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Volatility and Spillover Risks in Cryptocurrency Market: A VAR and GARCH Processes Perspective

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Abstract--- In this analysis; we study the four major cryptocurrency returns that are Bitcoin, Ethereum, XRP, and Litecoin, where the dynamics of volatility spillover are observed for a span of 7 years – 2013 to 2020; wherein the total number of sample observations collected and analyzed were 10,953 (Data Points). This paper investigates the behaviour and responses of cryptocurrency assets with respect to each other by using VAR Granger Causality and Bayesian VAR Model, we find that Ethereum and Litecoin prove to be independent in the cryptocurrency market. Whereas Bitcoin, XRP, and Binance coins tend to be the recipient of the spillover effect. Our study indicates that there is a conditional variance in these cryptocurrency assets and Bitcoin & Binance coins are more adversely affected due to the bad news in the market, leading to rigorous fluctuations in volatility. While approaching for the analysis, we conducted a GARCH (1,1), T-ARCH, and E-GARCH analysis along with a univariate GARCH model which we used to estimate and quantify the nature of volatility spillovers. Given the overall cryptocurrency bull-run in the first quarter of 2017-18 we have analyzed the saturation of the cryptocurrency markets; where investors sought to invest in Bitcoin and Ethereum, vehemently and this resulted in extremely high volatility during the December 17' period.

Keywords--- Cryptocurrency; Spillovers; Time-varying volatility; VAR Granger Causality; Bayesian VAR; GARCH; Static Forecasting

JEL CLASSIFICATIONS: - C46, C53, C58, G15, G17

I. INTRODUCTION

A cryptocurrency is defined as a digital form of currency that is created and managed via the use of advanced encryption techniques, basically known as cryptography. It is designed to function as a modern-day currency of exchange.

Baur et al. (2017) have shown that Bitcoin and its competitor's ROI are mostly not correlated with any other mainstream asset class like bonds and stocks, and this points towards diversification opportunities of the same. The findings of Li and Wang (2017), then show that parameters of financial and macro-economic activity have been driving Bitcoin returns and Kristoufek (2015) takes into consideration; the financial uncertainty associated with bitcoin trading volume specific to the Yuan alongside Google trends as potential factors behind the returns of Bitcoin.

Talking about Bitcoin returns in regards to the probable drivers of Bitcoin volatility, we take into account macroeconomic and financial factors, which are univariate in nature. In addition, Bitcoin specific variables, such as volumes of trade and the effects of good news/bad news have been analyzed which have a significant effect on volatility (*Annexure 1-5*). Additionally, we look into and study the drivers of the volatility in our research which allows for a comparison of the impacts on the different assets and brings about more useful insights for a classification of Bitcoin and its competitors like an asset class. We not only analyze Bitcoin but also its competitors – Ethereum, XRP, Litecoin, and Binance coin on basic grounds (According to market capitalization).

The second piece of literature was analyzed, which tries to emulate Bitcoin volatility, among the first paper, Balcilar et al. (2017), analyzed the degree of casualty of the relationship between volume of trade and Bitcoin's investment returns and volatility, which has been used as the reference for this research on grounds of causal relationship analysis too. They discovered that volume does not help to predict the volatility of Bitcoin's returns and Dyhrberg (2016) explored the volatility of Bitcoin with the help of GARCH models wherein, the model's predictions suggest that Bitcoin shows common factors with both gold and the dollar. This would help us classify the crypto market and analyze it as a separate asset class. This study attempts to review scholarly articles in order to understand how cryptocurrency assets are referred to in the literature wherein, the study on the attributes of these assets through a logical and systematic literature review. This paper is centred on the basis of secondary, or second-hand, data from pre-existing literature and other relevant secondary data from case studies on similar topics in the common domain. Although, in a fashion different from other currencies, Bitcoin has faced a multitude of hurdles, and with several applications in day-to-day life, have created a plethora of challenges only seen in the crpto user community.

When Bitcoin first came into circulation, it seemed to bring with itself hope for a brighter future, but it has been observed that the trends of bitcoin have been difficult to gauge. This asset class of digital coins had brought with itself an entirely new set of opportunities for both practitioners and academicians alike. Thus, this study aims to represent the “potential” of, highlighting the requirements, needs, consequences, and hurdles faced in the processing of business transactions. It is common in the literature to use Google Trends as a proxy representative of sentiment or interest. The question of which asset class these coins belong to is a recurring theme in the literature. Many people compare it with gold, while others compare it with precious metals. Or speculative assets (Bouri et al., 2017). Some academicians have classified the coins as an amalgamation of currency and commodity as in Dyhrberg (2016) for example. For similar up-to-date contributions, we would suggest you see Cheah et al. (2018); Khuntia and Pattanayak (2018); and Koutmos (2018).

II. LITERATURE REVIEW

It is seen that there is a positive relation of S&P 500 risk premium on Bitcoin volatility in the longer run, and there seems to be a higher degree of proportionality between the Baltic dry index and Bitcoin volatility (Conrad, Custovic, and Ghysels, 2017). Furthermore, factors such as volatility, the volume of trade, and market beta seem to be important determinants for all of the five cryptocurrencies -- Bitcoin, Litecoin, Ethereum, Bitcoin Cash, and Ripple. There certainly seems to be the factor of time being involved when assessing the attractiveness of cryptocurrencies and in other words, it can be said that it spreads slowly within the market. S&P500 index appears to have a rather insignificant positive long-run impact on Ethereum, Litecoin and Bitcoin,, while it turns to negative, and thus losing significance, in the short-run, barring Bitcoin that creates an estimated -0.20 at a 10% significance level. (Sovbetov, 2018). It is seen that cryptocurrency’s past volatility and shocks tend to impact its present conditional variance. (Katsiampa, Corbet, and Lucey, 2018) and Bitcoin as an investment strategy shows asymmetry in times of market shock, just like other precious metals.

However, its correlations behave in an entirely different manner than gold. Experts believe that Bitcoin is not a safer option and does not offer any hedging capabilities for developed economies. It is also notable that Bitcoin, with reference to an asset, does not have similarities with any other conventional asset from an econometric perspective (Klien, Thu and Walter, 2018). Also, the negative lagged return value for innovation has roughly four times the influence on conditional variance, as does positive return innovation and on the other hand, the three-month US Treasury bill rate was observed to be strongly linked with volatility. This is suggestive of the fact that higher interest rates, in turn, lead to increased volatility in equities returns (Robert F Engle and Andrew J Patton, 2000). Finally, they also discovered that the results obtained are influenced greatly by the frequency of sample collection which is a demerit of the GARCH measure. Mckenzie & Mitchell (2002) mention that the GARCH (1,1) model is favoured in the case of reactions to the improvement in the studied market too.

However, in countries where cryptocurrency finds acceptance, it is seen that cryptocurrency resembles financial assets as they tend to react to alike variables in the GARCH models and possess resembling hedging capabilities when responding to good and bad news. (Liu, and Serletis, 2019) Spillover Transmission: It is observed that Bitfinex and Gemini are leading exchanges in the way of return spillover transmission during the analysed time-frame, while Bittrex comes next. It was also found that the connectedness of overall returns fell considerably right before the Bitcoin price surge, whereas it levelled out during the period when the market was down. (Giudici and Pagnottoni, 2018). The Ethereum often responds independently compared to the other coins from our studied sample in VAR and SVAR Granger causality approaches which we have used here and that all cryptocurrencies have joint distribution when their extreme value is considered, which might consequently result in a simultaneous, downside trend with ‘bad news’ (Toan Luu, and Duc Huynh, 2019). Thus, the independent investors or portfolio managers must pay greater attention to their movement patterns along with the requisite information in order to take any actions straight away. And as A. M. Antonopoulos (2014), Rashid M.Imran M.Jafri A. R.Al-Somani T. F.See (2019), and De Andrade M. D. (2019) have mentioned in their studies – facts similar to Mastering Bitcoin: Unlocking Digital Cryptocurrencies, explaining

III. RESEARCH OBJECTIVES

1. Volatility spillover is influenced by shocks in Bitcoin prices (and others) and other exogenous events therefore, we aim to analyze the volatility in Cryptocurrency Market.

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2. To find out the returns and the nature of the returns via Cryptocurrency in the short well as long run (2013-20' data)
3. To understand the volatility modelling of cryptocurrency by deploying univariate GARCH processes and how can a model be framed to account for the high-risk volatility in the cryptocurrency market.

IV. RESEARCH METHODOLOGY

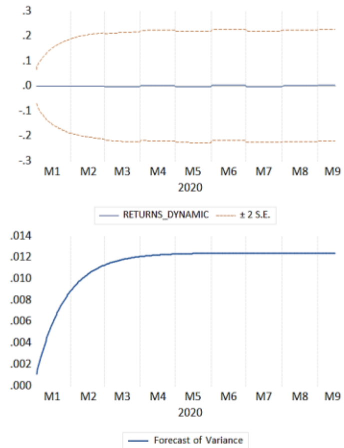
4.1 Measures:

Auto-regressive conditional heteroskedasticity (ARCH) methods along with the exponential GARCH (EGARCH) have been used to record volatilities and leverage impacts. Vector autoregressive (VAR) schemes and forecast error variance decomposition (FEVD) would be employed. The study here aims to analyze the cryptocurrency market's volatility spillover while accounting for all the contingencies discussed above and implements a methodology to record the cryptocurrency economy dynamics. First, we studied the volatility of cryptocurrency markets employing a univariate GARCH framework. In all financial markets, investors are operating across different time zones, as shown by the fractal market hypothesis. The GARCH model can capture conditional correlation and covariance, but it only provides information for a specific time period.

The integrated GARCH (IGARCH) methodologies, coupled with the dynamic conditional correlations, were adopted by Kumar and Anandarao (2019) and further as continued in the review literature. The Classical Pearson correlation estimates have been utilized in order to measure the interlinkages. In a different vein, for detecting the direction of volatility spillovers not only parametric but also non-parametric tests have been used. Moreover, the auto-regressive distributed lag (ARDL) methodology has been employed for the same purposes.

4.2 Method of Analysis

Various statistical tools such as ARCH, GARCH (Using standard deviation and variance methods), T-GARCH and EGARCH have been used in our analysis; along with stationarity tests using unit roots.



Forecast: RETURNS_DYNAMIC	
Actual: RETURNS	
Forecast sample: 1/02/2020 9/15/2020	
Included observations: 258	
Root Mean Squared Error	0.044807
Mean Absolute Error	0.027640
Mean Abs. Percent Error	108.6249
Theil Inequality Coef.	0.942982
Bias Proportion	0.000201
Variance Proportion	0.870673
Covariance Proportion	0.129126
Theil U2 Coefficient	1.003129
Symmetric MAPE	168.3629

The formula used for checking unit root in ADF is:

$$\Delta y_t = a + \beta_t + g y_{t-1} + \delta_1 \Delta y_{t-1} + u_t$$

Since the t-stats is less than the critical value, it indicates that our series has a unit root and is significant at a 1% level.

ADF TEST RESULT FOR BITCOIN.

Null Hypothesis: RETURNS has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 16 (Automatic - based on AIC, maxlag=27)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-10.48379	0.0000
Test critical values:	1% level	-3.961495	
	5% level	-3.411497	
	10% level	-3.127608	

*MacKinnon (1996) one-sided p-values.

4.2.1 TESTING FOR STATIONARITY

In order to test if the data collected are stationary or not, we undertook the Augmented Dickey-Fuller test. The stationarity of the crypto's ROI's series had been tested by the ADF test via carrying out a regression equation constructed on a random walk theory with an intercept or drift term (φ). Given the acceptance of the hypothesis, we can conclude the presence of a unit root in the y_t sequence, and the time series is non-stationary. If the ADF test statistic exceeds the Mackinnon critical value, we can disregard the null hypothesis, and we can assume that there is no unit root in the return series on a daily basis.

4.2.2 E-GARCH:

GARCH models are employed to capture thick tailed returns and measure volatility clustering, however, they are not useful to measure the "leverage effect" owing to the fact that the conditional variance is a factor only of the magnitudes of the lagged residuals and not their signs. Leverage effects can be affirmed by the hypothesis that γh & lt; 0. The impact is said to be asymmetric if we find that $\gamma h^1 = 0$.

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4.2.3 T-ARCH

The ARCH / GARCH models reflect both positive and negative shocks of the same measure having the same impact on the volatility of the series. The T-ARCH model assists in negating this limitation. Per this model, dt = 1 if εt < 0 and zero otherwise. According to the given model, positive news, εt-1 > 0 and bad news εt -1 < 0, have a differential impact on the conditional variance; positive news has an impact of αi, wand on the other hand negative news has an effect of αi + γi. If γi & gt; 0, it, thus, points towards unfavourable news pushing volatility higher, and thus we can infer that there is a leverage effect for the i-th order. If γi1 = 0, and so the news effect is considered asymmetric. The foremost aim of this particular model was to measure the asymmetries with respect to positive and negative changes in the market.

4.2.4 VOLATILITY CLUSTERING

Volatility clustering in basic terms is the likelihood of noticeable changes in the prices of financial assets (Cryptocurrency in this case) to cluster in a particular direction, which causes the unfluctuating of these measures of price alterations. This phenomenon is observed when there are continuous periods of high market volatility, as the current pandemic times; and the reverse of relatively lower for a longer duration of time as well. The phenomenon takes place to such an extent that it makes an IID of log-prices or asset returns unappealing, as mentioned by Li Y., Zhou J., Zheng X., Tian J., Tang Y. Y. (2019) in their noise modelling of cryptocurrency analysis. Hence, there is a need for us to check the volatility clustering of our data.

4.2.5 HETEROSKEDASTICITY

Heteroskedasticity occurs when the standard errors of a variable are observed over a given period of time and are not found to be constant. We have used the conditional heteroskedasticity test here, wherein the volatility in cryptocurrency is very closely related to the volatility priorly displayed. This model attempts to explore the reason behind periods of constant relatively higher volatility and lower volatility and therefore was necessary to be observed.

We found that the ARCH effect is present in this series for our study.

4.2.6 T-GARCH MODEL

For T-GARCH measurement, the Generalized Error Distribution is considered together with the off-set or skew parameter in the data. It was observed that the variance equation is statistically significant where both, alpha and beta are significant. The skewed distribution does fit the data and is significant in the distribution. Additionally, we also observe that the mean coefficient is considerably significant.

$$\sigma_t^2 = \alpha + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{h=1}^{r} \gamma_h \varepsilon_{t-h}^2 d_{t-h}$$

For the model, dt = 1 if εt < 0 and zero otherwise. The positive or good news' effect (εt-1 > 0) and negative news' effect ($\varepsilon_{t-1} < 0$), are observed to have a differential effect on the conditional variance. The good news is observed to have an impact of αi, and bad news on the other hand was observed to have an impact of $\alpha_i + \gamma_i$. If $\gamma_i > 0$, the study indicates that volatility is directly proportional to negative news, and it can be said that for the i-th order that a leverage effect is present. The news' impact would be asymmetric if $\gamma_{i1} = 0$ and the very purpose of this model is to catch asymmetries in terms of bad/negative and good/positive news.

4.2.7 E-GARCH MODEL

The model is different from the GARCH variance structure on the logarithm grounds, when log of the variance is observed. The following specifications as mentioned for the model, has also been used in financial literature (Dhamija and Bhalla, 2001). We use asymmetrical normal distribution instead of the Generalized Error Distribution. This model also uses the same variables as used in the previous model because if we had used different sets, it would be difficult to compare the same and draw statistically significant inferences.

Our E-GARCH Model had a Coefficient of asymmetrical term, negative, and was statistically significant at 1% level e-0.0106810 = 0.9833. C (17) indicates that for bitcoin, and we could therefore say that "Bad news is observed to have a larger effect on the volatility of the asset than good news."

$$\log\log\left(\sigma_t^2\right) = \alpha_0 + \sum_{j=1}^{q} \beta_j \log\log\left(\sigma_{t-j}^2\right) + \sum_{i}^{p} \alpha \frac{|\varepsilon_{t-i}|}{|\sigma_{t-i}|} + \sum_{h=1}^{r} \gamma_h \frac{\varepsilon_{t-h}}{\sigma_{t-h}}$$

The hypothesis that γh< 0; checks for the presence of leverage effects and the impact is asymmetric if $\gamma h^{1} = 0$.

4.2.8 GARCH FORECASTING

The GARCH process is an econometric term describing irregularities in the pattern of variation of variable or error term in the statistical model. Observations do not follow a linear pattern and tend to cluster, especially when heteroskedasticity is present. As a result, this had to be double-checked and accounted for. Let Xt be a series of observable financial data; in our example, this is the logarithm of the price return of different cryptocurrencies, then the GARCH model can be specified as follows:

$$\mathbf{X_t = \mu_t + \sigma_t Z_t}$$

We have used the standard GARCH model (Bollerslev,

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1986), denoted by S-GARCH (1, 1) model which is known to remove the computational problems that otherwise occur in other GARCH models and the same has:

$$\sigma^2_t = \omega + \alpha_1 Z^2_{t-1} + \beta_1 \sigma^2_{t-1}$$

for $\alpha 1 > 0$, $\beta 1 > 0$ and $\omega > 0$. The primary aspect of this and the other models is that they take into account and capture volatility clustering in the data.

4.2.9 STATIC & DYNAMIC FORECASTING

The Static Forecast (backtest) uses the true value of the explanatory variable to make predictions. In our scenario, we used static forecasts up to 2020. On the other hand, actual value is used in dynamic forecasting instead of lag-dependent variables.

To forecast a past date we need to know the value for @TREND, the month of forecasting, and also the value of the cryptocurrency growth in the month previous to the forecast month. The former parameters are easy to determine; however, the value of growth needs to be forecasted based on the static and dynamic forecasts. It is this lagged dependent variable that presents a problem or even opportunity. If we were to consider an example; like if we're forecasting for February 2020, we're on a good boat because we know the January value but for March or later months, we don't have the lagged value of cryptocurrency growth and we have analyzed the same here.

4.2.10 ADF TEST

The Augmented Dickey-Fuller test (ADF) is a unit root test of stationarity, in which the value p is reported when the hypothesis test is associated with the null hypothesis and the alternative hypothesis and the test statistic is calculated as the result. A p-value less than 5% indicates that we can reject the null hypothesis that there is a unit root. You can also compare the calculated DFT statistics with the critical values in the table in the appendix below.

The Augmented Dickey-Fuller adds **lagged differences** to these models:

i. No constant, no trend: $\Delta y_t = \gamma y_{t-1} + \sum_{s=1}^{m} a_s \Delta y_{t-s} + v_t$

ii. Constant, no trend: $\Delta y_t = \alpha + \gamma y_{t-1} + \sum_{s=1}^{m} a_s \Delta y_{t-s} + v_t$

iii. Constant and trend: $\Delta y_t = \alpha + \gamma y_{t-1} + \lambda_t + \sum_{s=1}^{m} a_s \Delta y_{t-s} + v_t$

4.2.11 VAR GRANGER CAUSALITY TEST

The Granger causality test is a statistical hypothesis test for determining whether a one-time series is useful in forecasting another. Granger defined the causality relationship based on two principles:

1. The cause happens before its effect.
2. The cause has unique information about the future values of its effect.

VAR Stability Condition Check (absolute value of complex roots – and they are smaller than 1, which indicates that this series is stationary. Hence, we can say VAR satisfies the stability conditions.)

First, the focus is on the benchmark model; the Bayesian VAR(3) model is described as follows:

$$Y_t = \beta_1 y_{t-1} + \beta_2 y_{t-2} + \beta_3 y_{t-3} + \epsilon t,\ \epsilon t \sim N(0, \Sigma\epsilon t), \text{ for } t=1$$

with T the number of total days of the data. Since this model is for every cryptocurrency, the equation above can be rewritten in stacked form:

$$Yt = Zt\beta + \epsilon t,\ \beta = vec(\beta 1, \beta 2, \beta 3),$$

$Z_t = (I_N \otimes X_t)$, **where** $X_t = [y_{t-1}, yt_{-2}, yt_{-3}]$ (for every cryptocurrency)

If the variables are non-stationary, then the test is done using first (or higher) differences. The number of lags to be included is usually chosen using an information criterion, such as the Akaike information criterion or the Schwarz information criterion.

Here, refer to the studies of Lütkepohl (2005) and Greene (2008) to briefly explain the VAR model in terms of linear regression without constraint placed on the coefficients. The VAR(p) model with exogenous variables is statistically written in the form as:

$$y_t = AY_{t-1} + B0\chi t + u_t$$

In which yt is the matrix with (K × 1) of endogenous variables; A is a matrix with (K × Kp) of coefficients of lagged values of Y (Yt−1); B0 is a matrix with coefficients of matrix χ; χt is the matrix (M × 1) of exogenous variables, and ut is the matrix (K × 1) of white noise innovations.

4.2.12 Model Selection

All of the GARCH-type models were fitted by the method of maximum likelihood. Many of the fitted models are not nested. Discrimination among them was performed using various criteria:

- the Akaike information criterion due to Akaike (1974) is defined by:

$$AIC = 2k - 2 \ln L(\Theta),$$

where k denotes the number of unknown parameters, Θ the vector of the unknown parameters, and (Θ) their maximum likelihood estimates;

- the Bayesian information criterion due to Schwarz (1978) is defined by:

$$BIC = k \ln n - 2 \ln L(\Theta),$$

where n denotes the number of observations;

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- the Hannan–Quinn criterion due to Hannan and Quinn (1979) is defined by:

$$HQC = -2 \ln L (\Theta b) + 2k \ln \ln n.$$

V. RESULT AND ANALYSIS

5.1 Data

5.1.1 Data Collection

We have modelled the volatility of various coins in this paper, and, we are investigating if there are any spillover effects, and we are modelling the risk of investing in crypto assets. The current study was based on five cryptocurrencies- Bitcoin, Ethereum, XRP, Litecoin, and Binance Coin. The data spans from the period of June 2013 to September 2020 (For Bitcoin – With 2649 observations.), August 2015 – September 2020 (For Ethereum – with 1867 observations) August 2013 – September 2020 (For XRP – with 2600 observations) May 2013 – September 2020 (For Litecoin – with 2696 observations) August 2017 – September 2020 (For Binance Coin – with 1141 observations)

The collection of these particular coins is based upon the market capitalization of each coin. Our dataset consists of the date, open, high, low, adjusted close price, log daily return, volume, and market capitalization. The dataset was checked for missing data and outliers.

5.2 Findings

5.2.1 Summary Statistics

Fig 1. Summary Statistics of Returns

Sr No.		Bitcoin	Ethereum	XRP	Litecoin	Binance Coin
1.	Mean	0.001150	0.000539	0.000339	0.000116	0.004996
2.	Median	0.001390	0.000379	-0.001884	-0.001047	0.000956
3.	Maximum	0.225119	0.234731	0.606885	0.389338	0.675174
4.	Minimum	-0.464730	-0.550714	-0.3988968	-0.449012	-0.542809
5.	Std. Dev.	0.043141	0.052766	0.060508	0.057684	0.074153
6.	Skewness	-1.040740	-1.209468	1.540150	0.124683	0.951854
7.	Kurtosis	17.35715	15.43217	22.14878	12.86377	17.80744
9.	Jarque-Bera	10005.64	7626.15	17883.46	4628.47	10596.30
10.	Probability	0.000	0.000	0.000	0.000	0.00
11.	Observation	1141	1141	1141	1141	1141

Following Figure 1, the daily mean return of the Binance coin is 0.0049, and therefore it is supposedly the largest daily mean return. It also has very high volatility, which is measured by the standard deviation (0.074153). Simultaneously, it is observed that the volatility (Std. Dev.) of the crypto assets are larger than the fiat currencies, commodities, and large-cap equities (pre-COVID). Furthermore, the larger negative value of skewness is associated with Ethereum and Bitcoin, which depicts that the assets have a huge chance of going down than going up. However, a larger positive value of skewness is associated with XRP, Binance Coin, and Litecoin, which depicts that the assets have a huge chance to go up than to go down, during our sample period. The variables have a

5.2.2 Test of Stationarity

Fig 2. Test of Stationarity

Sr No.	Variables	Augmented Dickey-Fuller Test	Phillips-Perron Test
1.	Bitcoin	-10.48379***	-34.94067***
2.	Ethereum	-7.694401***	-35.81606***
3.	XRP	-14.04458***	-33.36080***
4.	Litecoin	-17.03764***	-34.99914***
5.	Binance Coin	-10.87684***	-31.83983***

, **, and * shows that the assets are significant at the 10%, 5%, and 1% levels, respectively*

In order to understand that these observed results are not impartial and spurious, the has been used to ensure that our variables are stationary. To assess the stationarity between variables, we used the extended Dickey-Fuller unit root test (Dickey and Fuller, 1979) and the Phillips-Perron unit root test (Phillips and Perron, 1988). In addition, we checked for trends and intercepts as the data points of the crypto assets showed trends for the given sample period. Figure 2 represents the result of the Augmented Dickey-Fuller unit root test and the Phillips-Perron unit root test among the variables. Our findings show that all variables in the study are stationary when observed at the 1% significance level. This is indicative of our variables being integrated of the order zero; or I (0), which indicates that we reject our null hypothesis at a 1% significance level.

5.2.3 VAR Granger Causality

Fig 3. VAR Granger Causality Tests

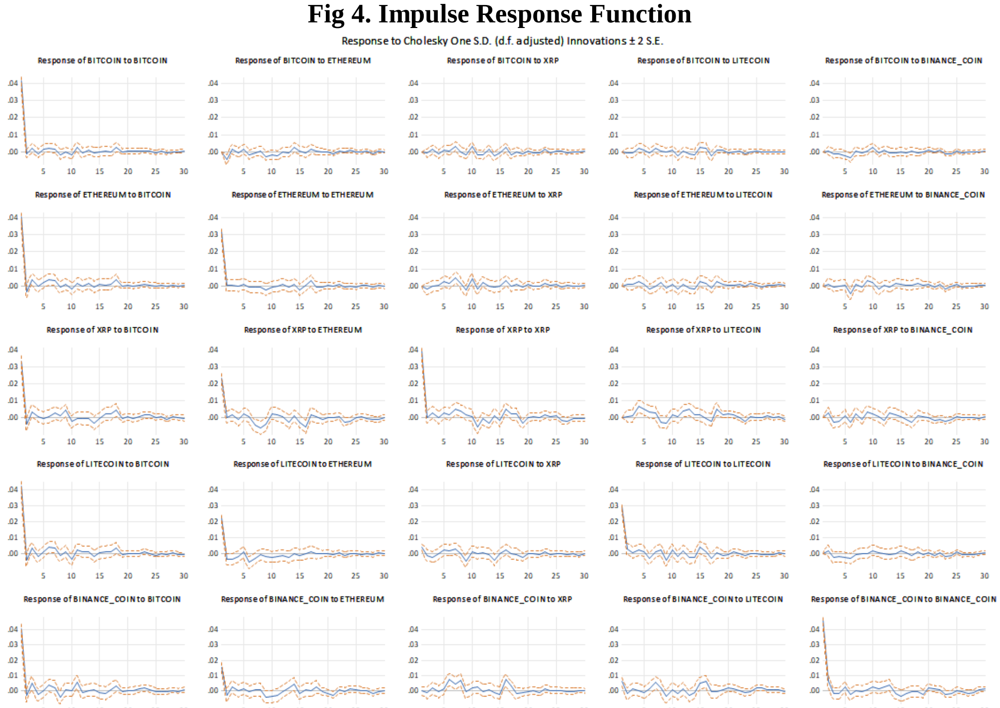
Receiver	**Origin**				
	Bitcoin	*Ethereum*	*XRP*	*Litecoin*	*Binance Coin*
Bitcoin	1.000	41.840***	37.830***	19.675	27.226*
Ethereum	21.410	1.000	33.971***	16.285	23.432
XRP	47.326***	44.658***	1.000	46.045***	33.830***
Litecoin	36.361***	37.885***	26.045*	1.000	23.230
Binance Coin	22.917	40.325***	63.139***	34.292***	1.000

, **, and * shows that the assets are significant at the 10%, 5%, and 1% levels, respectively*

In order to elucidate the underlying causal mechanism in the time series of crypto assets (spillover effect), we deployed the VAR Granger Causality test. In Figure 3, there is some contagion effect among the crypto assets. At the same time, XRP will likely bear spillover risk from Bitcoin, Ethereum, Litecoin, and Binance Coin at a 1% significance level respectively. Similarly, there is spillover risk on Binance Coin and Bitcoin from other coins such as Ethereum and XRP respectively. There is weak evidence that Binance Coin will have a spillover risk on Bitcoin, and XRP will have spillover risk on Litecoin at a 10% significance level. This low ratio is due to the fact that the cryptocurrency market has different returns factors (such as investor acceptance, changes in laws and regulations), as compared to the stock and bond markets,which are more dependent on economic growth, and driven by interest rates, and corporate profits.

5.2.4 VAR Impulse

Fig 4. Impulse Response Function



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The dependent variable is a function of its lagged values and lagged values of other variables in the model. VAR must be specified in levels and therefore VAR in differences would be misspecified (Cuthberson, K. 2002). In Figure 4, the reaction of Bitcoin, Ethereum, Litecoin, are constant to other coins; whereas the response of XRP and Binance Coin with respect to other coins are quite turbulent in nature. Overall, it can be said that the coins are less tranquil to each other in the long term. A one SD shock (innovation) to the coins initially has a huge impact as they gradually decrease in periods one to two. From the second period, many coins hit steady-state value until the thirtieth period. Shocks to XRP and Binance Coin will have a negative impact in the short run because the coins are turbulent with respect to other coins, also there is an asymmetrical impact of XRP, and Binance Coin on other coins.

5.2.5 Bayesian VAR

Fig 5. Bayesian VAR

	VAR		Bayesian VAR	
Sr No.	**RMSE**	**MAE**	**RMSE**	**MAE**
1.	0.061378	0.042192	0.043085	0.027742
2.	0.040217	0.027102	0.052667	0.034810
3.	0.049789	0.034106	0.060457	0.035881
4.	0.054236	0.037363	0.057637	0.038102
5.	0.054631	0.036661	0.074167	0.045206

In order to evaluate the overall performance of our BVAR model, we first evaluate the single-sample prediction to obtain the MAE value of the minimization function (the graph projection can be obtained in Appendix 5). We also compare the MAE estimate of the BVAR model with the estimate derived from the estimates of the same model, but only using the Ordinary Least Squares estimate (OLS), representing the standard VAR model. It can also be observed from Figure 5., that MAE of the one-step ahead forecast of the ordinary VAR model comes out to be in the range of 5% to 14%, and are better in comparison to the BVAR models.

5.2.6 ARCH LM Test

Fig 6. Heteroskedasticity Tests

ARCH test	Obs*R-squared	Probability Chi-square (1)
Bitcoin	101.117	0.000
Ethereum	46.040	0.000
XRP	230.030	0.000
Litecoin	102.526	0.000
Binance Coin	79.333	0.000

The results of the Langrage Multiplier test (LM test) for autoregressive conditional heteroskedasticity errors (ARCH) prove that there is an ARCH effect among the variables. As the p-value for all crypto assets is significant at a 1% level, it indicates that there is a presence of ARCH effect in the series.

5.2.7 Univariate GARCH Model (1,1)

The GARCH model is used for modelling the volatility of crypto-asset returns where the result of the GARCH (1,1) model shows the average returns of the crypto assets in the following figure:

Fig 7. GARCH (1,1) Mean Equation

Sr No.	Cryptocurrency	Mean Return	Past Variance
1.	Bitcoin	0.0014**	-0.0113
2.	Ethereum	0.0016	0.0157
3.	XRP	-0.0024***	0.0444*
4.	Litecoin	-0.0010	-0.0513***
5.	Binance Coin	0.0017	-0.0146

, **, and * shows that the assets are significant at the 10%, 5%, and 1% levels, respectively*

In Figure 7, the highest average return is of Binance Coin. However, the past value of the Binance coin is insignificant, which indicates it cannot significantly predict the return for Binance Coin. Whereas, XRP and Litecoin's past value has significant predictive power to forecast the return. All coefficients of the conditional variance specification meet the stability conditions of $0 < b_1 < 1$, $0 < \theta_1 < 1$, and $b_1 + \theta_1 = 1$. Coefficients of the constant variance term, ARCH and GARCH parameters are positive and significant at a 1%, 5%, and 10% level.

Fig 8. GARCH (1,1) Variance Equation

Sr No.	Cryptocurrency	ARCH term (b_1)	GARCH Term (θ_1)	$b_1 + \theta_1$
1.	Bitcoin	0.1621***	0.8135***	0.9756
2.	Ethereum	0.1824***	0.7499***	0.9323
3.	XRP	0.2833***	0.6861***	0.9694
4.	Litecoin	0.0840***	0.8864***	0.9704
5.	Binance Coin	0.1568***	0.8339***	0.9907

, **, and * shows that the assets are significant at the 10%, 5%, and 1% levels, respectively*

These findings establish the presence of time-varying conditional volatility of returns of the crypto assets. The results also clearly depict that the persistence of volatility shocks, as represented by the sum of the ARCH and GARCH parameters ($b1 + \theta_1$) is larger in Litecoin. It denotes that the effect of today's shock remains in the forecasts of variance for many periods in the future.

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5.2.8 Univariate T-ARCH Model (1,1)

The idea behind the threshold ARCH is to bdivide the innovation distribution into disjoint intervals, then approximating a piecewise linear function, followed by conditional standard deviation (Zakoian 1991) and conditional variance (Glosten et al., Jagannathan and Runkle 1993. The result of the T-ARCH model (1, 1) model indicates the average return of crypto assets analysed in the figure below:

Fig 9. T-ARCH (1,1) Mean Equation

Sr No.	Cryptocurrency	Mean Return	Past Variance
1.	Bitcoin	0.0011**	-0.0076
2.	Ethereum	0.0015	0.0162
3.	XRP	-0.0015	0.0426*
4.	Litecoin	-0.0005	-0.0573***
5.	Binance Coin	0.0016	-0.0234

, **, and * shows that the assets are significant at the 10%, 5%, and 1% levels, respectively*

In Figure 9, crypto-assets such as XRP's, and Litecoin's past value has significant predictive power on the present return of the assets. However, only Bitcoin has a significant daily mean return.

Fig 10. T-ARCH (1,1) Variance Equation

Sr No.	Cryptocurrency	T-ARCH term	ARCH term (b_1)	GARCH Term (θ_1)	$b_1 + \theta_1$
1.	Bitcoin	0.0439***	0.1413***	0.8110***	0.9523
2.	Ethereum	0.0098	0.1791***	0.7482***	0.9273
3.	XRP	-0.1679***	0.3743***	0.6651***	1.0394
4.	Litecoin	-0.0416***	0.0994***	0.8908***	0.9902
5.	Binance Coin	-0.0332* (Student-t with 10 parameters)	0.0931***	0.8957***	0.9888

, **, and * shows that the assets are significant at the 10%, 5%, and 1% levels, respectively*

In Figure 10, the coefficient of the asymmetric term for Bitcoin is positive and statistically significant at 1% level, which indicates that for Bitcoin there are asymmetries in the news, Whereas the coefficient of the asymmetric term for XRP, Litecoin, and Binance Coin is negative and statistically significant at a 1% significance level, this shows that for XRP, Litecoin, and Binance Coin there are asymmetries in the news.

i. Negative Shock $_{(Bitcoin)}$: $h_t = 0.0000812 + 0.8110\ h_{t-1} + (0.1413 + 0.0439)\ u^2_{t-1}$
ii. Positive Shock $_{(XRP)}$: $h_t = 0.000332 + 0.6651\ h_{t-1} + (0.3743)\ u^2_{t-1}$
i. Positive Shock $_{(Litecoin)}$: $h_t = 0.000125 + 0.8908\ h_{t-1} + (0.0994)\ u^2_{t-1}$
ii. Positive Shock $_{(Binance\ Coin)}$: $h_t = 0.000104 + 0.8957\ h_{t-1} + (0.0931)\ u^2_{t-1}$

Therefore, we can say that the difference between Bitcoin and other coins is the T-ARCH parameter, which is the coefficient of the asymmetric term.

5.2.9 Univariate E-GARCH Model (1,1)

Similar to the T-GARCH Model, the E-GARCH Model (Black 1976 and Nelson 1991) is to capture the leverage effects of shocks on the financial market. The result of the E-GARCH (1,1) model shows the average returns of the crypto assets in the following figure:

Fig 11. E-GARCH (1,1) Mean Equation

Sr No	Cryptocurrency	Mean Return	Past Variance
1.	Bitcoin	0.0013**	-0.0438***
2.	Ethereum	0.0017	-0.0193
3.	XRP	-0.0008	0.0338*
4.	Litecoin	-0.0002	-0.0594***
5.	Binance Coin	0.0023*	-0.0252

, **, and * shows that the assets are significant at the 10%, 5%, and 1% levels, respectively*

In Figure 11, crypto-assets such as Bitcoin's, XRP's, and Litecoin's past value has significant predictive power on the present return of the assets.

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Fig 12. E-GARCH (1,1) Variance Equation

Sr No.	Cryptocurrency	E-GARCH term (λ)	e^{λ}	ARCH term (b_1)	GARCH Term (θ_1)	$b_1 + \theta_1$
1.	Bitcoin	-0.0322***	0.9683	0.2892***	0.9338***	1.223
2.	Ethereum	0.0219 Student-t with 15 parameters	1.0221	0.2771***	0.9328***	1.2099
3.	XRP	0.1202***	1.1277	0.4669***	0.8379***	1.3048
4.	Litecoin	0.0383***	1.039	0.1615***	0.9575***	1.1190
5.	Binance Coin	-0.0260***	0.9743	0.2777***	0.9748***	

, **, and * shows that the assets are significant at the 10%, 5%, and 1% levels, respectively*

In Figure 12, the coefficients of the asymmetric term for Bitcoin and Binance Coin is negative and significant at a 1% level, this depicts that bad news is aggravating the behaviour of Bitcoin and Binance Coin. Whereas other coins asymmetric term is significant and positive which depicts that good news has a larger effect on volatility than bad news. In exponential terms, bad news will have a 96.8% and 97.4% effect on Bitcoin and Binance Coin volatility.

Since the E-GARCH parameter is significant and positive we can say that Ethereum, XRP, and Litecoin have a leverage effect**.**

VI. CONCLUSIONS

This paper investigates the spillover effects and modelled volatility in the crypto market by various quant techniques such as VAR, Bayesian VAR, GARCH, T-ARCH & E-GARCH. Referring to the Annex. 1 (Bad News (Adj. Closing Price): Sharp fall in 2018), it can be said that on Dec. 7, 2017, bitcoin's price shot past $16,000 and almost touched $20,000 on Indian exchange markets too and within a span of just 20 minutes, bitcoin's price rose by almost $2,000 to $19,000 on global exchanges, before crashing by $4,000 and subsequently rising again. This increase was proof of the relationship between cryptocurrency and data miners where, due to excessive mining, a supply shot was observed that led to the trading volume being doubled. The above fluctuations were the effects of the same because investors became optimistic about the rising trend and market havoc was created due to active investments from major Asian investors. As per in sample and out of sample trading performances, performance outcomes of T-ARCH and E-GARCH models outperform others respectively (refer to Fig. 10 T-ARCH and 11 E-GARCH)

Given the overall cryptocurrency bull-run in the first quarter of 2018, our research showed that it was joined by Ethereum which rallied upwards their intrinsic value to $1250 from a low of $712 on December 17'. Ethereum saw a market correction of 1397 on Jan 19'. When talking about XRP, it has seen almost a 12% drop in one day on Dec. 17' which further fell by 22% the next day (Appendix annex.5) and quite interestingly, it was observed that XRP was among seven of the top 10 coins that saw its trading volume increase during the bull-run rally. The opinions on XRP's were also quite sceptical but in general, nobody was particularly worried since the fervent supporters insisted on the levels being guaranteed to go higher again, investments started running in. Due to this rally and upsurging volumes of the crypto trading – specifically bitcoin and Ethereum, investors were running out of options due to the saturation in the Bitcoin, Ethereum, and XRP market and hence, they opted for Litecoin as they sought to invest in the same market but were unable to do so because of the already flooded demand by the crypto leaders. In our study – Fig.11 (E-GARCH (1,1) Variance Equation); we see that the observed negative values of Bitcoin and Binance coin are suggestive of volatility which is affected by bad news, whereas the other coins in the E-GARCH terms having a positive value suggest that good news affects their volatility in greater terms.

In this study, we found that Bitcoin, Ethereum, and Litecoin are likely to have an independent relationship as compared to the other coins in our research data, in comparison to the other coins with respect to the VAR Granger causality approach. This suggests that investors can use Bitcoin, Ethereum, and Litecoin for portfolio diversification and as hedging instruments in the cryptocurrency market. Furthermore, we find that Litecoin, XRP, and Ethereum use T-ARCH and Bitcoin & Litecoin; use E-GARCH models, respectively and we used the Akaike info criterion to estimate the best fit model for each of the cryptocurrencies.

As per the statistical performance of the model for the volatility of different cryptocurrencies, assets suggest that there will be time-varying volatility, in the returns of cryptocurrency assets. Furthermore, we forecast that by 2021 blockchain standards will expand and another rise in the position of the current market will be observed if the institutions continue to showcase their interest in cryptocurrency investments. The Bayesian vector autoregressive model would address the problem by accounting for prior beliefs about the long-run dynamics of the data and by combining the observed data, with the long run beliefs about the data, this model would've been able to produce sharper inference. However, when we refer to our study, it reveals that both, Standard VAR, and Bayesian

VAR analysis have significance, however, owing to the low RSME and MAE values of VAR (refer to Fig. 5 – Bayesian VAR) it can be said that the standard VAR analysis would fetch better results. Although, there might be a problem of overfitting.

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