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Original Article

Estimation of Bitcoin Volatility: GARCH Implementation

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***Abstract* - As bitcoin has been a topic of high interest for academic and professional life over recent years, a number of literature has examined its price movements, volatility, and predictions. Bitcoin is the first and perhaps the most popular cryptocurrency with a high volatility pattern compared to the other cryptocurrencies. This paper examines the models that explain the volatility of Bitcoin prices. The daily data for the Bitcoin prices are used through a period of July 31, 2017, to April 3, 2019, with a total number of observations of 484. Initially, unit root tests are implemented. Then, the heteroskedasticity problem is tested among variables. Based on the results of the heteroskedasticity test, it is decided to use ARCH models. Then, ARCH, GARCH, TGARCH, and EGARCH results are tested to find out the best fit model that explains the bitcoin price movements.*

Keywords* - Bitcoin, stationarity, ARCH, GARCH, TGARCH, EGARCH

I. INTRODUCTION

Cryptocurrency is defined as a digital currency that uses cryptography for security. By the launch of Bitcoin in 2009, it attracted the interest of many researchers, investors, and portfolio managers to evaluate it as an investment alternative. The recent discussions about the existence of Bitcoin cover the question of whether it is a currency or an asset. Some researchers suggest that Bitcoin currently can not be accepted as a currency since it does not have a function as a tool for exchange. Some researchers such as Ciaian et al. (2014), Bouoiyour et al. (2015), and Kristoufek (2013) define Bitcoin as one of the most innovative financial tools, while as some other researchers, e.g., Yermack (2014), Bouoiyour and Selmi 2015 criticize because of its unpredictable volatility in the market. Bitcoin, likewise other cryptocurrencies, is not regulated by central banks. Instead, the transactions are implied via blockchain technology (Nakamoto, 2008).

As historical daily price movements are overlooked, it is observed that Bitcoin hit a peak as high as $19,000 and got back to $7,000 after a couple of months. Because of this pattern of its volatility, Bitcoin is considered a speculative bubble for long-term investors. In literature, a number of different time series models have been applied to explain the price movements of Bitcoin.

This paper aims to examine a number of different models that best explain the price volatility of Bitcoin. The next section provides a brief summary of the related literature. The following section presents the daily data set for the Bitcoin prices through a period of July 31, 2017, to April 3, 2019, covering 484 observations. Initially, unit root tests are implemented. Then, the heteroskedasticity is tested. Based on the results of the heteroskedasticity test, a variety of ARCH models are applied. The results of ARCH, GARCH, TGARCH, and EGARCH models are tested to find out the best fit model that explains the bitcoin price movements.

II. RELATED LITERATURE

Because of its simplicity, innovative features, and transparency, the analysis of Bitcoin price movements and its volatility has recently received significant attention from researchers and investors (Urguhart (2017) and Dyhrberg (2016). The high volatility of Bitcoin makes it vulnerable to speculative price movements (Grinberg, 2011). Hence, Bitcoin has popularity in the financial markets and in portfolio management (Dyhrberg, 2016). Ozyesil (2019) examined the price movements of Bitcoin, USD, and Euro. There are various studies that predict the prices using historical movements. Furthermore, some studies mainly focus on different time series models that aim to explain the volatility of Bitcoin. Roy et al. l (2018) use autoregressive integrated moving average (ARIMA) models to explain Bitcoin volatility. They use a data set for Bitcoin covering the year 2013 through 2017. Katsiampa (2017) explores the optimal conditional heteroskedasticity model with regards to goodness-of-fit to Bitcoin price data using AR-GARCH, AR-EGARCH, AR-TGARCH, AR-APARCH, AR-CGARCH, and AR-ACGARCH models. The empirical findings indicate the AR-CGARCH model as the best model that explains the volatility of Bitcoin.

Some other studies run different GARCH type models. Glaser et al. (2014) and Gronwald (2014) use a linear GARCH; Dyhrberg (2016b);, Bouri et al. (2017) implement a Threshold GARCH (TGARCH). Dyhrberg, (2016a) runs an Exponential GARCH (EGARCH). Earlier studies mainly implement and conclude on a unique model. Less has a comparative analysis of GARCH models that better explain Bitcoin price data. Bouoiyour and Selmi (2015) use an optimal GARCH model on daily data. They show that the volatility of Bitcoin prices decreases in the periods of December 2010 to June 2015 and January 2015 to June 2015. Therefore, they use two intervals for modeling. Based upon their findings, the optimal model is determined as Threshold-GARCH in the first interval, whereas the optimal model is suggested as the Exponential-GARCH in the second interval. Katsiampa (2017) points that the AR-CGARCH model is the optimal model for Bitcoin volatility.

Stavroyiannis and Babalos (2017) apply univariate and multivariate GARCH models and autoregressive vector specifications to explain the dynamics of Bitcoin. Cermak (2017) uses a GARCH (1,1) to model Bitcoin's volatility movements considering several macroeconomic indicators. He targeted the countries where Bitcoin has a high trading volume. Chen et al. (2016) test various GARCH models to predict the volatility of Bitcoin, and they suggest that TGARCH (1,1) model is the optimal model to explain price movements. Naimy and Hayek (2018) compare the prediction power of GARCH and EGARCH models. According to their findings, the EGARCH (1,1) model outperforms the GARCH (1,1). Chu et al. (2017) fits 12 different GARCH models; namely, SGARCH (1,1), EGARCH (1,1), GJRGARCH (1,1), APARCH (1,1), IGARCH (1,1), CSGARCH (1,1), GARCH (1,1), TGARCH (1,1), AVGARCH (1,1), NGARCH (1,1), NAGARCH (1,1) and ALL GARCH (1,1) for seven major cryptocurrencies (Bitcoin, Dash, Dogecoin, Litecoin, Maidsafecoin, Monero and Ripple). Their findings support that IGARCH (1, 1) model best fits the volatility of Bitcoin, Dash, Litecoin, Maidsafecoin, and Monero, while the GJRGARCH (1, 1) model best fits the volatility of Dogecoin and the GARCH (1,1) model best fits for Ripple.

III. DATA AND MODELLING

Recent literature highlights the need for the use of nonlinear time series structures for modeling volatility. Bera and Higgins (1993) state the contribution of the ARCH family models to predict the changes in volatility. Campbell, Lo, and MacKinlay (1997) argue that constant volatility will exist over a period if the series moves through time. Summarizing that there exists a serial correlation if large data is followed by larger data and small data is followed by smaller data. Engle (1982) proposes to use an ARCH process to model time-varying conditional variance for time series. However, he proposes that a high ARCH order is required to properly capture the dynamic behavior of conditional variance. Since the Generalized ARCH (GARCH) model of Bollerslev (1986) fulfills this requirement as it is based on an infinite ARCH specification which minimizes the number of estimated parameters.

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

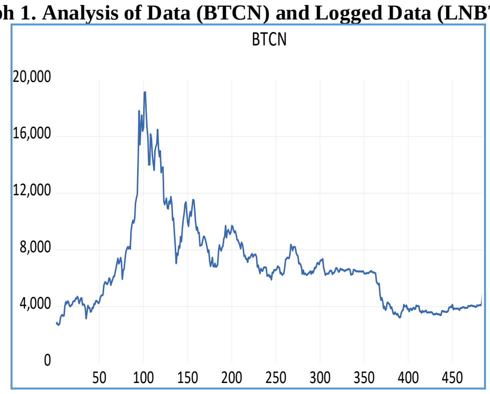
Where α_i, β_i, and ω are the parameters to estimate. Bouoiyour and Selmi (2016) indicate that the distributions of ARCH and GARCH models are symmetric and linear, although they detect volatility clustering and leptokurtosis. Addressing these problems, several GARCH extensions should be employed and compared. In this study, we test ARCH, GARCH, TGARCH, EGARCH occasions to predict the model that best explains the Bitcoin price movements. In this section, the characteristics of the data are first defined. The daily data for the Bitcoin prices are used through a period of July 31, 2017, to April 3, 2019. The total number of observations is 484. The median and the mean values for the Bitcoin prices throughout the modeled period are 6,478.5 USD and 6,772 USD, respectively. The maximum price is 19,118 USD, and the minimum price is 2,709 USD. The details of the descriptive data are illustrated in Table 1.

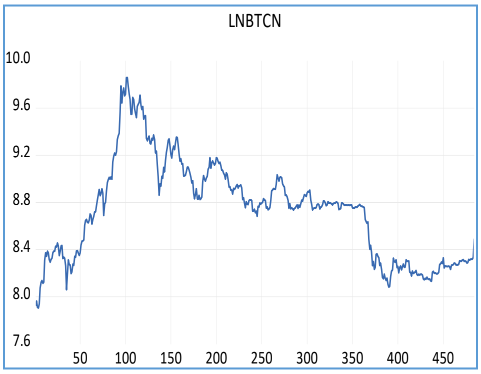
Table 1. Descriptive Statistics of Data

Mean (in USD)	6772.795
Median (in USD)	6478.480
Maximum (in USD)	19118.30
Minimum (in USD)	2709.560
Std. Dev. (in USD)	3110.329
Skewness	1.436629
Kurtosis	5.348141
Jarque-Bera	277.6824
Probability	0.000000
Observations	484

In this study, the natural logarithms of raw data are used. Graph 1 illustrates the movement patterns of the raw data (BTCN) and the logged values (LNBTCN). As observed in the graph, the logged data also has a stationarity problem. Hence, the unit root tests are conducted.

Graph 1. Analysis of Data (BTCN) and Logged Data (LNBTCN)





A. Unit Root Tests

Unit root tests are implemented for logged data. Augmented Dickey-Fuller and Philips-Peron Test statistics are used to determine the stationarity of the dataset. The H_0 and H_1 hypotheses are as follows:

H_0: Data has unit root / Data is not stationary
H_1: Data has no unit root / Data is stationary

The logarithmically transformed data has unit root in the level. So, the differencing method is used. Figure 1 and figure 2 exhibit the correlograms and the autocorrelation function (ACF) and partial autocorrelation function (PACF) for logged data and the first difference data. This highlights that the stationarity problem is solved by the differencing methodology.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.989	0.989	476.16	0.000
		2	0.977	-0.053	941.57	0.000
		3	0.964	-0.004	1396.3	0.000
		4	0.951	-0.050	1839.6	0.000
		5	0.937	-0.045	2270.7	0.000
		6	0.924	0.067	2691.3	0.000
		7	0.912	-0.016	3101.2	0.000
		8	0.898	-0.030	3500.1	0.000
		9	0.884	-0.043	3887.5	0.000
		10	0.871	-0.001	4263.7	0.000
		11	0.859	0.103	4630.7	0.000
		12	0.848	0.023	4989.3	0.000
		13	0.838	0.013	5340.0	0.000
		14	0.827	-0.065	5682.2	0.000
		15	0.813	-0.116	6014.1	0.000
		16	0.799	-0.022	6335.2	0.000
		17	0.785	-0.013	6645.4	0.000
		18	0.771	0.025	6945.1	0.000
		19	0.756	-0.049	7234.0	0.000
		20	0.742	0.041	7513.2	0.000
		21	0.731	0.093	7784.5	0.000
		22	0.720	0.024	8048.2	0.000
		23	0.709	0.017	8304.6	0.000
		24	0.698	-0.022	8554.0	0.000
		25	0.688	-0.023	8796.7	0.000
		26	0.678	-0.002	9032.9	0.000

Fig. 1 Correlogram for the Logged Data

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.068	0.068	2.2686	0.132
		2	-0.038	-0.043	2.9811	0.225
		3	0.065	0.071	5.0213	0.170
		4	0.089	0.079	8.9059	0.063
		5	-0.022	-0.029	9.1494	0.103
		6	0.040	0.047	9.9263	0.128
		7	0.048	0.029	11.043	0.137
		8	0.037	0.032	11.723	0.164
		9	-0.005	-0.007	11.736	0.229
		10	-0.034	-0.044	12.322	0.264
		11	-0.013	-0.017	12.406	0.334
		12	-0.055	-0.062	13.884	0.308
		13	0.093	0.106	18.150	0.152
		14	0.149	0.139	29.194	0.010
		15	0.019	0.015	29.378	0.014
		16	0.009	0.020	29.423	0.021
		17	-0.019	-0.057	29.610	0.029
		18	0.059	0.054	31.336	0.026
		19	-0.065	-0.079	33.439	0.021
		20	-0.138	-0.149	43.109	0.002
		21	-0.029	-0.041	43.543	0.003
		22	0.016	-0.013	43.673	0.004
		23	-0.028	0.016	44.083	0.005
		24	-0.001	0.041	44.084	0.007
		25	-0.031	-0.011	44.573	0.009
		26	-0.010	0.023	44.622	0.013

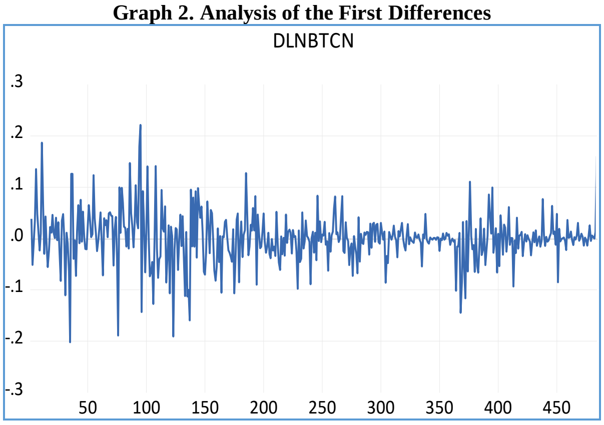
Fig. 2 Correlogram for the First Differences

Table 2 summarizes the unit root test statistics, and Graph 2 exhibits that the volatility is normalized after differencing method.

Table 2. Unit Root Test Statistics

Stationarity	Augmented Dickey-Fuller		Phillips_Perron	
	T-Statistics	P-Value	T-Statistics	P-Value
Level	-1.9575	0.3058	-2.0472	0.2666
First Difference	-4.6339	0.0000	-20.2728	0.0000

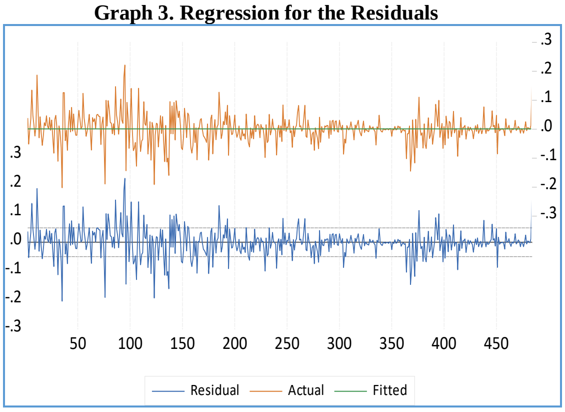
Graph 2. Analysis of the First Differences



B. Heteroskedasticity and ARCH Tests

As a next step, the regression line is run to check the residuals. As seen in Graph 3, the periods of low volatility are followed by periods of low volatility and vice verca. If this happens for residuals, then it provides a justification for the ARCH family model. However, this can be double-checked by the ARCH test whether the ARCH family model should be run or not.

Graph 3. Regression for the Residuals



Next, the heteroskedasticity test is implemented. As seen by the p values, the null hypothesis is rejected that states the circumstance that there is no ARCH effect. The ARCH effect test outputs are summarized in Table 3 below.

Table 3. Heteroskedasticity Test: ARCH

F-statistic	27.11743	Prob. F(1,480)	0.0000
Obs*R-squared	25.77431	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 07/09/19 Time: 00:14
Sample (adjusted): 3 484
Included observations: 482 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001897	0.000272	6.970492	0.0000
RESID^2(-1)	0.235333	0.045192	5.207440	0.0000

R-squared	0.053474	Mean dependent var	0.002465
Adjusted R-squared	0.051502	S.D. dependent var	0.005619
S.E. of regression	0.005473	Akaike info criterion	-7.573976
Sum squared resid	0.014376	Schwarz criterion	-7.556640
Log-likelihood	1827.328	Hannan-Quinn criter.	-7.567162
F-statistic	27.11743	Durbin-Watson stat	1.993536
Prob(F-statistic)	0.000000		

The study continues to model by implementing different occasions using the ARCH family. These models are fitted by the method of maximum likelihood using various information criteria such as Akaike Information Criteria (AIC), Schwarz Information Criteria (SIC), and Hannan-Quinn Criterion (HQC). The smaller the values of these criteria, the better the fit. Table 4 below states the summarized outputs for each model.

Table 4. Information Criterion for the Implemented Models

Statistics	ARCH (1)	GARCH (1,1)	TARCH(1, 1)	EGARCH(1, 1)
AIC	-3.200	-3.3410	-3.3368	-3.3125
SIC	-3.174	-3.3063	-3.2936	-3.2693
HQC	-3.189	-3.3274	-3.3198	-3.2955

As illustrated in Table 4, the best model that explains the movements of Bitcoin prices is predicted as GARCH (1,1), which denotes the lowest AIC, SIC, and HQC values.

IV. CONCLUSION

Cryptocurrencies have attracted a big interest from investors and researchers in recent years. After its launch in the market by 2009, Bitcoin has increased its market value up to $165,383B. Although Bitcoin is perceived as an innovative tool for exchange, it is not yet used as a medium of trading. This reality opened a discussion of whether Bitcoin is a currency or an asset to invest in. The related literature highlights this question and the general terms point out that Bitcoin is an investment tool for portfolios. Furthermore, another concern is the unpredictable volatility of Bitcoin that makes it perceived as a bubble. A number of studies focus on the models that explain the daily price/return movements of Bitcoin. Some also contribute to the forecasting reliability of these models. The majority of these models run the GARCH family for predictions.

Inspired by the literature, we compare different GARCH models that explain the volatility of Bitcoin prices. The database includes the daily data for the Bitcoin prices in USD through a period of July 31, 2017, to April 3, 2019. The models are run for 484 observations that are logged and differenced. According to heteroskedasticity test results, we run various GARCH models. The results of ARCH, GARCH, TGARCH, and EGARCH are tested to find out the best fit model that explains the bitcoin price movements. The results are compared to AIC, SIC, and HQC criteria. The empirical results show that GARCH (1,1) fits best to explain the volatility of Bitcoin through the sampling period.

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