGARCH model (Zakoian, 1994) and asymmetry may be inverted between large and small values. They further suggested employing a richer dataset than their study. Ewing & Malik (2017) performed a similar study with oil price return to analyze asymmetric volatility. Another study to analyze the impact of positive and negative news on the Indian stock market by using asymmetric volatility GARCH and TGARCH models concluded that negative news results in more volatility in the Indian stock market (Goudarzi & Ramanarayanan, 2011). Wang & Yang, (2009) in a study significantly tested for asymmetric volatility in four major bilateral exchange rates and stated that negative returns are associated more with risk than positive ones.

Sabiruzzaman, et al., (2010) in their comparative study found that TGARCH models are superior in capturing leverage effect when asymmetric information about a time series is available. While testing the impact of news on volatility, Engle & Ng (1993) suggested that the GJR GARCH model given by Glosten, Jagannathan, and Runkle (1993) is the best model to capture asymmetric volatility also known as the GJR GARCH model. Varughese & Mathew (2017) studied the leverage effect and impact of FPI on stock market volatility, the study used ARCH family models; GARCH, E-GARCH, and TARCH.

While volatility and its impact have been studied by many authors but very little focus has been given to asymmetric volatility and its impact on the various financial markets and cryptocurrency markets. It is well known that there is a paradigm shift towards investment alternatives by investors and they are investing a huge pool of money in cryptocurrency markets. These markets are impacted by asymmetric volatility in their price returns which becomes a big concern for investors in decision-making.

For these reasons, this study aims to investigate the impact of asymmetric volatility on the financial market, the cryptocurrency market, and other investment alternatives by employing the Threshold GARCH model (Zakoian, 1990).

3. METHODOLOGY

Given the importance to capture the impact caused to financial markets by asymmetric volatility causing the behavioral preferences of investors' decision-making, many approaches have extensively been discussed in the literature by various authors. The most useful in analyzing asymmetric volatility in time series data is the Threshold GARCH model, an extension of the simple GARCH model.

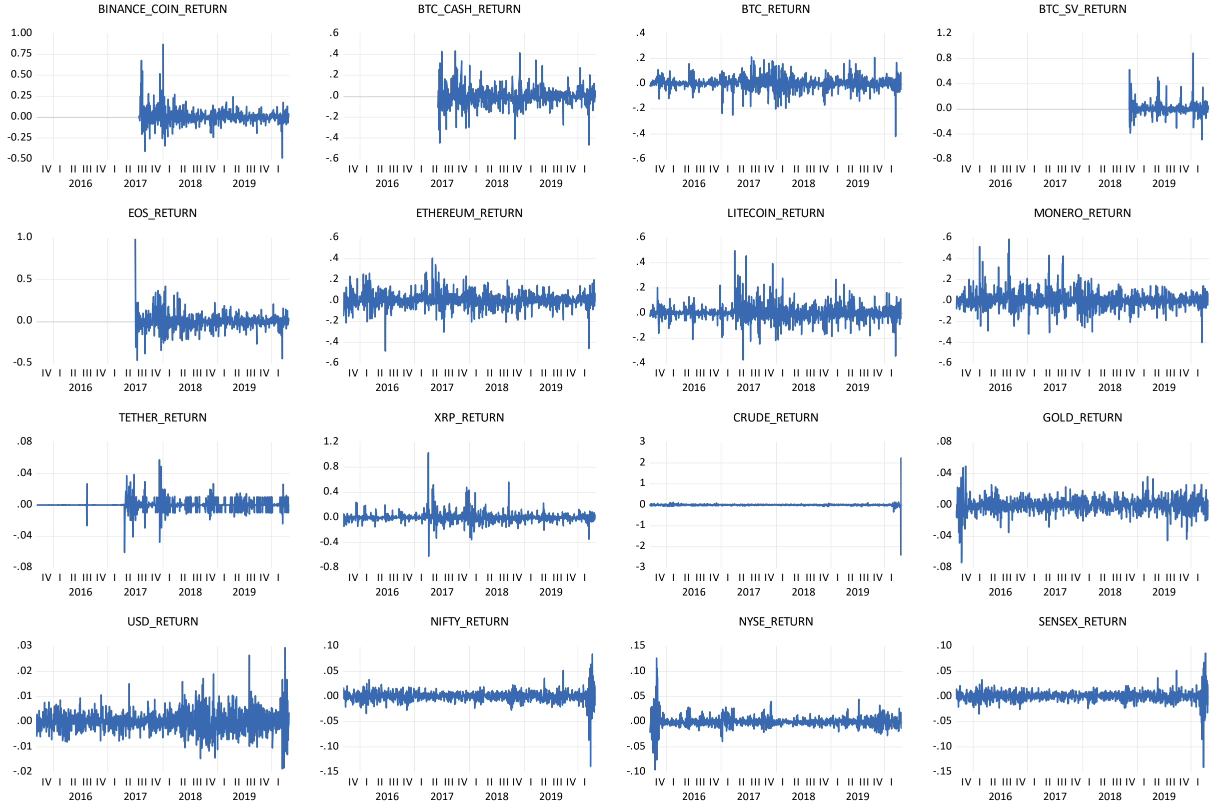

Figure 2 Representing Stationary Time Series Returns of Selected Dataset. (Source: The Author)

The dataset considered in the study is the daily close prices time series from period 7 October 2015 to 29 April 2020 of financial markets and investment alternatives are NYSE DJ, NIFTY, SENSEX, Crude Oil, Gold, and USD along with 10 cryptocurrencies namely, Binance coin, Bitcoin cash, Bitcoin SV, Bitcoin, EOS, Ethereum, Litecoin, Monero, Tether and Ripple from emerging financial market extracted from yahoo finance and coin market cap. The exceptions are Bitcoin SV, Binance coin, EOS, and Bitcoin cash whose data starts from 5 November 2018, 25 July 2017, 30 June 2017, and 05 June 2017 respectively.

By taking the natural logarithm of the ratio of two consecutive values (present-day and previous-day values), time series returns of the selected dataset are calculated, figure 2 represents the graphs of the dataset employed in the study and is a mean reverting process.

The techniques applied in the study are "the Jarque-Bera test for normality", "the Augmented Dickey-Fuller" unit root test for stationarity followed by the Heteroskedasticity test by "LM ARCH (Lag range Multiplier Auto-Regressive Conditional Heteroskedasticity Test)". "Ljung Box test" is used to observe the autocorrelation of time series residuals followed by the "Threshold GARCH (1,1,1)" model.

4. DATA ANALYSIS AND INTERPRETATION

4.1 Jarque-Bera Test for Normality

"The Jarque- Bera test is a goodness of fit test" that evaluates the skewness and kurtosis of sample data to determine whether or not they follow a normal distribution. Jarque-Bera test for normality test signifies kurtosis in time series returns. The normality of time series data should be tested on a model's residuals to see whether there is any unexplained variance. Also, while severely skewed data might be troublesome, the assumptions of independence, linearity, and heteroskedasticity can have a greater impact on the test's reliability than distribution assumptions.

To check for asymmetric volatility kurtosis and skewness are analyzed and are observed to be more significant than the normal distribution. The positive larger value of the Jarque-Bera test and the low value of the p-value indicates that the time series returns are not normally distributed and are rejected that the data is normally distributed.

Table 1: Jarque-Bera Test for Normality(Source: The Author)

SN	TIME SERIES	JARQUE-BERA VALUE	p-VALUE
1	BINANCE COIN	34.10332	0.0000
2	BITCOIN	67.95077	0.0000
3	BITCOIN CASH	1752.656	0.0000
4	BITCOIN SV	114.2875	0.0000
5	EOS	501.015	0.0000
6	ETHEREUM	1517.129	0.0000
7	LITECOIN	1589.783	0.0000
8	MONERO	1690.327	0.0000
9	RIPPLE	23166.58	0.0000
10	TETHER	34404.53	0.0000
11	CRUDE OIL	102.8631	0.0000
12	GOLD	202.5309	0.0000
13	USD	69.70167	0.0000
14	NIFTY	76.15442	0.0000
15	NYSE DJ	56.88713	0.0000
16	SENSEX	70.32612	0.0000

The p-value of all 16-time series returns is 0.0000 which is less than 0.05, we consider that the selected time series are not normally distributed, hence the kurtosis and skewness of the series are also not that of normally distributed and are significantly different from a normal distribution. The Jarque-Bera test result indicates that the series are having asymmetric volatility.

4.2 Augmented Dickey-Fuller Test for Stationarity

The ADF test is used on the time series' first difference. It is the progression of change from one epoch to the next. In a random walk model, each series takes a random path away from its previous value. The series is considered to be auto-correlated if the value does not take a random route and instead follows its prior value.

Table 2: Augmented Dickey-Fuller Unit Root Test for Stationarity. (Source: The Author)

SN	TIME SERIES	ADF p-VALUE	Ho: Time series has unit roots or series is not stationarity	Number of Lags
1	BINANCE COIN	0.0000	Rejected	0
2	BITCOIN	0.0000	Rejected	0
3	BITCOIN CASH	0.0000	Rejected	0
4	BITCOIN SV	0.0000	Rejected	0

SN	TIME SERIES	ADF p-VALUE	Ho: Time series has unit roots or series is not stationarity	Number of Lags
5	EOS	0.0000	Rejected	0
6	ETHEREUM	0.0000	Rejected	0
7	LITECOIN	0.0000	Rejected	0
8	MONERO	0.0000	Rejected	2
9	RIPPLE	0.0000	Rejected	1
10	TETHER	0.0000	Rejected	0
11	CRUDE OIL	0.0000	Rejected	4
12	GOLD	0.0000	Rejected	0
13	USD	0.0000	Rejected	1
14	NIFTY	0.0000	Rejected	6
15	NYSE DJ	0.0000	Rejected	7
16	SENSEX	0.0000	Rejected	6

To test for stationarity of time series data, ADF unit root test (Augmented Dickey-Fuller test). The results of the ADF test are presented in table 2 that shows since all the p-values are less than 0.05, we reject the null hypothesis that time series has unit roots. Hence it can be illustrated that all the time series undertaken in the study are mean reverting and are stationary. Figure 2 represents that all the 16-time series returns are stationary and are autocorrelated to their previous values.

Once the ADF test is significant and suggests that selected time series returns are stationary, we check for the presence of volatility clustering in the data by employing Engle's LM-ARCH (Lagrange Multiplier Autoregressive Conditional Heteroskedasticity) test.

4.3 Engle's LM-ARCH Test for Heteroskedasticity

Volatility is the indication of fluctuation in prices and suggests that the market is uncertain and unpredictable. There is always the risk of volatility in the market because of events, happenings, and news. Volatility is not similar in the case of a positive or negative market event creating a leverage or asymmetric effect in the financial markets.

In statistics When the conditional variance in time series data is not constant, then there is heteroscedasticity present in the data. Conditional variance is the variation in the dependent variable y that each value of the explanatory variables X, or for each value of time period t.

Table 3: Engle's LM-ARCH Test for Heteroskedasticity (Source: The Author)

SN	TIME SERIES	P-VALUE	Ho: No ARCH effect present or There is no volatility clustering in the time series	Number of Lags
1	BINANCE COIN	0.0000	Rejected	1
2	BITCOIN	0.0000	Rejected	1
3	BITCOIN CASH	0.0000	Rejected	4
4	BITCOIN SV	0.0319	Rejected	3
5	EOS	0.0000	Rejected	1
6	ETHEREUM	0.0095	Rejected	1
7	LITECOIN	0.0000	Rejected	1
8	MONERO	0.0023	Rejected	2
9	RIPPLE	0.0000	Rejected	1

SN	TIME SERIES	P-VALUE	Ho: No ARCH effect present or There is no volatility clustering in the time series	Number of Lags
10	TETHER	0.0000	Rejected	1
11	CRUDE OIL	0.0000	Rejected	1
12	GOLD	0.0000	Rejected	1
13	USD	0.0000	Rejected	1
14	NIFTY	0.0000	Rejected	1
15	NYSE DJ	0.0000	Rejected	1
16	SENSEX	0.0000	Rejected	1

Conditional heteroskedasticity is frequently observed in the prices of stocks and bonds in financial markets. These shares', financial markets', commodities', or cryptocurrencies' volatility cannot be forecast over any time period. It refers to a systematic shift in the spread of residuals throughout the range of observed values, or uneven scatter. Heteroskedasticity occurs more frequently in datasets having a large range of values between the highest and lowest recorded values. Our dataset also consists of a wide range.

Hence, we apply Engle's LM-ARCH (Lagrange Multiplier Autoregressive Conditional Heteroskedasticity) test to assess conditional heteroskedasticity based on our data, where future value may be predicted based on the previous value. Table 3 summarises for autocorrelation of residuals of selected time series returns and confirms the ARCH effect or volatility clustering, since all the p-values are less than 0.05, we reject the null hypothesis that there is no volatility clustering in the time series. Hence it can be illustrated that all the time series undertaken in the study are having ARCH effect present in them or there is significant volatility clustering present in the dataset and is prone to heteroskedasticity.

5. EMPIRICAL RESULTS

5.1 Application of ARIMA-TGARCH (1,1,1) Model

When using forecasting methods like "AR", "ARMA", and "ARIMA" to model time series, a change in variance or volatility over time might pose issues. There are several approaches to dealing with variable variation. GARCH is generally regarded as a good model. The "ARCH" technique, or "Autoregressive Conditional Heteroskedasticity", is a methodology to describe a time-dependent change in variance in a time series. "GARCH" models are incapable of dealing with this problem since our data reveals indications of asymmetric volatility. The "TGARCH" model, also known as the "GJR" model, is used to solve the asymmetric model issue.

The "AR", "MA", "ARMA", and "ARIMA" models are used to anticipate the observation at (t+1) using past data from prior time points. In time series analysis, researchers use historical data to forecast the present and future values. However, this isn't always enough. Unexpected events, such as natural catastrophes, financial events, occurrences, financial crises, or wars, can cause a rapid change in values, producing uneven fluctuations in asset prices. There is a need for models that can use previous data as a basis for projections while also being able to swiftly react to unexpected shocks. However, it is important to ensure that the time series remains stationary across the observation period's past information. “ARMA” is the abbreviation for “Autoregressive Moving Average” and was created by combining two simpler models: the “Autoregressive” (AR) and “Moving Average” (MA).

The Auto Correlation function considers all previous observations, regardless of their impact on the future or current time period. In today's spectrum estimate, the “AR” model is frequently employed. It is one of the ways of model parametric spectrum analysis and is a widely used model in contemporary spectrum estimation. The “AR” parameters are estimated first, and then the “MA” parameters are determined based on these “AR” parameters in the calculation of the “ARMA” parameter spectrum. The “ARMA” model's spectral estimations are then obtained.

The study undergoes “ARMA” (Autoregressive moving average) method for selecting mean equations before applying “TGARCH” (1,1,1) model in the selected time series returns. Asymmetric volatility means that investors’ reaction is different in both positive and negative circumstances. Since this behavior cannot be explained by a simple “GARCH” model, which estimates the impact of symmetric volatility only, our estimation to predict the impact caused to financial markets by asymmetric information is based on the TGARCH (1,1,1) model. The threshold GARCH (or TGARCH) model is another frequently used volatility model to address leverage effects; see Glosten, Jagannathan, and Runkle (1993) and Zakoian (1993); Zakoian (1994). To perform the TGARCH model, a multiplicative dummy variable is added to the variance equation to examine the impact of asymmetric volatility on the selected dataset.

TGARCH (1,1,1) conditional model equation is:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma\varepsilon_{t-1}^2 D_{t-1}$$

Where h_t is volatility persistence, ω is constant, $\alpha\varepsilon_{t-1}^2$ is ARCH term, βh_{t-1} is GARCH term, βh_{t-1} is TGARCH term and D_{t-1} is the dummy variable and is considered ‘1’ in case of bad news and ‘0’ in case of good news.

1.1 Binance coin

The TGARCH coefficient ‘γ’ is positive with a value of 0.02 but is not statistically significant 5 % level as the p-value is 0.0913, so, the Binance coin Time series do not have asymmetries in the information or in the news that impact the cryptocurrency market. Hence we conclude from the result that there is no asymmetric volatility in the market and both, positive and negative, information will have a similar effect or a symmetric impact on the Binance coin time series. Therefore, the GARCH model will estimate a better forecasting model for the series.

The model for the Binance coin is given below:

$$h_t = 0.0000086 + 0.9162\varepsilon_{t-1}^2 + 0.064h_{t-1} + 0.0203\varepsilon_{t-1}^2 D_{t-1}$$

The difference between the impact of the good or bad information on the Binance coin is determined by the coefficient 'γ', ie, 0.0203 but the model is not statistically significant at a 5 % confidence level.

1.2 Bitcoin Cash

The TGARCH coefficient 'γ' is negative and has a value of -0.029 and is statistically significant 5 % level of confidence as the p-value is 0.033, so, Bitcoin cash prices have asymmetries in the information or in the news that impact its volatility. This further indicates that the impact of negative information will be significantly lower on the volatility of Bitcoin cash prices than the impact of positive information or news on the volatility.

The model for Bitcoin cash is given below:

$$h_t = 0.000395 + 0.888\varepsilon_{t-1}^2 + 0.067h_{t-1} + (-0.029)\varepsilon_{t-1}^2 D_{t-1}$$

The difference between the impact of the good or bad information on the Bitcoin cash is determined by the coefficient 'γ', ie, -0.029

1.3 Bitcoin

The TGARCH coefficient 'γ' is positive having a value of 0.060 and is statistically significant 5 % level of confidence as the p-value is 0.019, so, Bitcoin prices have asymmetries in the information or in the news that impact its volatility. This further indicates that the impact of negative information will be significantly higher on the volatility of Bitcoin than the impact of positive information or news on the volatility.

The model for Bitcoin is given below:

$$h_t = 0.0000086 + 0.763\varepsilon_{t-1}^2 + 0.13h_{t-1} + 0.060\varepsilon_{t-1}^2 D_{t-1}$$

The difference between the impact of good or bad information on Bitcoin is determined by the coefficient 'γ', ie, 0.060

1.4 Bitcoin SV

The TGARCH coefficient 'γ' is positive with a value of 0.0738 but is not statistically significant 5 % level as the p-value is 0.446, so, Bitcoin cash prices do not have asymmetries in the information or in the news that impact the cryptocurrency market. Hence we conclude from the result that there is no asymmetric volatility in the market and both, positive and negative, information will have a similar effect or symmetric impact on the Bitcoin SV time series. Therefore, the GARCH model will estimate a better forecasting model for the series.

The model for Bitcoin SV is given below:

$$h_t = 0.000828 + 0.6188\varepsilon_{t-1}^2 + 0.4358h_{t-1} + 0.0738\varepsilon_{t-1}^2 D_{t-1}$$

The difference between the impact of the good or bad information on the Bitcoin SV is determined by the coefficient 'γ', ie, 0.0738 but the model is not statistically significant at a 5 % confidence level.

1.5 EOS

The TGARCH coefficient 'γ' is negative and has a value of -0.0303 and is statistically significant 5 % level of confidence as the p-value is 0.0007, so, EOS prices have asymmetries in the information or in the news that impact its volatility. This further indicates that the impact of negative information will be significantly lower on the volatility of EOS prices than the impact of positive information or news on the volatility.

The model for EOS is given below:

$$h_t = 0.000101 + 0.9606\varepsilon_{t-1}^2 + 0.0365h_{t-1} + (-0.0303)\varepsilon_{t-1}^2 D_{t-1}$$

The difference between the impact of the good or bad information on the EOS is determined by the coefficient 'γ', ie, -0.0303

1.6 Ethereum

The TGARCH coefficient 'γ' is negative and has a value of -0.0443 and is statistically significant 5 % level of confidence as the p-value is 0.0041, so, Ethereum prices have asymmetries in the information or in the news that impact its volatility. This further indicates that the impact of negative information will be significantly lower on the volatility of Ethereum prices than the impact of positive information or news on the volatility.

The model for Ethereum is given below:

$$h_t = 0.000355 + 0.8414\varepsilon_{t-1}^2 + 0.1169h_{t-1} + (-0.0443)\varepsilon_{t-1}^2 D_{t-1}$$

The difference between the impact of the good or bad information on Ethereum is determined by the coefficient 'γ', ie, -0.0443

1.7 Litecoin

The TGARCH coefficient 'γ' is negative and has a value of -0.039 and is statistically significant 5 % level of confidence as the p-value is 0.0000, so, Litecoin prices have asymmetries in the information or in the news that impact its volatility. This further indicates that the impact of negative information will be significantly lower on the volatility of Litecoin prices than the impact of positive information or news on the volatility.

The model for Litecoin is given below:

$$h_t = 0.000000866 + 0.9519\varepsilon_{t-1}^2 + 0.0453h_{t-1} + (-0.039)\varepsilon_{t-1}^2 D_{t-1}$$

The difference between the impact of the good or bad information on Litecoin is determined by the coefficient 'γ', ie, -0.039.

1.8 Monero

The TGARCH coefficient 'γ' is negative and has a value of -0.068 and is statistically significant 5 % level of confidence as the p-value is 0.0000, so, Monero prices have asymmetries in the information or in the news that impact its volatility. This further indicates that the impact of negative information will be significantly lower on the volatility of Monero prices than the impact of positive information or news on the volatility.

The model for Monero is given below:

$$h_t = 0.000309 + 0.8721\varepsilon_{t-1}^2 + 0.1143h_{t-1} + (-0.068)\varepsilon_{t-1}^2 D_{t-1}$$

The difference between the impact of the good or bad information on the Monero is determined by the coefficient 'γ', ie, -0.068.

1.9 Tether

The TGARCH coefficient 'γ' is negative with a value of -0.0612 but is not statistically significant 5 % level as the p-value is 0.0711, so, the Tether Time series do not have asymmetries in the information or in the news that impact the cryptocurrency market. Hence we conclude from the result that there is no asymmetric volatility in the market and both, positive and negative, information will have a similar effect or a symmetric impact on the Binance coin time series. Therefore, the GARCH model will estimate a better forecasting model for the series.

The model for the Binance coin is given below:

$$h_t = 0.000000276 + 0.7512\varepsilon_{t-1}^2 + 0.215h_{t-1} + (-0.0612)\varepsilon_{t-1}^2 D_{t-1}$$

The difference between the impact of the good or bad information on the Binance coin is determined by the coefficient 'γ', ie, -0.0612 but the model is not statistically significant at a 5 % confidence level.

1.10 Ripple

The TGARCH coefficient 'γ' is negative and has a value of -0.1611 and is statistically significant 5 % level of confidence as the p-value is 0.0000, so, Ripple prices have asymmetries in the information or in the news that impact its volatility. This further indicates that the impact of negative information will be significantly lower on the volatility of Ripple prices than the impact of positive information or news on the volatility.

The model for Ripple is given below:

$$h_t = 0.000273 + 0.7887\varepsilon_{t-1}^2 + 0.2629h_{t-1} + (-0.1611)\varepsilon_{t-1}^2 D_{t-1}$$

The difference between the impact of the good or bad information on Ripple is determined by the coefficient 'γ', ie, -0.1611.

1.11 Crude Oil

The TGARCH coefficient 'γ' is positive and has a value of 0.0821 and is statistically significant 5 % level of confidence as the p-value is 0.0000, so, Crude oil prices have asymmetries in the information or in the news that impact its volatility. This further indicates that the impact of negative information will be significantly higher on the volatility of crude oil prices than the impact of negative information or news on the volatility.

The model for crude oil is given below:

$$\mathrm{h_t} = 0.00000370 + 0.7064\varepsilon_{t-1}^2 + 0.6754\mathrm{h}_{t-1} + 0.0821\varepsilon_{t-1}^2 \mathrm{D}_{t-1}$$

The difference between the impact of the good or bad information on the Crude oil price volatility is determined by the coefficient 'γ', ie, 0.0821.

1.12 Gold

The TGARCH coefficient 'γ' is negative with a value of -0.0147 but is not statistically significant 5 % level as the p-value is 0.211, so, the Gold Time series do not have asymmetries in the information or in the news that impact the cryptocurrency market. Hence, we conclude from the result that there is no asymmetric volatility in the market and both, positive and negative, information will have a similar effect or a symmetric impact on the Gold time series. Therefore, the GARCH model will estimate a better forecasting model for the series.

The model for Gold is given below:

$$\mathrm{h_t} = 0.000000203 + 0.9324\varepsilon_{t-1}^2 + 0.0451\mathrm{h}_{t-1} + (-0.0451)\varepsilon_{t-1}^2 \mathrm{D}_{t-1}$$

The difference between the impact of the good or bad information on the Gold is determined by the coefficient 'γ', ie, -0.0451 but the model is not statistically significant at a 5 % confidence level.

1.13 USD

The TGARCH coefficient 'γ' is negative and has a value of -0.068 and is statistically significant 5 % level of confidence as the p-value is 0.0041, so, USD has asymmetries in the information or in the news that impact its volatility. This further indicates that the impact of negative information will be significantly lower on the volatility of USD than the impact of positive information or news on the volatility.

The USD model is given below:

$$h_t = 0.0000000706 + 0.8444\varepsilon_{t-1}^2 + 0.1522h_{t-1} + (-0.068)\varepsilon_{t-1}^2 D_{t-1}$$

The difference between the impact of the good or bad information on the USD is determined by the coefficient ‘γ’, ie, −0.068.

1.14 Nifty

The TGARCH coefficient ‘γ’ is positive and has a value of 0.23819 and is statistically significant 5 % level of confidence as the p-value is 0.0000, so, Nifty has asymmetries in the information or in the news that impact its volatility. This further indicates that the impact of negative information will be significantly higher on the volatility of Nifty prices than the impact of positive information or news on the volatility.

The model for Nifty is given below:

$$h_t = 0.000000402 + 0.8430\varepsilon_{t-1}^2 \pm 0.012h_{t-1} + 0.23819\varepsilon_{t-1}^2 D_{t-1}$$

The difference between the impact of the good or bad information on the Nifty is determined by the coefficient ‘γ’, ie, 0.23819.

1.15 NYSE DJ

The TGARCH coefficient ‘γ’ is positive and has a value of 0.3873 and is statistically significant 5 % level of confidence as the p-value is 0.0000, so, NYSE has asymmetries in the information or in the news that impact its volatility. This further indicates that the impact of negative information will be significantly higher on the volatility of NYSE prices than the impact of positive information or news on the volatility.

The model for NYSE is given below:

$$h_t = 0.000000107 + 0.8421\varepsilon_{t-1}^2 + (-0.005)h_{t-1} + 0.3873\varepsilon_{t-1}^2 D_{t-1}$$

The difference between the impact of the good or bad information on the NYSE is determined by the coefficient ‘γ’, ie, 0.3873.

1.16 SENSEX

The TGARCH coefficient ‘γ’ is positive and has a value of 0.2324 and is statistically significant 5 % level of confidence as the p-value is 0.0000, so, SENSEX has asymmetries in the information or in the news that impact its volatility. This further indicates that the impact of negative information will be significantly higher on the volatility of SENSEX prices than the impact of positive information or news on the volatility.

The model for SENSEX is given below:

$$h_t = 0.000000380 + 0.8489\varepsilon_{t-1}^2 + (-0.013)h_{t-1} + 0.2324\varepsilon_{t-1}^2 D_{t-1}$$

The difference between the impact of the good or bad information on the SENSEX is determined by the coefficient 'γ', ie, 0.2324.

Table 4: ARMA-TGARCH (1,1,1) Results (Source: The Author)

SN	TIME SERIES	ARMA	α	β	γ	p-Value
1	BINANCE COIN	1,1	0.916	0.0643	0.02	0.0913
2	BITCOIN CASH	2,2	0.8889	0.067	-0.029	0.033
3	BITCOIN	1,1	0.763	0.13	0.060	0.0019
4	BITCOIN SV	1,1	0.618	0.4358	0.073	0.446
5	EOS	5,5	0.9606	0.0365	-0.030	0.0007
6	ETHEREUM	1,1	0.8414	0.1169	-0.044	0.0041
7	LITECOIN	2,2	0.9519	0.0459	-0.039	0.000
8	MONERO	2,2	0.8721	0.1143	-0.068	0.000
9	RIPPLE	1,1	0.7887	0.2629	-0.0612	0.0711
10	TETHER	1,1	0.751	0.215	-0.1411	0.0000
11	CRUDE OIL	1,1	0.7064	0.0821	0.675	0.0000
12	GOLD	6,6	0.9324	0.0451	-0.0147	0.219
13	USD	1,2	0.844	0.1522	-0.068	0.0041
14	NIFTY	3,3	0.843	-0.0120	0.238	0.0000
15	NYSE DJ	3,3	0.8421	-0.0051	0.387	0.0000
16	SENSEX	5,5	0.8489	-0.013	0.232	0.0000

The result shows that the positive value of γ signifies that the negative event, news, or happening has more impact than the positive news and the negative value of γ signifies that positive news has more impact on the volatility. The significant p-value is the indication of asymmetric volatility presence.

It is worth highlighting that from the selected time series of various financial markets. Binance coin, Bitcoin cash, Bitcoin SV, Crude oil, Nifty, NYSE DJ, and SENSEX are series whose prices will be highly impacted by the negative news and all except the Binance coin and Bitcoin SV have significant results. Whereas, Bitcoin, EOS, Ethereum, Litecoin, Monero, Ripple, Tether, Gold, and USD prices will fluctuate more with the positive news rather than the negative ones. Among these, except Gold and Ripple, all the series are indicating a significant result.

6. CONCLUSION

Individual investors' decisions are influenced by their age, investment portfolio, education, income, and other demographic characteristics. In foreign exchange markets, traders, arbitrageurs, speculators, and hedgers are involved. Sebi's board has been tasked with protecting investors' interests since its inception in 1992. Minimum investment thresholds for high-risk goods, including portfolio management services, are part of the path to safeguard investor interests. Many international investors engage in India through portfolio investments.

Digital coin investments make up a small portion of bullion market holdings in India, but younger Indians prefer cryptocurrencies instead of other investment alternatives. While gold, crude oil, and financial markets are seen as good hedges in times of economic depression, more young Indians appear to be changing their minds. Despite this, India is falling behind in developing appropriate financial literacy about the commodity, owing to legal and legislative ambiguities. This poses a risk because the crypto business is still in its early stages, with a plethora of currencies and tokens. Many of them will eventually perish, putting the money of major investors at risk.

Asymmetric volatility or leverage effect is often, by researchers, investors, or authors, a common phenomenon associated with an unequal change in the market price or different reactions to the market price caused by a variety of events, circumstances, news, or happenings related to the financial, economic, political or technical environment. It leads investors to consider this effect caused by asymmetric information as an indication while making investment decisions.

All the previous studies have studied the impact of volatility but very few among them have kept their focus on measuring the impact of asymmetric volatility on the prices of investment alternatives. Keeping this into consideration, this study empirically investigates the impact of asymmetric volatility of 16 major time series belonging to various financial markets and serving as great investment options for investors. These include cryptocurrencies and other investment alternatives namely; NYSE DJ, NIFTY, SENSEX, Crude Oil, Gold, and USD along with 10 cryptocurrencies namely, Binance coin, Bitcoin cash, Bitcoin SV, Bitcoin, EOS, Ethereum, Litecoin, Monero, Tether and Ripple from FY 2015 to FY 2020.

This paper makes an important contribution to the already existing literature with the help of obtained results by applying the TGARCH model to 16-time series close price. We observe that some of the time series are showing the inverted asymmetric effect on the market prices, that is, the positive news or events have a more significant impact on the price volatility than the bad ones. These findings will benefit largely the investors in making an essential financial decision in times of uncertainty and turmoil situation, such as crude oil supply shock resulting in a drastic decline in the prices due to the pandemic faced by the world in 2020. However, there is scope for further research to forecast and predict the asymmetric volatility impact on the price’s other financial markets with the advanced and accurate applications of methods and techniques.

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REFERENCES

Akyildirim, E., Corbet, S., Lucey, B., Sensoy, A., & Yarovaya, L. (2020). The relationship between implied volatility and cryptocurrency returns. Finance Research Letters, 33, 101212.

Arezki, R. and Nguyen, H. (2020). Coping with a Dual Shock: COVID-19 and Oil Prices, https://www.worldbank.org/en/region/mena/brief/coping-with-a-dual-shock-coronavirus-covid-19-and-oil-prices.

Asymmetric volatility. (n.d.) Financial Glossary. (2011). Retrieved September 25 2021 from https://financial-dictionary.thefreedictionary.com/Asymmetric+volatility.

Balcilar, M., Bouri, E., Gupta, R., & Roubaud, D. (2017). Can volume predict Bitcoin returns and volatility? A quantiles-based approach. Economic Modelling, 64, 74-81.

Beckers, B., Herwartz, H., & Seidel, M. (2017). Risk forecasting in (T) GARCH models with uncorrelated dependent innovations. Quantitative Finance, 17(1), 121-137.)

Berggren, E., & Folkelid, F. (2015). Which GARCH model is best for Value-at-Risk?.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31(3), 307-327.

Bouoiyour, J., & Selmi, R. (2015). Bitcoin price: Is it really that a new round of volatility can be on its way?

Bouoiyour, J., & Selmi, R. (2016). Bitcoin: A beginning of a new phase. Economics Bulletin, 36(3), 1430-1440.

Bouri, E., Azzi, G., & Dyhrberg, A. H. (2017). On the return-volatility relationship in the Bitcoin market around the price crash of 2013. Economics, 11(1).

Brunnermeier, M., Oehmke, M., & Jel, G. (2009). Complexity in financial markets. Princeton University, 8.

Catania, L., Grassi, S., & Ravazzolo, F. (2018). Predicting the volatility of cryptocurrency time-series. In Mathematical and statistical methods for actuarial sciences and finance (pp. 203-207). Springer, Cham.

Catania, L., Grassi, S., & Ravazzolo, F. (2018). Predicting the volatility of cryptocurrency time-series. In Mathematical and statistical methods for actuarial sciences and finance (pp. 203-207). Springer, Cham.

Cheikh, N. B., Zaied, Y. B., & Chevallier, J. (2020). Asymmetric volatility in cryptocurrency markets: New evidence from smooth transition GARCH models. Finance Research Letters, 35, 101293.

Costa, F. J. M. (2017). Forecasting volatility using GARCH models (Doctoral dissertation).

Das, K., (2021). Decoded | What's driving demand for cryptocurrencies in India, https://www.indiatoday.in/business/story/decoded-why-more-indians-are-investing-in-cryptocurrencies-bitcoin-ether-dogecoin-1845122-2021-08-25

Engle, R. F. (2001). GARCH 101: An Introduction to the Use of ARCH/GARCH Models in Applied Econometric (Vol. 30). NYU Working Paper No. FIN-01.

Engle, R. F., & Ng, V. (1982). An Introduction to the Use of ARCH/GARCH models in Applied Econometrics. Journal of Business, New York.

Engle, R. F., & Ng, V. K. (1993). Measuring and testing the impact of news on volatility. The journal of finance, 48(5), 1749-1778.

Ewing, B. T., & Malik, F. (2017). Modeling asymmetric volatility in oil prices under structural breaks. Energy Economics, 63, 227-233.

Goudarzi, H., & Ramanarayanan, C. S. (2011). Modeling asymmetric volatility in the Indian stock market. International Journal of Business and Management, 6(3), 221.

Goudarzi, H., & Ramanarayanan, C. S. (2011). Modeling asymmetric volatility in the Indian stock market. International Journal of Business and Management, 6(3), 221.)

Green, H. G., & Pearson, M. A. (1995). Artificial intelligence in financial markets. In Proceedings of ICNN'95-International Conference on Neural Networks (Vol. 2, pp. 839-844). IEEE.

Grinberg, R. (2012). Bitcoin: An innovative alternative digital currency. Hastings Sci. & Tech. LJ, 4, 159.

Gronwald, M. (2014). The economics of bitcoins--market characteristics and price jumps.

Hassan, M. E., Miami, H., & Babikir, A. (2018). Volatility Parameters Estimation and Forecasting of GARCH (1, 1) Models with Johnson's SU Distributed Errors. Time Series Analysis and Applications, 41.

Jansen, D. J. (2011). Does the Clarity of Central Bank Communication Affect Volatility in Financial Markets? Evidence from Humphrey-Hawkins Testimonies. Contemporary Economic Policy, 29(4), 494-509.

Jiang, W. (2012). Using the GARCH model to analyze and predict the different stock markets. Masters's Degree Dissertation, Department of Statistics, Uppsala University, Sweden.

Katsiampa, P. (2017). Volatility estimation for Bitcoin: A comparison of GARCH models. Economics Letters, 158, 3-6.

Katsiampa, P. (2019). An empirical investigation of volatility dynamics in the cryptocurrency market. Research in International Business and Finance, 50, 322-335.

Katsiampa, P., Corbet, S., & Lucey, B. (2019). High-frequency volatility co-movements in cryptocurrency markets. Journal of International Financial Markets, Institutions, and Money, 62, 35-52.

Kaul, A. (2021). Meet the investors betting big on crypto from https://www.livemint.com/money/personal-finance/crypto-trading-is-creating-wealth-for-some-but-it-is-not-free-of-risks-11630440563745.html.

Lillo, F., & Mantegna, R. N. (2000). Variety and volatility in financial markets. Physical Review E, 62(5), 6126.

Liu, J., & Serletis, A. (2019). Volatility in the cryptocurrency market. Open Economies Review, 30(4), 779-811.

Mamtha, D., & Srinivasan, K. S. (2016). Stock market volatility–conceptual perspective through literature survey. Mediterranean Journal of Social Sciences, 7(1), 208.

Othman, A. H. A., Alhabshi, S. M., & Haron, R. (2019). Cryptocurrencies, Fiat money or gold standard: empirical evidence from volatility structure analysis using news impact curve. International Journal of Monetary Economics and Finance, 12(2), 75-97.)

Phillip, A., Chan, J., & Peiris, S. (2019). On long memory effects in the volatility measure of cryptocurrencies. Finance Research Letters, 28, 95-100.

Poon, Ser-Huang, and Clive W.J. Granger. 2003. "Forecasting Volatility in Financial Markets: A Review." Journal of Economic Literature, 41 (2): 478-539

Rabemananjara, R., & Zakoian, J. M. (1993). Threshold ARCH models and asymmetries in volatility. Journal of applied econometrics, 8(1), 31-49.

Ruppert, D. (2011). GARCH models. In Statistics and Data Analysis for Financial Engineering (pp. 477-504). Springer, New York, NY.

Sabiruzzaman, M., Huq, M. M., Beg, R. A., & Anwar, S. (2010). Modeling and forecasting trading volume index: GARCH versus TGARCH approach. The Quarterly Review of Economics and Finance, 50(2), 141-145.

Sotomayor, L. R., & Cadenillas, A. (2009). Explicit solutions of consumption-investment problems in financial markets with regime switching. Mathematical Finance: An International Journal of Mathematics, Statistics and Financial Economics, 19(2), 251-279.

Sovbetov, Y. (2018). Factors influencing cryptocurrency prices: Evidence from bitcoin, ethereum, dash, litcoin, and monero. Journal of Economics and Financial Analysis, 2(2), 1-27.

Teräsvirta, T. (2009). An introduction to univariate GARCH models. In Handbook of Financial time series (pp. 17-42). Springer, Berlin, Heidelberg.

Tsantekidis, A., Passalis, N., Tefas, A., Kanniainen, J., Gabbouj, M., & Iosifidis, A. (2017, August). Using deep learning to detect price change indications in financial markets. In 2017 25th European Signal Processing Conference (EUSIPCO) (pp. 2511-2515). IEEE.

Valenti, D., Fazio, G., & Spagnolo, B. (2018). Stabilizing effect of volatility in financial markets. Physical Review E, 97(6), 062307.

Vishwanath, T., & Kaufmann, D. (2001). Toward transparency: New approaches and their application to financial markets. The World Bank Research Observer, 16(1), 41-57.

Vo, N. N., & Xu, G. (2017, October). The volatility of Bitcoin returns and its correlation to financial markets. In 2017 International Conference on Behavioral, Economic, Socio-cultural Computing (BESC) (pp. 1-6). IEEE.

Wajdi, M., Nadia, B., & Ines, G. (2020). Asymmetric effect and dynamic relationships over the cryptocurrencies market. Computers & Security, 96, 101860.

Wang, J., & Yang, M. (2009). Asymmetric volatility in the foreign exchange markets. Journal of International Financial Markets, Institutions, and Money, 19(4), 597-615.)

Williams, B. (2011). Betreuung: Prof. Dr. Rainer Dahlhaus.

Zakoian, J. M. (1994). Threshold heteroskedastic models. Journal of Economic Dynamics and control, 18(5), 931-955.

Narayanaswamy, T. & Karthika, P. (2018). Cryptocurrency : Invisible or Invincible Currency – Answers for Unanswered Questions, Indian Journal of Finance. 12. 63. 10.17010/ijf/2018/v12i6/128140.

Chopra, Monika & Saldi, Rupish. (2022). Investment in Bitcoin : A Delusion or Diligence?. Indian Journal of Finance. 16. 8. 10.17010/ijf/2022/v16i7/170632.

Bhattacharjee, S., & Kaur, H. (2015). An overview of alternative currency: The Bitcoin. Indian Journal of Finance, 9(6), 51– 60. https://doi.org/10.17010/ijf/2015/v9i6/71162.

Joshi, D. J. (2011). Impact of dollar fluctuation on gold and crude oil prices. Indian Journal of Finance, 5(5), 3–12. http://www.indianjournaloffinance.co.in/index.php/IJF/article/view/72509.

Bishnoi, Ashwani & Sheera, Ved. (2018). Indian Stock Market Volatility and Economic Fundamentals : MIDAS Approach. Indian Journal of Finance. 12. 7-21. 10.17010/ijf/2018/v12i8/130741.

Varughese, Ashish & Mathew, Tomy. (2017). Asymmetric Volatility of the Indian Stock Market and Foreign Portfolio Investments : An Empirical Study. Indian Journal of Finance. 11. 36-49. 10.17010/ijf/2017/v11i6/115595.