Estimation of Bitcoin Volatility: GARCH Implementation

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Abstract
As bitcoin is a topic of high interest for academic and professional life over recent years, a number of literature has examined its the 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 explains 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, a total number of observations of 484. Initially, unit root tests are implemented. Then, the heteroskedasticity problem is tested among variables. Based on 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 an 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 existency of Bitcoin cover the question whether its 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 tool 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 as a speculative bubble for long-term investors. In literature, a number of different time series models has applied to explain the price movements of Bitcoin. This paper aims to examine a number of different models that best explains the price volatility of Bitcoin. 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 by 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 a 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 (2018) uses autoregressive integrated moving average (ARIMA) models to explain Bitcoin volatility. They use a date set for Bitcoin covering 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 AR-CGARCH model as the best model that explains 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) uses 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 modelling. 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 AR-CGARCH model is the optimal model for Bitcoin volatility.

Stavroyiannis and Babalos (2017) applies univariate and multivariate GARCH models and vector autoregressive 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) tests 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) compares 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), GJR-GARCH (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 Dogecoin and the GARCH (1,1) model best fits for Ripple.

III. DATA AND MODELLING

Recent literature highlight the need for the use of nonlinear time series structures for modelling the volatility. Bera and Higgins (1993) states about the contribution of the ARCH family models to predict the changes in the volatility. Campbell, Lo, and MacKinlay (1997) argues that a 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 ARCH process to model time-varying conditional variance for time serieses. However, he proposes that a high ARCH order is required to properly capture the dynamic behaviour of conditional variance. Since the Generalized ARCH (GARCH) models of Bollerslev (1986) fulfills this requirement as it is based on an infinite ARCH specification which minimizes the number of estimated parameters.

Where \( \alpha_i, \beta_i, \) and \( \omega \) are the parameters to estimate. Bouoiyour and Selmi (2016) indicates 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 is first defined. The daily data for the Bitcoin prices are used through a period of July 31, 2017 to April 3, 2019. Total number of observations is 484. The median and the mean values for the Bitcoin prices throughout the modelled 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 is illustrated in Table 1.

Table 1. Descriptive Statistics of Data

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (in USD)</td>
<td>6772.795</td>
</tr>
<tr>
<td>Median (in USD)</td>
<td>6478.480</td>
</tr>
<tr>
<td>Maximum (in USD)</td>
<td>19118.30</td>
</tr>
<tr>
<td>Minimum (in USD)</td>
<td>2709.560</td>
</tr>
<tr>
<td>Std. Dev. (in USD)</td>
<td>3110.329</td>
</tr>
<tr>
<td>Skewness</td>
<td>1.436629</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>5.348141</td>
</tr>
<tr>
<td>Jarque-Bera Probability</td>
<td>0.000000</td>
</tr>
<tr>
<td>Observations</td>
<td>484</td>
</tr>
</tbody>
</table>

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 stationarity problem. Hence, the unit root tests are conducted.

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

\[ \sigma_i^2 = \omega + \sum_{i=1}^{\infty} \alpha_i \epsilon_{i-1}^2 + \sum_{i=1}^{\infty} \beta_j \sigma_{i-j}^2 \]
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 $H_1$ hypothesis are as follows:

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

The logarithmic 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, which highlights that the stationarity problem is solved by the differencing methodology.

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

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 versa. If this happens for residuals, then it provides a justification for ARCH family model. However, this can be double checked by ARCH test whether the ARCH family model should be run or not.

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

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>0.001897</td>
<td>0.000272</td>
<td>6.970492</td>
<td>0.0000</td>
</tr>
<tr>
<td>RESID^2(1-1)</td>
<td>0.235333</td>
<td>0.045192</td>
<td>5.207440</td>
<td>0.0000</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.053474</td>
<td>Mean dependent var</td>
<td>0.002465</td>
<td></td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.051502</td>
<td>S.D. dependent var</td>
<td>0.005619</td>
<td></td>
</tr>
<tr>
<td>S.E. of regression</td>
<td>0.005473</td>
<td>Akaike info criterion</td>
<td>-7.573976</td>
<td></td>
</tr>
<tr>
<td>Sum squared resid</td>
<td>0.014376</td>
<td>Schwarz criterion</td>
<td>-7.556640</td>
<td></td>
</tr>
<tr>
<td>Log likelihood</td>
<td>1827.328</td>
<td>Hannan-Quinn criterion</td>
<td>-7.567162</td>
<td></td>
</tr>
<tr>
<td>F-statistic</td>
<td>27.11743</td>
<td>Durbin-Watson stat</td>
<td>1.993536</td>
<td></td>
</tr>
<tr>
<td>Prob(F-statistic)</td>
<td>0.000000</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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 of 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 medium of trading. This reality opened a discussion of whether Bitcoin is a currency or an asset to invest. 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 focuses on the models that explain the daily price/return movements of Bitcoin. Some also contribute with the forecasting reliability of these models. Majority of these models run 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 criterion. The empirical results show that GARCH (1,1) fits best to explains the volatility of Bitcoin through sampling period.

### REFERENCES


