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MODELING CRYPTOCURRENCIES VOLATILITY USING GARCH MODELS: A COMPARISON BASED ON NORMAL AND STUDENT'S T-ERROR DISTRIBUTION

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Abstract: This study measures the volatility of cryptocurrency by utilizing the symmetric (GARCH 1,1) and asymmetric (EGARCH, TGARCH, PGARCH) model of GARCH family using a daily database designated in different digital monetary standards. The results for an explicit set of currencies for entire period provide evidence of volatile nature of cryptocurrency and in most of the cases, the PGARCH is a better-fitted model with student's t distribution. The findings show positive shocks heavily affected conditional volatility as a contrast with negative stuns. Those additional analyses can be provided further support their findings and worthwhile information for economic thespians who are engrossed in adding cryptocurrency to their equity portfolios or are snooping about the capabilities of cryptocurrency as a financial asset.

Keywords: Cryptocurrency; GARCH models; Normal Distribution; Student's T Distribution

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JEL Classifications: B26, C01, C19

1. Introduction

Cryptocurrency is a controversial issue for researchers in the recent era, this is just because of its volatile and digital nature is considered as an important concept for many economic and financial applications, such as portfolio optimization and risk management (Bhosale and Mavale 2018). Cryptocurrency is a secure virtual medium of exchange in the form of digital currency by using cryptography to secure and verify the specific transaction (Mukhopadhyay, Skjellum et al. 2016, Chu, Chan et al. 2017, Chuen, Lee et al. 2017). The digital currency eliminates the centralized system or third parties and their high fee of the transaction (Canetti, Dodis et al. 2007). This advanced digital type of currency looks for after to enhance regular money related structure to back trades without incorporation of revealed in unattainable, while making

unquestionable cryptographic guarantees. The trusted outsider third party sustain rescinds reliance over a definite obstacle in both of portion mysterious and installment affirmation.

The vitality about cryptographic authorizations through corroboration of work, which can ensure an unsurprising and exact reliable system in the whole deal, anyway entrapment may rise in without further upheaval installment confirmation (Farell 2015, DeVries 2016, Dyhrberg 2016, Gkillas and Katsiampa 2018). Bitcoin is being introduced as a first cryptocurrency in 2008, after facing the many time's failures by using the centralized system. Nowadays, Bitcoin has become the most popular and high capital contributing legal currency (Glaser, Zimmermann et al. 2014, Cermak 2017). Volatility unswervingly affects pricing, hedging, development of risk management and financial decisions (Ané 2006, Drachal 2017). The volatility of bitcoin is extreme as compare to other cryptocurrencies and affected by previous positive shocks (Bouoiyour and Selmi 2015, Bouri, Azzi et al. 2016, Dyhrberg 2016). (Bouri, Azzi et al. 2016) explained the importance of cryptocurrencies in his research the digital currency not correlated with the prices of traditional assets.

The block chain process registers individual transaction and maintains the record of transactions with specific coding (tokenization & Forking) i.e. past, public and ritualistic transaction verification. The systematic process eliminates the dispute occurring chances and makes transactions more secure and reliable. (Baur and Dimpfl 2018, Conrad, Custovic et al. 2018, Ekinici, Akyildirim et al. 2019) by using the VIX and VSTOXX measured the impact of volatility of cryptocurrency on United State and European financial markets. The study concluded that the volatility of cryptocurrency effect fluctuation of the financial market. (Sockin and Xiong 2018) explained the volatile nature of cryptocurrencies in his research by functioning with 456 digital currencies.

Cryptocurrency indicates a positive relation between volatility and shocks in the Pre-crash period (Bouri, Azzi et al. 2016). The expanded use and idolization of cryptocurrency create a need to measure its volatility. In this study, we expand upon the existing literature by demonstrating cryptographic currency's volatility. The GARCH type model has used with two error distribution techniques to measure the volatility of cryptocurrency as well as the better fitted model from GARCH family. The purpose of this study is to investigate which conditional heteroskedasticity model can describe the divergent cryptocurrencies price volatility better over the whole period.

In section 2 entails on the brief introduction of a specific set of cryptocurrency, Section 3 comprises a source of data and methodology used in this study. Section 4, 5 contain results discussion and conclusion.

Brief introduction of Currencies:

Bitcoin: The first peer-to-peer digital currency allows online payments (Nakamoto 2008, Bouoiyour and Selmi 2015, Dyhrberg 2016).

Ethereum: A virtual and completely programmable currency which comes with moderen febrication of different apps and technologies (Bhosale and Mavale 2018).

Ripple: this digital currency removed blockchain network for convinient access for transctions in contrast to most digital currencies. Its convinient and faster as well as it defenceless against programmer assquaults.

Stellar: An open-source, decentralized convention for computerized money to fiat money exchanges which permits cross-fringe exchanges between any combine of monetary standards. The Stellar convention upheld by a philanthropic, the Stellar Development Foundation.

Litecoin: A cryptographic money that was made with a goal to be the 'advanced silver' contrasted with Bitcoin's 'computerized gold.' It is additionally a fork of Bitcoin, however not at all like its forerunner, it can create squares multiple times quicker and have multiple times the most extreme number of coins at 84 mln.

Monero: A digital currency with private exchanges capacities and a standout amongst the most dynamic networks, which is because of its open and security centered standards.

Dash: It's a two-level system. The main level is diggers that safe the network system and record exchanges, while the second one comprises of 'ace hubs' that transfer exchanges and empower Instant send and Private send sort of exchange. The previous is essentially quicker than Bitcoin, though the last is mysterious.

NEO: It's a brilliant contract organize that takes into account a wide range of money related contracts and outsider dispersed applications to produce over it. It has a large number of indistinguishable objectives from Ethereum, yet it produced in China, which can conceivably give it a few favorable circumstances because of enhanced association with Chinese controllers and local organizations.

Data Description

This study deals with the secondary daily global price indices of particular cryptocurrencies. The sample consist of 8 cryptocurrencies (BTC, ETH, LTC, XPR, XLM, NEO, DASH & XMR) is from top fifteen cryptocurrencies of November 2018, ranked by market capitalization. The span period of data is different for each cryptocurrency due to the availability of data. The data obtained more up to date for this analysis which available publically (Table 1).

Table 1. Research Sample	
Currency/Variable	Sample Period
Bitcoin (BTC)	18 Jul. 2010 to 02 Nov. 2018
Ethereum (ETH)	07 Aug. 2013 to 02 Nov. 2018
Ripple (XRP)	04 Aug. 2013 to 02 Nov. 2018
Stellar (XLM)	05 Aug. 2014 to 02 Nov. 2018
Litecoin (LTC)	28 Apr. 2013 to 02 Nov. 2018
Monero (XMR)	21 May 2014 to 02 Nov. 2018
Dash (DASH)	14 Feb. 2014 to 02 Nov. 2018
NEO (NEO)	09 Sep. 2016 to 02 Nov. 2018

2. Methodology

When modeling volatility deal GARCH family Models, the adequacy of the mean equation is significantly important. Mean equation is given below:

$$\text{Mean Equation with constant, } r_t = \mu + \varepsilon_t$$

This study has to use GARCH type models, i.e. GARCH, EGARCH, PGARCH & TGARCH, each model which has a divergent purpose, with normal error distribution technique to measure the volatility of cryptocurrencies. Specifically, by using GARCH, EGARCH, PGARCH & TGARCH, we modeled the variance for the above Mean equations. The compassion of the result's estimation the distribution assumptions are checked the estimation results of the model. In 1982 Engle examined modeling volatility using conditionally heteroscedastic regression with the Autoregressive Conditional Heteroskedasticity (ARCH) model, but the large lag length is the major problem with such modeling which means large numbers of parameters are required to predict volatility. While using the Generalized Autoregressive Conditional Model (GARCH), conditional variance allows depending upon its lag, typically lessen the number of obligatory ARCH lags when measuring the volatility.

The equation is a general form of conditional variance equation:

$$\text{Variance Equation: } \varepsilon_t = \sqrt{h_t} v_t \sim iid(0,1)$$

Volatility Modeling

The existing family of GARCH type models divided into two main categories, i.e. Symmetric and Asymmetric models. The base of these categories is on; the symmetric models contain the conditional variance only depend on the magnitude not on the underlying assets whereas asymmetric models measure the different effect on future volatility on the same magnitude with negative and positive shocks (Omari, Mwita et al. 2017).

Symmetric Models

GARCH (1, 1) Model

The Generalized Autoregressive conditional Model by (Bollerslev 1986) denotes by GARCH (p,q) has:

$$r_t = \mu + y_t, \quad y_t = \sigma_t \varepsilon_t$$

$$\sigma_t^2 = \omega + \sum_{i=1}^p \alpha_i y_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2$$

In this equation r_t denotes the logarithmic return of the financial time series in respect t time, μ is mean value of return's representative, y_t is shows the mean equation's error term as well as it can riven into two stochastic pieces i.e. ε_t and σ_t , ε_t depicts independent and identical distributional zero mean, is assumed to have normal distribution $\omega > 0$, $\alpha_i \geq 0$, $\beta_i \geq 0$, with limitation and σ_t is dependent standard deviation.

GARCH (1, 1) model has presented by the following equation:

$$\sigma_t^2 = \omega + \alpha_1 y_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

$$\sum_{i=1}^p \alpha_i + \sum_{j=1}^q \beta_j < 1$$

A positive variance guaranteed in almost all the cases, under the following limitations $\omega > 0$ and $\alpha_1, \beta_1 \geq 0$, but a new GARCH extension models which deals with the weakness of GARCH (1, 1) model and capture diverse features of the financial time series, $\alpha + \beta < 1$ show the persistency of data.

Asymmetric Models

Exponential GARCH (1, 1) Model (EGARCH)

(Nelson 1990, Nelson 1991) introduced the Exponential GARCH model which measured the leverage effects (the asymmetry in return volatility). The following equation gives the general form of EGARCH (p,q):

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^p \alpha_i \left| \frac{y_{t-i}}{\sigma_{t-i}} \right| + \gamma_i \frac{y_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^q \beta_j \ln \sigma_{t-j}^2$$

In this equation, γ is representative of a leverage effect or the asymmetric response parameter that can appear with negative or positive sign to depict the future uncertainty. EGARCH (1, 1) shows in the following equation:

$$\ln \sigma_t^2 = \omega + \alpha_1 \left| \frac{y_{t-1}}{\sigma_{t-1}} \right| + \gamma_1 \frac{y_{t-1}}{\sigma_{t-1}} + \beta_1 \ln \sigma_{t-1}^2$$

For the good news, $\frac{y_{t-1}}{\sigma_{t-1}} > 0$ the equation is:

$$\ln \sigma_t^2 = \omega + (\alpha_1 + \gamma_1) \frac{y_{t-1}}{\sigma_{t-1}} + \beta_1 \ln \sigma_{t-1}^2$$

When bad news, $\frac{y_{t-1}}{\sigma_{t-1}} < 0$ the equation is:

$$\ln \sigma_t^2 = \omega + (\alpha_1 + \gamma_1) \frac{y_{t-1}}{\sigma_{t-1}} + \beta_1 \ln \sigma_{t-1}^2$$

The Threshold GARCH (1, 1) Model (TGARCH)

The following equation represents the Threshold GARCH model (Zakoian 1994):

$$\sigma_t^2 = \omega + \sum_{i=1}^p \alpha_i y_{t-i} + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 + \gamma_i I_{t-i} y_{t-i}$$

Only “I” is a new term in this equation which represents the dummy variable. The threshold GARCH model and the GJR-GARCH model (Glosten, Jagannathan et al. 1993) are almost the same. In TGARCH (1, 1) model, $\varepsilon_{t-1} > 0$ (positive shocks) and $\varepsilon_{t-1} < 0$ (negative shocks) produce a differential effect on volatility. $\varepsilon_{t-1} > 0$ (Positive shocks) have an effect on α (ARCH term) and $\varepsilon_{t-1} < 0$ (negative shocks) on $(\alpha + \gamma)$.

The Power GARCH Model (PGARCH)

The variance equation of Asymmetric Power ARCH (APARCH (p,q)) Model introduced by (Ding, Granger et al. 1993, Ling and McAleer 2002, Tully and Lucey 2007) in the following equation:

$$\sigma_t^\delta = \omega + \sum_{i=1}^p (\alpha_i |y_{t-i}| - \gamma_i y_{t-i})^\delta + \sum_{j=1}^q \beta_j \sigma_{t-j}^\delta$$

Where $\omega > 0$, $\delta > 0$, $\alpha_i \geq 0$, $-1 < \gamma_i$ and $\beta_j \geq 0$ are shows constant, power parameter, ARCH term, Leverage effect as well as GARCH term respectively. With the change of δ 's power the results become different at the power 1 the conditional standard deviation will be drawn, and at the power 2 leverage effects will be estimated and it's become (above equation) classic GARCH model as (Kovačić 2007).

Distribution model and selection criteria

In the analysis of this study Normal Gaussian Distribution which introduced by Carl Friedrich Gauss in 1809 is used (Alspach and Sorenson 1972, Barndorff-Nielsen 1977) with the best fitted criterion of Maximum Log Likelihood (Akaike 1974, Bozdogan 1987), minimum the Akaike Information Criterion (AIC) and The Bayesian Information Criterion (BIC) by (Schwarz 1978) respectively.

Distribution Model

An equation of the error distribution model given below:

Normal Gaussian distribution by Carl Friedrich Gauss in 1809 (Azzalini 1985)

$$\text{Log}L(\theta_t) = \sum_{t=1}^T L(\theta_t) = -\frac{1}{2} \text{Log}[2\pi] - \frac{1}{2} \sum_{t=1}^T \text{Log}(\sigma_t^2) - \frac{1}{2} \sum_{t=1}^T \frac{\mu_t^2}{\sigma_t^2}$$

where $\mu_t^2 = [y_t - \gamma y_{t-1}]^2$

Student's t distribution by (Fernández and Steel 1998)

$$L(\theta)_t = -\frac{1}{2} \log \left[\frac{\pi[v-2] \Gamma\left[\frac{v}{2}\right]^2}{\Gamma\left[\frac{v+1}{2}\right]^2} \right] - \frac{1}{2} \log \sigma_t^2 - \left[\frac{v+1}{2} \right] \log \left[1 + \frac{[y_t - x_t' \gamma]^2}{\sigma_t^2 [v-2]} \right]$$

Selection criteria

Equations of Log likelihood by Akaike (1974) and the Bayesian Information Criterion by (Schwarz 1978) presented below:

$$\begin{aligned} LL &= 2k - 2 \ln L(\hat{\theta}) \\ AIC_c &= AIC + \frac{2k(K+1)}{n-k-1} \\ BIC &= k \ln n - 2 \ln L(\hat{\theta}) \end{aligned}$$

3. Empirical results

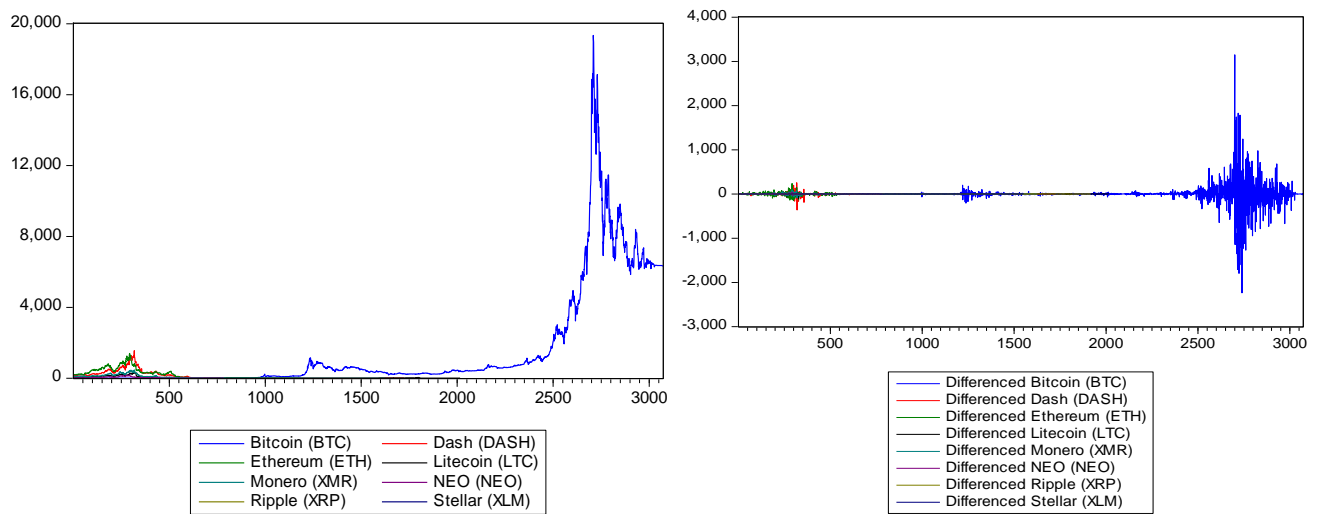
Table 2 comprises the results of descriptive statistics for the daily closing return prices of 8 cryptocurrencies the daily average return of BTC (0.003635), ETH (-0.00362), XRP (-0.00227), XLM (-0.00295), LTC (-0.00123), XMR (-0.00258), DASH (-0.0035) and NEO (-0.00429) with positive standard deviation. Except for Ethereum (ETH), the skewness value of all cryptocurrencies is negative which indicate a long left tail, and the excess kurtosis value from 3 shows the leptokurtic behavior. The Jarque-Bera (JB) test is significant at 1% level, so the statistics value of JB depicts departure from the normality as (Ané 2006, Miron and Tudor 2010, Drachal 2017, Katsiampa 2017). ARCH (5) test for conditional heteroskedasticity rejected the null hypothesis and confirmed the occurrence of ARCH affect in returns of cryptocurrencies which indicates that the GARCH techniques can perform with different specifications (Diebold 2004, Omolo 2014).

Table 2. Descriptive Statistics

	BTC	ETH	RP	LM	LTC	XMR	DASH	NEO
Mean	0.003635	-0.00362	-0.00227	-0.00295	-0.00123	-0.00258	-0.0035	-0.00429
Maximum	0.42458	1.302106	0.616273	0.366358	0.513925	0.378215	0.467565	0.522543
Minimum	-0.49153	-0.41234	-1.02736	-0.7231	-0.82897	-0.58464	-1.27057	-0.80117
Std. Dev.	0.056959	0.078639	0.078217	0.081641	0.067176	0.075264	0.081822	0.104733
Skewness	-0.34428	3.496276	-2.00101	-1.95562	-1.78314	-0.65797	-3.03693	-1.07869
Kurtosis	15.30196	68.91756	29.84154	17.83798	28.86838	8.950268	45.07816	13.38094
Jarque-Bera	19425.66*	216588.6*	58795.98*	15207.02*	57222.06*	2514.512*	129685.5*	3672.328*
Probability	0	0	0	0	0	0	0	0
Observations	3071	1183	1916	1550	2014	1625	1722	784
μ	0.003635*	-0.00362*	-0.00227*	-0.00295*	-0.00123*	-0.00258*	-0.0035*	-0.00429*
Probability	0.001028	0.002286	0.001787	0.002074	0.001497	0.001867	0.001972	0.00374
ARCH (5)	247.6041*	81.79713*	37.12448*	62.49783*	16.90387*	20.87508*	9.351001*	27.40471*
Probability	0	0	0	0	0	0	0	0

1%, 5%, 10% significance level are represented with *, **, *** respectively

Graphical Representation of Cryptocurrencies' Price and Returns



Description of GARCH type Models

The manifestation of ARCH effect allows to applied the GARCH type models on sample data (Shaw 2018). The figurative analysis deals with GARCH (1,1) model for observing the symmetric effect and EGARCH (1,1), PGARCH (1,1) & TGARCH (1,1) for awry effect with Normal & Student's *t* Error Distribution.

Table. 3 BITCOIN

	Normal Error Distribution				Students' t Error Distribution			
	GARCH	EGARCH	TGARCH	PGARCH	GARCH	EGARCH	TGARCH	PGARCH
Mean	0.001891*	0.004344*	0.002058*	0.002489*	7.24E-07	0.001006*	1.31E-06	-3.03E-09
μ (Constant)	0.000550	0.000196	0.000568	0.000462	2.40E-05	0.000270	2.74E-05	2.33E-07
Variance	0.000069*	-0.614515*	6.75E-05*	0.000440*	1.82E-10	-0.378045*	3.84E-10	5.85E-05
ω (Constant)	0.000002	0.019040	2.31E-06	0.000089	1.21E-09	0.035099	2.65E-09	0.000555
α (ARCH term)	0.213610*	0.365511*	0.230717*	0.220567*	1.397243*	0.487165*	1.160150*	0.542236*
	0.008478	0.011025	0.013994	0.007835	0.690377	0.083689	0.303864	0.122304
β (GARCH term)	0.795849*	0.940209*	0.797679*	1.470625*	0.569058*	0.973009*	0.701818*	0.542684*
	0.005494	0.002293	0.005807	0.054570	0.008551	0.004322	0.008997	0.020473
γ (Leverage effect)	----	0.015886**	-0.038593*	-0.029818***	----	0.010945	-0.262955***	-0.053873
	----	0.007267	0.014113	0.017675	----	0.021766	0.143846	0.049143
δ (Power)	----	----	----	0.807038*	----	----	----	0.816293*
	----	----	----	0.005110	----	----	----	0.007932
$\alpha + \beta$	1.009459	1.305720	1.028396	1.691192	1.966301	1.460174	1.861968	1.084920
LL	5348.701	5349.832	5350.212	5357.922	6059.93	5973.494	6060.853	6270.692
AIC	-3.481	-3.480842	-3.481089	-3.485459	-3.9433	-3.886353	-3.943245	-4.079252
SIC	-3.473	-3.471024	-3.471272	-3.473678	-3.93348	-3.874572	-3.931465	-4.065508
ARCH (5)	0.738	0.404977	0.753036	1.345983	0.000326	0.01257	0.000326	0.000326
Probability	0.595	0.8456	0.5838	0.2418	1	0.9999	1	1
Jarque-Bera	17455.380*	23804.94*	17869.8*	18939.42*	1.20E+09*	6880193*	1.20E+09*	1.20E+09*
Probability	0.000	0	0	0	0	0	0	0

1%, 5%, 10% significance level are represented with *, **, *** respectively

In table 3 the results of first and foremost (Xu and Livshits 2018) digital currency “Bitcoin” are presented. The outcomes of bitcoin show significance at 1% level towards constant of mean and variance under a specific set of GARCH type models with Normal Error Distribution whereas the student's t distribution show significance only under Exponential GARCH model. The leverage coefficient is positively significant in the EGARCH model and negatively significant in TGARCH & PGARCH model at 5%, 1% & 10% respectively with a normal distribution as (Bouri, Azzi et al. 2016).

Under student's t distribution only Power GARCH is significant at 10% level with a negative sign. The results of both distributions indicate the absence of leverage effect, but previous positive shocks or good news has a stronger effect on the subsequent volatility of Bitcoin (Chu, Chan et al. 2017). The Power GARCH is significant at 1% level under both error distribution techniques. The convergence of α & β is $= 1$ or ≥ 1 which direct inconsistency of error term. The selection criterion (maximum LL, minimum AIC, SIC) indicate the Power GARCH model with Student's t distribution is better to fit as (Watanabe, 2010). The ARCH (5) governed Bitcoin Price Index free from the serial correlation and aberrant distribution of error is observed by the significance of Jarque-Bera test at 1% level as (Ané 2006).

Table 4. Ethereum

	Normal Error Distribution				Student's t Error Distribution			
	GARCH	EGARCH	TGARCH	PGARCH	GARCH	EGARCH	TGARCH	PGARCH
Mean μ (Constant)	-0.001529	-0.003523*	-0.002422***	-0.00283**	0.000718	0.0001	0.00066	0.000201
Variance ω (Constant)	0.001271	0.001117	0.001426	0.001457	0.001187	0.001178	0.00122	0.001076
α (ARCH term)	0.000153*	-0.633624*	0.000174*	0.00059**	0.000186*	-0.643994*	0.000208*	0.010127
	2.63E-05	0.043939	2.77E-05	0.000282	7.21E-05	0.110715	7.75E-05	0.006869
β (GARCH term)	0.242809*	0.405707*	0.136033*	0.229518*	0.305193*	0.448671*	0.237256*	0.226925*
	0.018861	0.027322	0.020594	0.01868	0.081512	0.072602	0.081352	0.040009
γ (Leverage effect)	0.773658*	0.936608*	0.780136*	1.587702*	0.780331*	0.932065*	0.77336*	0.645491*
	0.015592	0.006071	0.014666	0.164664	0.029358	0.017096	0.030493	0.201822
δ (Power)	-0.104712*	-0.166393*	0.202395*	0.049574	-0.056031	0.119964	0.013799	0.013799
	0.016089	0.029912	0.049574	0.078585*	0.039224	0.083484	0.110855	0.798357*
$\alpha + \beta$				0.015635				0.029001
LL	1.016467	1.342315	0.916169	1.81722	1.085524	1.380736	1.010616	0.872416
AIC	1623.373	1630.278	1629.271	1630.236	1710.708	1720.288	1711.45	1719.873
SIC	-2.737739	-2.747723	-2.746021	-2.745961	-2.883699	-2.898204	-2.883263	-2.895812
ARCH (5)	-2.720577	-2.72627	-2.724568	-2.720217	-2.862246	-2.87246	-2.857519	-2.865777
Probability	1.764135	5.516272*	2.179313**	2.892423*	1.940619	6.632512*	2.213135**	6.741273*
Jarque-Bera	0.1174	0	0.0542	0.0133	0.085	0	0.0508	0
Probability	5175677*	738.1487*	398.7966*	461.1296*	521.9442*	1092.204*	4.54E+02*	1.71E+03*
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

1%, 5%, 10% significance level are represented with *, **, *** respectively

The results of Ethereum are composed of in table 4 in which easily see the mean constant is significant in EGARCH at 1%, TGARCH at 10% and in PGARCH at 5% level with Normal distribution as well as insignificant with student's t distribution. The constant of variance equation is significant at 5% level under PGARCH model with normal distribution and at 1% level rest of models with both error distribution techniques except PGARCH with student's t distribution. The ARCH and GARCH term are significant at 1% level of confidence in a specific set of GARCH type models with both distribution techniques. The sign of negativity with leverage value has assured the presence of leverage effect in Ethereum price index. Leverage effect is significant under EGARCH with normal distribution at 1% level indicates the negative shocks are having a greater impact on the volatility of Ethereum as compare to positive shocks.

TGARCH and PGARCH also showed a positive significance toward leverage effect which also supports the negative shock impact on volatility. With student's t distribution, leverage effect is insignificant in EGARCH with a negative sign and TGARCH & PGARCH with a positive sign. The coefficient of Power GARCH is significant at 1% level with both distributions. The convergence of α & β is $= 1$ or ≥ 1 which direct error terms are not persistence (Abdullah, Siddiqua et al. 2017). The selection criterion (maximum LL, minimum AIC, SIC) indicate the Exponential GARCH model with Student's t distribution is better to fit as (Bozdogan 1987). The ARCH (5) governed Ethereum Price Index cannot eliminate the serial correlation and significance of Jarque-Bera test shows errors are anomalously distributed.

Table. 5 LITE COIN

	Normal Error Distribution				Student's t Error Distribution			
	GARCH	EGARCH	TGARCH	PGARCH	GARCH	EGARCH	TGARCH	PGARCH
Mean μ (Constant)	0.001033	0.001293**	0.001018	0.001307*	0.000698	0.000785*	0.000561	0.001032*
	0.000665	0.000685	0.000777	0.000232	0.000558	0.000552	0.000555	0.000309
Variance ω (Constant)	5.69E-05*	-0.41575*	5.71E-05*	0.01521*	0.000132	-0.289952*	0.000102	0.014668*
	5.35E-06	0.020343	5.41E-06	0.002112	9.57E-05	0.040762	9.74E-05	0.005575
α (ARCH term)	0.253656*	0.355672*	0.251041*	0.193714*	0.66317	0.431569*	1.12838	0.154944*
	0.013601	0.015881	0.022405	0.011138	0.457579	0.098109	1.036155	0.02637
β (GARCH term)	0.793734*	0.969885*	0.793638*	0.261818*	0.817264*	0.98115*	0.862913*	0.166606***
	0.007762	0.002489	0.007875	0.04659	0.017603	0.005384	0.013815	0.106764
γ (Leverage effect)		-0.018833	0.005046	0.119567*		0.099009*	-0.893885	-0.068347
		0.013316	0.027861	0.048871		0.03877	0.831444	0.113379
δ (Power)				0.810446*				0.850017*
				0.007765				0.015022
$\alpha + \beta$	1.04739	1.325557	1.044679	0.455532	1.480434	1.412719	1.991293	0.32155
LL	3178.346	3237.442	3178.35	3308.811	3484.764	3530.747	3493.715	3568.921
AIC	-3.15228	-3.209973	-3.151291	-3.279852	-3.455575	-3.500245	-3.463471	-3.537161
SIC	-3.141142	-3.19605	-3.137369	-3.263145	-3.441653	-3.483539	-3.446764	-3.51767
ARCH (5)	1.759746	1.555313	1.756065	1.81356	1.48893	1.504354	1.301053	1.98529
Probability	0.1179	0.1695	0.1187	0.1069	0.1902	0.1852	0.2606	0.0778
Jarque-Bera	2917271	2631.758	2913.696	2035.776	2888.775	3325.583	3911.417	2392.004
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

1%, 5%, 10% significance level are represented with *, **, *** respectively

Table 5 consists the results of Lite coin. The constant of mean is significant under EGARCH, and PGARCH of both distributions and rest of models show an insignificant trend toward mean equation. The constant of variance and ARCH term are significant at 1% level in all except GARCH and TGARCH of student's t distribution. The GARCH term is significant at 10% level in PGARCH with student's t distribution and 1% level under remaining models with both distributions. Leverage effect is positively significant under PGARCH of normal error distribution and EGARCH of student's t distribution. The Power GARCH is significant at 1% level in both error distribution techniques. Maximizing log likelihood and minimizing AIC & SIC governs power GARCH model is the best model for Lite coin from a selected group of GARCH family models. The insignificance of ARCH (5) indicates Lite coin price index has no more serial correlation and the Jarque-Bera's significance shows error is beyond to normal distribution.

Table 6. Stellar

	Normal Error Distribution				Student's t Error Distribution			
	GARCH	EGARCH	TGARCH	PGARCH	GARCH	EGARCH	TGARCH	PGARCH
Mean μ (Constant)	0.002359**	0.005087*	0.004993*	0.00611*	0.003929*	0.004782*	0.004702*	0.005089*
	0.001053	0.001052	0.00118	0.001041	0.001049	0.001055	0.00109	0.000911
Variance ω (Constant)	0.000267*	-0.80859*	0.00023*	0.004895*	0.000578*	-0.956083*	0.000445*	0.018365**
	0.000033	0.054045	2.89E-05	0.001604	0.000129	0.126842	0.000108	0.008657
α (ARCH term)	0.394873*	0.527842*	0.619804*	0.317444*	0.586362*	0.61604*	0.785406*	0.336713*
	0.026744	0.028427	0.053898	0.021632	0.103722	0.068224	0.149092	0.042759
β (GARCH term)	0.650600*	0.920068*	0.673959*	0.962183*	0.51813*	0.899339*	0.569624*	0.644232*
	0.014884	0.008071	0.016333	0.104295	0.041333	0.019398	0.039473	0.149038
γ (Leverage effect)		0.142179*	-0.427487*	-0.322863*		0.106506*	-0.431216*	-0.194643*
		0.019285	0.054771	0.044876		0.037348	0.129749	0.078824
δ (Power)				0.725507*				0.666828*
				0.015025				0.033775
$\alpha + \beta$	1.045473	1.447910	1.293763	1.279627	1.104492	1.515379	1.355030	0.980945
LL	2057.661	2090.016	2078.205	2092.992	2169.278	2186.917	2175.024	2192.016
AIC	-2.650	-2.690343	-2.675103	-2.692893	-2.79262	-2.814087	-2.798741	-2.819375

SIC	-2.636	-2.673098	-2.657857	-2.672199	-2.77537	-2.793393	-2.778047	-2.795232
ARCH (5)	0.767	0.524712	0.786809	0.761625	0.626259	0.511572	0.774734	0.520529
Probability	0.574	0.7577	0.5591	0.5775	0.6798	0.7677	0.5679	0.7609
Jarque-Bera	1313.920*	946.5384*	724.1884*	1060.739*	2266.575*	1234.02*	1237.651*	2392.325*
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

1%, 5%, 10% significance level are represented with *, **, *** respectively

The results of Stellar coin displayed in table 6 in which easily observed the constant of mean, constant of variance, ARCH term, and GARCH term are significant at 1%, 5% under all specific models with both error distribution techniques. Leverage effect is also shown its significance at 1% level of confidence under EGARCH, TGARCH & PGARCH with normal and Student's *t* distribution. Positive significance of EGARCH and negative significance of TGARCH & PGARCH directs the leverage effect is not present in returns but the positive news having an impact on the volatility of Stellar. No more ARCH (5) effect observed in return series. Significance of Jarque-Bera test pointed toward not normal distribution of errors term. Power GARCH is significant at 1% level with a positive sign. Selection criterion leads to PGARCH with student's *t* distribution as a better-fitted model for Stellar.

Table 7. Ripple								
	Normal Error Distribution				Student's <i>t</i> Error Distribution			
	GARCH	EGARCH	TGARCH	PGARCH	GARCH	EGARCH	TGARCH	PGARCH
Mean μ (Constant)	0.002664*	0.002653*	0.002918*	0.002607*	0.002697*	0.00278*	0.002761*	0.001977*
Variance ω (Constant)	0.000633	0.000739	0.000776	0.000647	0.000666	0.000683	0.00069	0.000482
	0.000107*	-0.67343*	0.000105*	0.002648*	0.000668**	-1.097227*	0.000624**	0.019389*
α (ARCH term)	1.22E-05	0.029128	1.22E-05	0.000524	0.000324	0.10735	0.000295	0.007304
	0.451215*	0.571824*	0.479072*	0.336183*	1.504763**	0.937303*	1.588926**	0.411596*
β (GARCH term)	0.019542	0.018302	0.030284	0.013797	0.703186	0.175619	0.737089	0.069602
	0.666825*	0.950439*	0.670846*	0.909856*	0.4784*	0.880229*	0.489232*	0.592201*
γ (Leverage effect)	0.009024	0.00434	0.009143	0.064272	0.0319	0.016827	0.031862	0.116451
		0.039393*	-0.063537	-0.060535**		0.053135	-0.271718	0.028074
δ (Power)		0.014805	0.041883	0.030892		0.046143	0.293927	0.070902
				0.75116*				0.675136*
$\alpha + \beta$				0.009309				0.027139
	1.11804	1.522263	1.149918	1.246039	1.983163	1.817532	2.078158	1.003797
LL	2849.234	2870.017	2849.661	2876.203	3068.981	3083.61	3069.385	3095.396
AIC	-2.96997	-2.990624	-2.969375	-2.996036	-3.19831	-3.212537	-3.197688	-3.223796
SIC	-2.95837	-2.976119	-2.95487	-2.978631	-3.18381	-3.195132	-3.180283	-3.20349
ARCH (5)	1.17923	0.922545	1.138426	1.541312	1.477363	1.081215	1.451788	1.210077
Probability	0.3169	0.4652	0.3378	0.1737	0.194	0.3687	0.2026	0.3018
Jarque-Bera	1536.774*	1789.901*	1559.386*	1802.69*	3124.864*	2987.619*	3095.64*	3467.183*
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

1%, 5%, 10% significance level are represented with *, **, *** respectively

The results of Ripple coin displayed in table 7 in which easily observed the constant of mean, constant of variance, ARCH term, and GARCH term are significant at 1%, 5% under all specific models with both error distribution techniques. Leverage effect is shown its significance at 1% and 5% level of confidence under EGARCH & PGARCH with normal. Positive significance of EGARCH and negative significance of PGARCH directs the leverage effect is not present in returns but the positive news having an impact on the volatility of Ripple.

Power GARCH is significant at 1% level with a positive sign. Selection criterion leads to PGARCH with student's *t* distribution as a better-fitted model for Stellar. No further ARCH effect observed and non-normality of returns distribution by whom significance of Jarque-Bera test at 1% level.

Table 8. Monero

	Normal Error Distribution				Student's t Error Distribution			
	GARCH	EGARCH	TGARCH	PGARCH	GARCH	EGARCH	TGARCH	PGARCH
Mean μ (Constant)	0.000449	0.001262	0.000837	0.001741	0.000805	0.001201	0.000697	0.001864***
Variance ω (Constant)	0.000256*	-0.5911*	0.000217*	0.005337*	0.000356*	-0.429662*	0.000113*	0.007144**
α (ARCH term)	0.216637*	0.371291*	0.235549*	0.182569*	0.246235*	0.298356*	0.223406*	0.142621*
β (GARCH term)	0.762421*	0.940736*	0.783418*	0.771489*	0.732203*	0.958843*	0.879281*	0.540805*
γ (Leverage effect)	0.01806	0.00736	0.016462	0.118409	0.033858	0.011539	0.018717	0.171245
δ (Power)	0.019582	-0.064855**	-0.114067**	0.060634	0.078824*	-0.183311*	-0.329122*	0.105358
$\alpha + \beta$	0.018708	0.032433	0.826754*	0.014181	0.02481	0.039298	0.866048*	0.018939
LL	1.11804	1.522263	1.149918	1.246039	1.983163	1.817532	2.078158	1.003797
AIC	2094.13	2108.939	2095.17	2113.799	2151.032	2168.71	2157.656	2174.113
SIC	-2.57247	-2.589463	-2.572517	-2.594215	-2.64127	-2.661797	-2.648192	-2.667216
ARCH (5)	-2.55919	-2.572869	-2.555923	-2.574301	-2.62468	-2.641883	-2.628278	-2.643983
Probability	1.098378	1.071339	1.11024	1.1674	1.137127	1.341863	2.063717	1.716095
Jarque-Bera	0.3593	0.3744	0.3528	0.3229	0.3385	0.2438	0.0673	0.1277
Probability	236.724*	301.2746*	252.471*	308.0951*	251.08*	367.944*	465.8041*	378.2268*
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

1%, 5%, 10% significance level are represented with *, **, *** respectively

Table 8 shows the results of Monero which indicate the constant of mean is insignificant in almost all cases except PGARCH with student's t distribution. The constant of variance, ARCH and GARCH term in PGARCH with student's t distribution presents the significance at 5% level and under a remaining set of models the significance level of constant is 1%. In above table, it can be observed that the leverage of EGARCH having positive value or absence of leverage effect in Monero price index but in term of volatility Monero effected by positive shocks. The significance of leverage effect governs leverage effect magnitude and sign of leverage value indicates its direction (Miron and Tudor 2010). No more ARCH (5) effect observed in return series. Significance of Jarque-Bera test pointed toward not normal distribution of errors term. The power GARCH is better-fitted model according to a selection criterion.

Table 9. DASH

	Normal Error Distribution				Student's t Error Distribution			
	GARCH	EGARCH	TGARCH	PGARCH	GARCH	EGARCH	TGARCH	PGARCH
Mean μ (Constant)	-0.00024	0.00064	0.000683	0.000585	0.001761***	0.001744***	0.001912***	0.001617***
Variance ω (Constant)	0.000942	0.000924	0.001053	0.000911	0.000966	0.000966	0.000988	0.00095
α (ARCH term)	8.79E-05*	-0.383805*	7.76E-05*	0.001169*	0.000264*	-0.624393*	0.000215*	0.005076***
β (GARCH term)	1.18E-05	0.017743	1.14E-05	0.000287	7.19E-05	0.086131	6.05E-05	0.002895
γ (Leverage effect)	0.238898*	0.380795*	0.304515*	0.210785*	0.328698*	0.458254*	0.393902*	0.234224*
δ (Power)	0.011244	0.015109	0.018299	0.009979	0.063038	0.054195	0.084416	0.033476
$\alpha + \beta$	0.796734*	0.978249*	0.812374*	0.99023*	0.727649*	0.939721*	0.757743*	0.819855*
LL	0.007053	0.002753	0.007953	0.079767	0.027779	0.01311	0.026042	0.191313
AIC		0.065366*	-0.151458*	-0.135962*		0.052164***	-0.178129*	-0.066674
SIC		0.012482	0.023398	0.040611		0.030599	0.073932	0.082667
Probability			0.842444*	0.006717				0.802378*
Probability	1.035632	1.359044	1.116889	1.201015	1.056347	1.397975	1.151645	1.054079
Probability	2357.24	2374.777	2364.56	2378.132	2502.461	2515.61	2505.228	2516.567

AIC	-2.73315	-2.752355	-2.740488	-2.75509	-2.90065	-2.914762	-2.902703	-2.914712
SIC	-2.72049	-2.736526	-2.724659	-2.736096	-2.88482	-2.895768	-2.88371	-2.892553
ARCH (5)	1.70042	1.834161	1.676498	2.646254**	1.509484	1.320513	1.491543	2.614365**
Probability	0.1313	0.1031	0.137	0.0216	0.1836	0.2525	0.1894	0.0231
Jarque-Bera	1432.271*	1307.01*	1281.97*	1236.586*	1982.464*	2161.891*	1651.57*	1887.009*
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

1%, 5%, 10% significance level are represented with *, **, *** respectively

In table 9 the results of Dash are presented which indicated the constant of the mean equation is insignificant under all GARCH models with normal error distribution. The constant mean with student's t distribution is significant at 10% level under all specific models. The constant variance shows significance at 1% and 10% with both distributions and models. The ARCH and GARCH terms are also significant at 1% level. The fluctuation of volatility according to time periods refers the presence of volatility clustering. Except for PGARCH with student's t distribution leverage effect is significant in all cases. The positive significance of EGARCH indicates the absence of leverage effect but the impact of positive events on future future volatility. Power GARCH is significant at 1% level with both distributions. PGARCH with student's t distribution is a best-fitted model for Dash coin. In two cases ARCH (5) is significant at 5% level which indicates the presence of serial correlation in returns and rest of 6 models are shown the elimination of serial correlation. PGARCH model with both distributions indicates the presence of serial correlation and returns not normally distributed observed by the significance of Jarque-Bera's significance at 1% level.

Table 10. NEO

	Normal Error Distribution				Student's t Error Distribution			
	GARCH	EGARCH	TGARCH	PGARCH	GARCH	EGARCH	TGARCH	PGARCH
Mean	0.002849	0.005194*	0.004115***	0.007173*	0.005139*	0.004995*	0.005474*	0.004454*
μ (Constant)	0.002096	0.002087	0.002342	0.00129	0.002182	0.002138	0.002219	9.60E-05
Variance	0.000805*	-0.995727*	0.000754*	0.021225*	0.0012*	-0.66618*	0.00117*	0.024165*
ω (Constant)	0.000127	0.103227	0.000129	0.008501	0.00043	0.146727	0.000416	0.013397
α (ARCH term)	0.423003*	0.556713*	0.555838*	0.285987*	0.383487*	0.439263*	0.603118*	0.17487**
	0.041213	0.044561	0.083843	0.029069	0.108607	0.078629	0.188051	0.039893
β (GARCH term)	0.593808*	0.875837*	0.602493*	0.630423*	0.626661*	0.918507*	0.609725*	0.339403*
	0.029126	0.016708	0.032064	0.136638	0.060033	0.024719	0.061647	0.18312
γ (Leverage effect)		0.061644**	-0.236816*	-0.201356*		0.056005	-0.322054**	-0.132551
		0.029483	0.08684	0.070413		0.046291	0.165542	0.15311
δ (Power)				0.702001*				0.811888*
				0.023564				0.034422
$\alpha + \beta$	1.016811	1.43255	1.158331	0.91641	1.010148	1.35777	1.212843	0.514273
LL	803.4419	815.0867	805.7186	818.3656	857.2878	868.2853	859.4079	871.6313
AIC	-2.03939	-2.066548	-2.042649	-2.072361	-2.1742	-2.199707	-2.177061	-2.205692
SIC	-2.0156	-2.0368	-2.012902	-2.036664	-2.14446	-2.16401	-2.141364	-2.164045
ARCH (5)	2.2423**	1.901734	2.078825	1.79591	2.316644**	1.901614	2.123423	8.05556*
Probability	0.0484	0.0918	0.066	0.1113	0.042	0.0918	0.0607	0.0047
Jarque-Bera	264.600*	277.4045*	283.7157*	260.0377*	305.5128*	314.3786*	333.188*	347.2067*
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

1%, 5%, 10% significance level are represented with *, **, *** respectively

In table 10 the results of NEO are given. The constant of the mean equation is significant in all models at 1% & 10% level except GARCH model with a normal distribution. Constant of conditional variance is negatively significant at 1% level in EGARCH (1,1) model and positively significant at 1% level in rest of models. The ARCH term (α) and the GARCH term (β) are significant at 1% level. The greater value of α directed a strong reaction of volatility and β depicts clustering volatility, if the sum of ARCH and GARCH term is less than unity, so data is close to stationary. The leverage effect of EGARCH is positively significant at 5% level with normal distribution and insignificant with a positive sign with student's t

distribution which shows no leverage effect in data. The leverage effect of TGARCH & PGARCH model is negative and significant with normal error distribution and EGARCH, and PGARCH with student's t distribution is insignificant with the positive and negative sign respectively. The negativity of the PGARCH (1,1)'s leverage effect indicates that positive news has more impact on volatility and ratifies the presence of a leverage effect. Power GARCH model is significant at 1% level of confidence. By ARCH (5) test shows that the serial correlation not eliminated observed from NEO prices index. JB explained errors not normally distributed. The maximum value of Log Likelihood (LL) and a minimum value of AIC and SIC governed the PGARCH (1,1) model is a better-fitted model for NEO.

Conclusions

Cryptocurrency and its volatility is a burning issue in the present decade for investors, financial manager, researchers and policy makers. The substantial volatile nature and high growth rate of cryptocurrency increase more interest of investors; because of more fluctuating prices the return rate has keenly effected (Bouoiyour and Selmi 2015). This study not only determined the high rate volatility of volatility in cryptocurrency prices but the better GARCH fitted model with efficient measuring error distribution technique. The findings of Bitcoin, Stellar, Ripple, Monero, Dash, NEO, Lite coin have shown the Power GARCH model with student's t distribution is better fitted model according to selection criterion i.e. LL, AIC & SIC as (Bouri, Azzi et al. 2016, Cermak 2017, Katsiampa 2017). Only Ethereum directs toward Exponential GARCH model with student's t distribution. The smaller and thus asymmetric volatility response to positive shocks explained with contrarian behavior of all digital currencies except Lite coin and Ethereum.

The negativity of leverage effect for Lite coin and Ethereum show these both currencies are effected by previous negative shocks in the line of (Baur & Dimpfl, 2018; Chan *et al.*, 2018). Cryptocurrency may suffer the effect of information asymmetry, as its framework is moderately perplexing and in this way may not be effortlessly comprehended by all clients (Ciaian et al. 2014). This study will provide a guideline for investors to check the volatility of cryptocurrency and the effect of both types of shocks (positive & negative) at the fluctuation of cryptocurrency that legitimate safety efforts are winding up more reasonable for general society by guaranteeing that Bitcoin is as protected as would be prudent.

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