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Performance of ARCH and GARCH Models in Forecasting Cryptocurrency Market Volatility

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ABSTRACT

The cryptocurrency market is highly volatile; this can be attributed to several factors such as being an emerging market that is purely digital and still evolving with many speculations taking place aligning with behavioural finance factors such as media and investors profile. This study aims to investigate the Autoregressive Conditional Heteroskedasticity (ARCH) and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) in forecasting selected 9 cryptocurrencies that represent over 80% of the total market capitalization. This study carries a time-series of daily data ranges from 2010 to 2020 base on each cryptocurrency starting date. The results show that the ARCH and GARCH have a significant effect in forecasting cryptocurrency market volatility which means that the past volatility of cryptocurrencies affects the current volatility of it. It also shows that bad and good news can significantly affect the conditional volatility of all cryptocurrencies returns. This study contributes to the investors' understanding of the dynamics of the cryptocurrency market which enhances the ability to make informed decisions based on a scientific approach.

Keywords: Cryptocurrencies, Volatility, ARCH, GARCH

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1. INTRODUCTION

Over the centuries, money systems have significantly evolved. From barters to commodity money, metallic money, paper money, credit money, and plastic money. In each phase, technological innovations, economic needs and the comparable efficiency of completing a transaction constituted the factors to determine the continuity of one money form over another. In recent years, an escalating rise in the global resentment toward the current monetary system persists, especially after the financial turmoil which hit the financial markets during 2007-2009 lifting severe economic impacts globally.

In 2009, Bitcoin (the first cryptocurrency) has launched. According to its white paper, it aimed to create a radical change to the global monetary system. A few years later, the idea of bitcoin has taken significant consideration of the public interest as crowds started to use bitcoin derived by many reasons inter alia, the need for an alternative monetary system that is less engaged with the current traditional system. Amid this public interest, many other cryptocurrencies have launched derived by profits leading the cryptocurrency market to significantly evolve.

Cryptocurrencies are unique as they build on Blockchain technology to conduct transactions and exchange information among users, according to Park and Park (2020), Blockchain is an online distributed ledger that is highly secured, decentralized, and faster in conducting transactions. Though cryptocurrencies using this technology are not regulated by a specific government; instead, they use an independent platform. Because this technology is an open-source technology, a large number of stakeholders derived by the demand on bitcoin has started to launch their cryptocurrencies, as of March 2021 there are 4,482 different cryptocurrencies with a total market value of USD 1.74 trillion.

However, only 10 of these cryptocurrencies value over 85% of the total market capitalization, with Bitcoin being the leader taking 60% of all the market share. In its early phases, the market users according to (Yelowitz and Wilson, 2015) were concentrated on computer programming enthusiasts, speculative investors, libertarians and criminals, however, normal users started to pour into this market; since big corporation and merchants started to accept it for transactions.[1] This increase in demand caused a massive increase in the price along with the number of trades done daily. Partly in response to the perceived challenge posed by private currencies, central banks around the world have started to explore how these innovations could be used to establish state-controlled digital currencies, also the large acceptance of cryptocurrencies has driven two of the big financial exchanges markets to start trading futures in Bitcoin; specifically, Chicago Board Options Exchange (CBOE) and Chicago Mercantile Exchange (CME).

Being mid of these fast-paced developments, and as the volatility of cryptocurrencies is normally high during this phase of huge demand, therefore, it is important to evaluate as well as estimate risk metrics. In this study, we aim to investigate the Autoregressive Conditional Heteroskedasticity (ARCH) and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) effects in the cryptocurrency market by employing time series analysis. Notably, standard (GARCH) models can deliver a volatility estimation/ prediction in financial markets (Bauwens *et al.,* 2010, 2014). Researchers studied the volatility of cryptocurrencies and found that GARCH model is significantly forecast the cryptocurrency returns (Ardia *et al.*, 2019; Bauwens *et al.,* 2010, 2014; Chu *et al.,* 2017). However, this study differs from other studies in term of the basis of sample selection where we select the sample base on the weight of market capitalization which led us considering the following cryptos for analysis: Bitcoin, Ethereum, Ripple, Litecoin, Ethereum classic, Link, EOS, USDT and BCH.

2. LITERATURE REVIEW

Cryptocurrency is built on Blockchain technology which offers reliable transition of assets through novel cryptography technique; this technology qualifies it as a financial asset in some views. Glaser *et al*. (2014), state that cryptocurrencies are mainly used as an investment however, it is now used as a medium of exchange due to some of the big corporations among other merchandiser started to accept it for their transactions. Moreover, other uses include using it as an instrument to raise capital by corporations which are referred to ICOs (Initial Coin Offering) (Momtaz, 2019).

Subtle investment decisions require identifying the market structure and its efficiency, the efficient market hypothesis proposes that prices reflect all available information in the market, while behaviour finance theory argues that psychological factors play important role in determining the prices (Almansour, 2015; Almansour and Arabyat, 2017; Barber and Odean, 2008; Fama, 1970). Madhavan (2000) state that the informational efficiency of a market, as well as the information structure, play an important role in prices formation. Jiang *et al.* (2018) and Alvarez-Ramirez *et al.* (2018) asserted that pricing and information in the cryptocurrency market are inefficient which means the cryptocurrency market is considered inefficient.

Inefficient markets are highly volatile; therefore, researchers paid attention to study the volatility of the cryptocurrency market, Bouoiyour *et al.* (2016) for example compared bitcoin volatility to the US implied volatility index (VIX) and found that there is a negative association between Bitcoin realized volatility and the VIX. Interesting studies have measured bitcoin popularity by measuring the increasing number of tweets (Twitter) rather than using google trends. By employing linear and nonlinear Granger causality tests they found that the number of tweets is a significant driver of next day trading volume and realized volatility (Kim *et al*., 2017).

High volatility requires accurate forecasting models, researchers have concentrated on studying the Bitcoin returns, Ardia *et al.* (2019) applied the GARCH model to study the volatility of Bitcoin by employing time series data throughout 2011 to 2018 and found strong evidence that the GARCH model performs well in forecasting Bitcoin volatility. Chu *et al.* (2017) studied the volatility of seven cryptocurrencies namely Bitcoin, Maidsafecoin, Dash, Litecoin, Dogecoin, Ripple and Monero. By employing time series data from 2014 to 2017 and found that GARCH–type specifications provide the best in-sample performance. Cermak (2017) also applied GARCH model

[1] https://finance.yahoo.com/news/15-biggest-companies-accept-bitcoin-165115491.html

to study Bitcoin's volatility by considering several macroeconomic factors in China, the U.S, Europe and Japan, findings indicated that Bitcoin behaves in the U.S., Europe and China but not in Japan in a similar way to fiat money expecting that if the trend continues it as its first six years it will function as fiat money during 2019 and 2020 which didn't happen.

A Bitcoin price is among the largest prices per unit comparing to currencies, bonds, commodities and stocks (Briere *et al.,* 2013; Chowdhury, 2016; Chowdhury and Mendelson, 2013). The relationship between exchange rates and Bitcoin returns was explored by Almansour *et al.* (2020) who employed a time series analysis using ARMA analysis, the results showed that the exchange rates do not significantly affect Bitcoin returns. Similarly, Dyhrberg (2016) studied the behaviour of Bitcoin volatility with a comparison to exchange rates and gold by employing GARCH model, the results indicated that there is a positive relationship between the volatility of Bitcoin and the volatility of gold.

Liu and Tsyvinski (2020) discovered through reviewing the performance of three major cryptocurrencies -Bitcoin, Ethereum, and Ripple- that these cryptocurrencies have a complete set of price drivers comparing to stocks because of their nature, mainly being unregulated and relatively new financial assets. They concluded that their Betas of CAPM were sizably lower than the listed stocks which means that cryptocurrencies' correlation with the market and exposure to systematic risk are vulnerable and statistically insignificant. Another study has found that transaction volume is not a good predictor for bitcoin returns and volatile (Balcilar *et al.,* 2017).

This study contributes in three facets. First, it will extend the literature on cryptocurrencies volatility. Second, we study nine cryptocurrencies that constitute 85% of the market capitalization. Third, investors would understand the volatility prices movement and co-movement which build further awareness concerning avoiding the high-risk of this investment.

3. RESEARCH METHODOLOGY

This section commences in two phases, first: data collection, second: an econometric approach. In the following lines, we will clarify the data collection procedure.

3.1 Data Collection

This study employed time series data which consists of daily US Dollars closing prices of (Bitcoin, Ethereum, Ripple, Litecoin, Ethereum classic, Link, EOS, USDT, and BCH). The sample of this study was collected using CoinMarketCap and Yahoo finance, this sample represents the highest market capitalization in the cryptocurrency market representing more than 85% of the market capitalization (citation is needed). The time's span of the collected data varies base on the initial release date of each cryptocurrency ranging from 2010 to 2020. Table 1 summarizes the data of the study.

3.2 Econometric Approach

This study used Eviews to analyze our dataset, the study employed ARCH and GARCH models to forecast the volatility of the cryptocurrency market for each cryptocurrency, as well as for the overlapping period of the whole dataset. The ARCH model aims to elaborate the variance clustering in the residuals as well as to indicates the squared errors in the nonlinear dependence of the first-moment model. Engle (1982) extracted the ARCH model from the ARIMA method to restrict the model for the conditional variance assumption for more accuracy in the prediction of the volatility. The process of extracting the ARCH model commences as follow:

$$a_t = \sigma_t \varepsilon_t, \quad \text{and} \quad \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots + \alpha_m a_{t-m}^2 \tag{1}$$

where

$$\sigma_t^2 = E\left(a_t^2 \mid F_{t-1}\right) = Var(a_t \mid F_{t-1}) = Var(Y_t \mid F_{t-1})$$

Table 1. Selected leading cryptocurrencies and their market capitalization

	Cryptocurrencies Definitions	Ticker	Start date to 11. Nov. 2020	Market Capitalization
1.	Bitcoin	BTC	1 Jan. 2015	$891,582,221,493
2.	Ethereum	ETH	7 Aug. 2015	$169,691,395,988
3.	Tether	USDT	24 Dec.2016	$36,386,560,441
4.	Ripple	XRP	17 Dec.2014	$20,927,583,888
5.	Litecoin	LTC	17 Sep. 2014	$11,685,273,705
6.	LINK	LINK	20 Sep. 2017	$11,093,324,380
7.	Bitcoin Cash	BCH	23 July 2017	$9,096,437,945
8.	EOS.IO	EOS	1 July 2017	$3,487,746,178
9.	Ethereum Classic	ETHC	24 July 2016	$1,246,865,891

Letting

$$e_t = a_t^2 - E\left(a_t^2 \mid F_{t-1}\right)$$

Through the ARIMA model presented from the above equation, the autoregressive conditional heteroscedastic (ARCH) model was developed as follow:

$$a_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots + \alpha_m a_{t-m}^2 + e_t \tag{2}$$

This model assumes that $\alpha_0 > 0$, and $\alpha_1 \geq 0$ for $i > 0$. The error term ε_t follows a Normal distribution of the ARCH model, the function is:

$$\ell(\underline{\alpha}) = \sum_{t=m+1}^{n} \left[-0.5\ell n\left(\sigma_t^2\right) - 0.5\left(a_t^2 / \sigma_t^2\right)\right] \tag{3}$$

Researches showed that the assumption of normality may not always be acceptable (Knief and Forstmeier, 2018). Therefore, non-normal distributions may be considered such as standard Cauchy distribution, Student-t distribution, and Generalized Error Distribution (Bollerslev, 1987; Braun *et al*., 1995).

To observe cryptocurrencies volatility, the cryptocurrencies' returns are calculated as log(price t) – log (price $_{t-1}$).

3.2.1 GARCH Models

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) was extended by Bollerslev (1987) to allow the conditional variance to follow the process of ARMA which can be stated as

$$\begin{aligned} &a_t = \sigma_t \varepsilon_t, \quad \text{and} \\ &\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots + \alpha_m a_{t-m}^2 \\ &\qquad + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_r \sigma_{t-r}^2 \end{aligned} \tag{4}$$

where

$\alpha_0 > 0,\ \alpha_i \geq 0,\ \beta_j \geq 0$, and

$$\sum\nolimits_{i=1}^{\max(m,\,r)} \left(\alpha_i + \beta_i\right) < 1$$

The model above will be equal to equation (3) if r equal to zero. Equation (4) shows that even though the conditional variance occurs over time, $\alpha_i + \beta_i$ confirms that the unconditional variance a_t is finite.

4. EMPIRICAL RESULTS

This section presents the results of this study in two sections, 4.1 illustrates the preliminary statistics of the dataset, where section 4.2 presents the ARCH and GARCH results.

4.1 Preliminary Statistics

Table 2 illustrates the overall period descriptive statistics for and the normality test (Jarque-Bera (J-B)) for the daily returns of the selected cryptocurrencies, this summary represents the analysis over the whole period for each crypto.

The results showed that the highest average returns are found in Ethereum and Ethereum classic. However, Bitcoin and Ripple recorded the lowest average returns. The maximum return was found for the LINK crypto which records 3.23 the highest value compared to all other mentioned cryptocurrencies. The minimum return was found for Ethereum classic which records a value of -0.72 over the whole period. We notice that the returns distribution is positively skewed for all employed cryptocurrencies. The normality distribution was analyzed for each cryptocurrency using (Jarque-Bera (J-B)), the results showed that all cryptocurrencies returns were normally distributed. Figure 1 presents the histogram of each cryptocurrency, it can be seen that all selected cryptocurrencies are normally distributed.

Table 3 illustrates the overlapping period descriptive statistics and normality test (Jarque-Bera test, (J-B)) for

Table 2. Summary statistics of the selected cryptocurrencies (overall period)

Crypto	# obs.	Mean	Max.	Min.	Std. Dev.	Skewness	Kurtosis	J-B
BCH	1540	0.004348	1.793	-0.460	0.083	8.150	150.81	1418967***
BTC	1013	0.000014	0.058	-0.047	0.006	0.501	17.75	9226.02***
EOS	1605	0.003108	0.667	-0.402	0.061	2.109	22.16	25758.26***
ETH	820	0.006182	0.617	-0.271	0.085	1.43	10.08	1994.431***
ETHC	1374	0.006138	0.507	-0.728	0.072	0.492	17.17	11550.94***
LINK	1123	0.005781	3.238	-0.372	0.120	17.55	470.36	10278427***
LTC	878	0.004925	1.69	-0.320	0.098	6.450	104.29	381467.8***
USDT	1529	0.002422	0.252	-0.211	0.039	0.029	8.55	1968.04***
XRP	863	0.002222	0.536	-0.3619	0.083	1.622	12.83	3853.774***

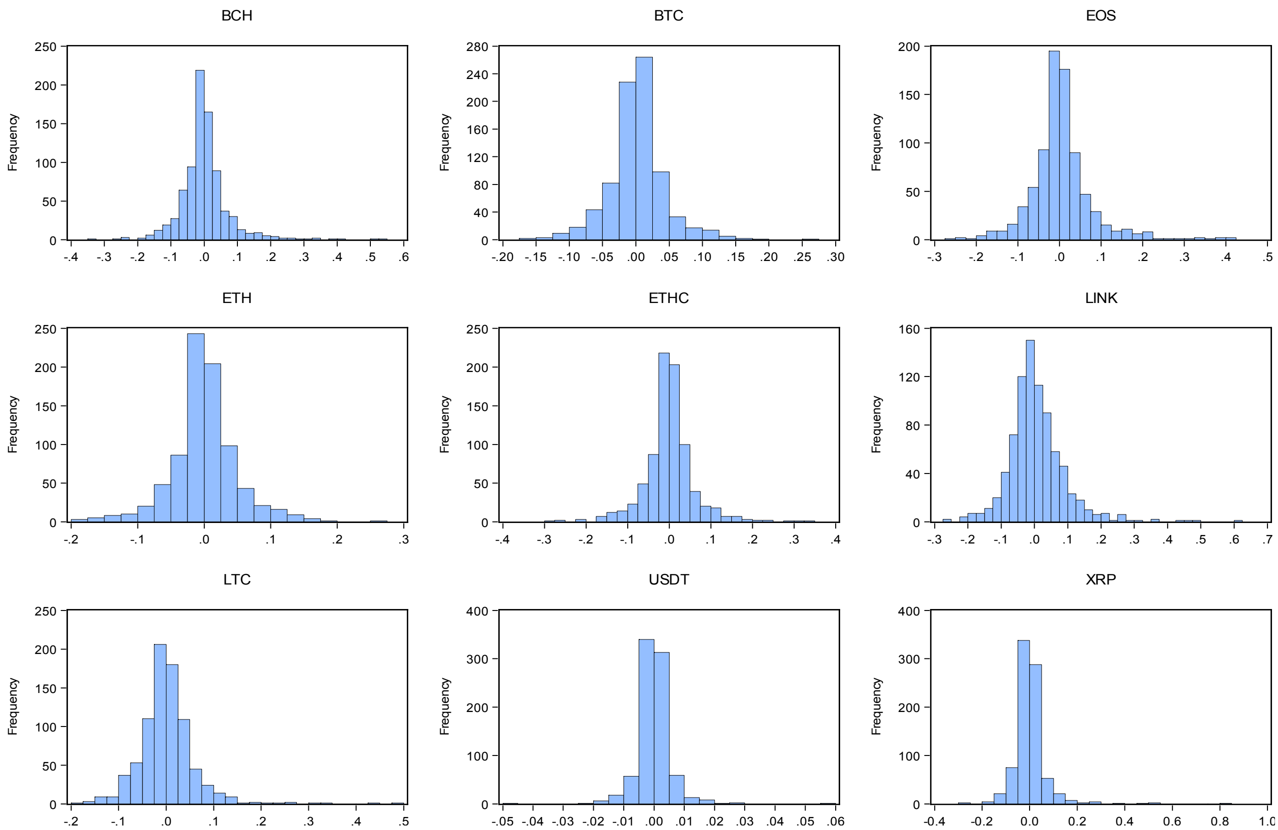

Figure 1. The histogram of major cryptocurrencies.

Table 3. Summary statistics of selected cryptocurrencies (Overlapping period)

Crypto	# obs.	Mean	Max.	Min.	Std. Dev.	Skewness	Kurtosis	J-B
BCH	820	0.00140	0.536	-0.32	0.074	1.566	12.76	3594***
BTC	820	0.00164	0.252	-0.16	0.042	0.395	6.662	479***
EOS	820	0.00439	0.420	-0.26	0.075	1.290	8.998	1456***
ETH	820	0.00030	0.264	-0.18	0.050	0.094	5.650	241***
ETHC	820	0.00051	0.329	-0.29	0.060	0.276	8.109	902***
LINK	820	0.00618	0.617	-0.27	0.085	1.43	10.085	1994***
LTC	820	0.00134	0.475	-0.19	0.059	1.839	14.54	5018***
USDT	820	0.00002	0.058	-0.04	0.005	0.884	24.34	15676***
XRP	820	0.00225	0.834	-0.29	0.070	3.811	38.71	45564***

the daily returns of the selected cryptocurrencies used in our analysis throughout Sep. 2017 – Nov. 2020.

Results showed that the highest average returns are found in the LINK and EOS cryptos while Ethereum and USDT recoded the lowest average returns. The maximum return was found for LINK which records 0.83 the highest value compared to all other mentioned cryptocurrencies while the minimum return is found for Bitcoin Cash which records a value of –0.32 over the overlapping period. The returns distribution is positively skewed for all employed cryptocurrencies. The normality distribution was analyzed for each cryptocurrency using (Jarque-Bera (J-B)), the results showed that all cryptocurrencies returns were normally distributed the generated figures were as similar as Figure 1.

4.2 Empirical Results of ARCH and GARCH

The returns evaluation over the whole period of this study is presented in Figure 2. It is obvious that the returns have a persistency. The persistency is defined as the ability of fluctuations to follow from one day to the next. The presented figure showed that there is an increasing trend in returns which leads to high volatility. These results suggest that if the cryptocurrency highly fluctuates today, it will most likely fluctuate highly as well in the next day. otherwise, if the fluctuation of the cryptocurrency market is low today, it will most likely to be low in the next day. Furthermore, it can be observed that periods of low volatility tend to be followed by periods of low volatility for a prolonged period, and periods of high volatility are followed by periods of high volatility for a prolonged period. This is the reason behind applying ARCH and GARCH models due to the characteristics of clustering volatility of the financial time series data (Al-Yahyaee *et al*., 2020; Cheikh *et al*., 2020).

Table 4 reports correlations analysis of daily returns between the selected cryptocurrencies used in our analysis over the whole period. The results indicated that a positive relationship is shown between Bitcoin and all cryptocurrencies except Bitcoin Cash (BCH); which showed a negative relationship recording a value of -0.076. This means that when the Bitcoin price goes up by 100%, the Bitcoin Cash (BCH) price will go down by 7.6% and vice versa. It is also observed that the Bitcoin price has a strong and positive relationship with Ethereum (ETH) and Litcoin (LTC) prices which record values of 73.3% and 70.5% respectively. This means that when the Bitcoin price goes up by 100%, the Ethereum (ETH) and Litcoin (LTC) prices will go up by 73.3% and 70.5% respectively, and vice versa. The results also show that there is a positive association between Bitcoin price with Ethereum classic and EOS price, as when the bitcoin price goes up by 100% the price of Ethereum Classic and EOS would increase by 60.8% and 60.6% respectively and vice versa.

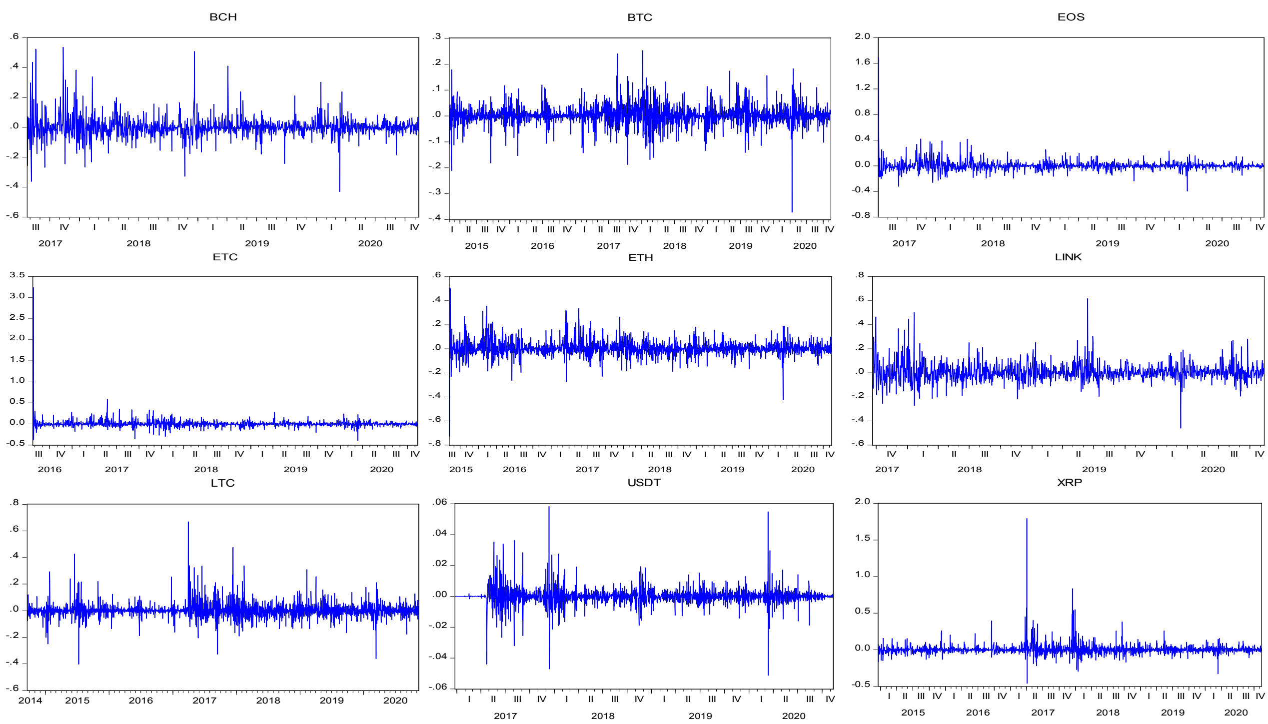

Figure 2. Log return.

Table 4. Correlations between selected cryptocurrencies

	BTC	BCH	EOS	ETH	ETHC	LINK	LTC	USDT	XRP
BTC	1								
BCH	-0.076	1							
EOS	0.608	-0.002	1						
ETH	0.737	-0.028	0.698	1					
ETHC	0.606	0.003	0.619	0.73	1				
LINK	0.415	-0.05	0.416	0.511	0.409	1			
LTC	0.705	-0.043	0.646	0.803	0.652	0.393	1		
USDT	0.026	-0.004	-0.081	-0.011	-0.046	0.004	0.051	1	
XRP	0.484	-0.009	0.55	0.635	0.539	0.372	0.559	-0.035	1

Note: Bitcoin is the base of our comparison.

Table 5 reports correlation analysis of daily returns between the selected cryptocurrencies over the period Sep 2017 – November 2020 (Overlapping period). The results in this analysis are similar to the previous analysis with a difference in the strength of the correlation value.

From the previous analysis, we notice that investors will face difficulties in term of diversification their investments in this market; as the market structure is highly and positively connected, which means the difficulty of avoiding risk for risk-averse investors, this indicates that the cryptocurrency market is associated with high risks thus high returns meaning that even after good optimization for investment in the selected cryptocurrencies the portfolio will remain risky in nature.

The results of the variance equation of ARCH and GARCH models for the cryptocurrencies returns are illustrated in Table 6. This table reports parameters and log-likelihood values for the asymmetric GARCH models over the whole period as well as throughout Sep 2017 – Nov 2020.

Concerning the results of the variance equation of the GARCH model on cryptocurrencies returns, it can be observed that the constants and RESID $(-1)^2$ are statistically significant at 1%, which recorded probability values of 0.000. The GARCH (-1) term is also statistically significant at 1% for all cryptocurrencies which recorded probability values of 0.000, which means that the past square residual terms can significantly affect the volatility of risk. The sum of the ARCH and GARCH terms is greater than 0.5 and closer to 1 (See Table 7), this means that the past volatility of cryptocurrencies affects the direction of the current volatility of cryptocurrencies, this result is consistent with Katsiampa (2019), Ardia *et al.* (2019), Bauwens *et al.* (2010, 2014), Chu *et al.,* (2017). This asserts that shocks to the market die out very slowly which means that it accounts for volatility persistence more. In other words, investors in the cryptocurrency market pay the most attention to news that flow to the cryptocurrency market, which means that the previous shocks in the market influence the current conditional volatility significantly. The evidence of volatility persistence suggests that the investors in the cryptocurrency market who want to make gains across trading scales should consider the forecasting methods of cryptocurren-

Table 5. Correlations between selected cryptocurrencies (Overlapping period)

	BTC	BCH	EOS	ETH	ETHC	LINK	LTC	USDT	XRP
BTC	1								
BCH	-0.058	1							
EOS	0.566	0.029	1						
ETH	0.697	0.011	0.676	1					
ETHC	0.568	0.03	0.586	0.723	1				
LINK	0.358	-0.028	0.379	0.452	0.376	1			
LTC	0.661	-0.011	0.599	0.782	0.613	0.331	1		
USDT	0.153	-0.065	-0.024	0.121	0.053	0.075	0.175	1	
XRP	0.427	0.018	0.51	0.602	0.51	0.33	0.511	0.029	1

Note: Bitcoin is the base of our comparison.

Table 6. Variance equation of GARCH model on cryptocurrencies returns

	Whole Period			Overlapping Period		
Cryptos.	ω	α	β	ω	α	β
BCH	0.000175***	0.081551***	0.887203***	0.000484***	0.09880***	0.81511***
BTC	0.000072***	0.152280***	0.814866***	0.0000991***	0.09110***	0.85241***
EOS	0.000318***	0.125590***	0.813091***	0.0000202***	0.02266***	0.97215***
ETH	0.000477***	0.207179***	0.694788***	0.000214***	0.07930***	0.835523***
ETHC	0.000328***	0.194547***	0.725841***	0.000267***	0.12737***	0.80371***
LINK	0.000086***	0.078370***	0.911495***	0.0000631***	0.07802***	0.915556***
LTC	0.000169***	0.061623***	0.886121***	0.000363***	0.08708***	0.800401***
USDT	0.000557***	0.309548***	0.610795***	0.000000676***	0.23011***	0.727939***
XRP	0.000401***	0.389859***	0.582015***	0.000172***	0.180074***	0.797065***

GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1). The ω, α, and β represent the constant, the ARCH and GARCH terms, respectively. Significance codes: *** express significance at the 0.999 level, ** at 0.99, * at 0.95.

Table 7. ARCH and GARCH estimation for all cryptocurrencies

Ticker	Whole Period	Overlapping Period
BCH	$h_t = 0.000175 + 0.081551u_{t-1}^2 + 0.887203h_{t-1}$	$h_t = 0.000484 + 0.09880u_{t-1}^2 + 0.81511h_{t-1}$
BTC	$h_t = 0.0.000072 + 0.152280u_{t-1}^2 + 0.814866h_{t-1}$	$h_t = 0.0000991 + 0.09110u_{t-1}^2 + 0.85241h_{t-1}$
EOS	$h_t = 0.000318 + 0.125590u_{t-1}^2 + 0.813091h_{t-1}$	$h_t = 0.0000202 + 0.02266u_{t-1}^2 + 0.97215h_{t-1}$
ETH	$h_t = 0.000477 + 0.207179u_{t-1}^2 + 0.694788h_{t-1}$	$h_t = 0.000214 + 0.07930u_{t-1}^2 + 0.835523h_{t-1}$
ETHC	$h_t = 0.000328 + 0.194547u_{t-1}^2 + 0.725841h_{t-1}$	$h_t = 0.000267 + 0.12737u_{t-1}^2 + 0.80371h_{t-1}$
LINK	$h_t = 0.000086 + 0.078370u_{t-1}^2 + 0.911495h_{t-1}$	$h_t = 0.0000631 + 0.07802u_{t-1}^2 + 0.915556h_{t-1}$
LTC	$h_t = 0.000169 + 0.061623u_{t-1}^2 + 0.886121h_{t-1}$	$h_t = 0.000363 + 0.08708u_{t-1}^2 + 0.800401h_{t-1}$
USDT	$h_t = 0.000557 + 0.309548u_{t-1}^2 + 0.610795h_{t-1}$	$h_t = 0.000000676 + 0.23011u_{t-1}^2 + 0.727939h_{t-1}$
XRP	$h_t = 0.000401 + 0.389859u_{t-1}^2 + 0.582015h_{t-1}$	$h_t = 0.000172 + 0.180074u_{t-1}^2 + 0.797065h_{t-1}$

cy persistence as this will help to improve as well as forecast volatility in the cryptocurrency market.

Concerning the prediction of the cryptocurrency market, there is a high volatility persistence in the nine cryptocurrencies employed in this study. This suggests that the prediction of the cryptocurrency market is less certain which leads to make it a highly risky market where the speculators make their investment decisions that carry more risk. In other words, a cryptocurrency market is a place where investors carry too much risk therefore, it is considered a high-risk financial market. As this market is a target for speculation purposes, investors should understand the volatility prices movement and co-movement since the movement of prices can influence investors' investment decisions. Furthermore, the results indicated that the GARCH model can predict major cryptocurrency prices. The results of this study offer perception into interrelationship within the participants in the cryptocurrency market such as investors, speculators, as well as risk managers.

5. CONCLUSIONS

This paper aims to perform ARCH and GARCH models in forecasting cryptocurrency market volatility. We employed Bitcoin, Ethereum, Ripple, Litecoin, Ethereum classic, Link, EOS, USDT and BCH as they construct more than 80% of the market capitalization. The results indicated that there is a significant effect of ARCH and GARCH Models in forecasting cryptocurrency market volatility, meaning that the past volatility of cryptocurrencies affects the current volatility of cryptocurrencies. Interestingly, it is shown that the negative shocks in the cryptocurrency market increase the level of volatility more than positive shocks of equal magnitude due to asymmetry term which is found to be positive for all cryptocurrencies employed in this study. Furthermore, we concluded that the GARCH model can predict the cryptocurrency prices in the market. Interested parties may compare and select the most appropriate model of ARCH family models for forecasting such as GARCH, EGARCH, PARCH, and TARCH. We recommend researchers formulate a cryptocurrency market index for the largest cryptos based on market capitalization and then employ the forecasting GARCH models for the constructed cryptocurrency market index.

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All authors contributed equally to this research.

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