The effect of symmetric and asymmetric information on volatility structure of crypto-currency markets

A case study of bitcoin currency

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Abstract

Purpose – This paper aims to examine whether the crypto-currencies’ market returns are symmetric or asymmetric informative, through analysing the daily logarithmic returns of bitcoin currency over the period of 2011-2017.

Design/methodology/approach – In doing so, the symmetric informative analysis is estimated by applying the generalised auto-regressive conditional heteroscedasticity (GARCH) (1,1) model, whereas asymmetric informative or leverage effects analysis is estimated by exponential GARCH (1,1), asymmetric power ARCH (1,1) and threshold GARCH (1,1) models. In addition, the generalized autoregressive conditional heteroskedasticity in mean (GARCH-M (1,1)) was applied to examine whether the risk-return trade-off phenomenon was persistent in crypto-currencies market.

Findings – The main findings indicate that bitcoin market return or volatility is symmetric informative and has a long memory to persist in the future. Furthermore, the sympatric volatility is found to be more sensitive to its past values (lagged) than to the new shock of the market values. However, asymmetric informative response of volatility to the negative and the positive shocks do not exist in the bitcoin market or, in other words, there is no leverage effect. This suggests that the bitcoin market is in harmony with the efficient market hypothesis (EMH) with respect to the asymmetric information and violated the EMH with regard to the symmetric information. Hence, the market price or return of bitcoin currency could not be predicted by simply exercising such past market information in the short-run investment. In addition, the estimated coefficient of conditional variance or risk premium ($\alpha$) in the mean equation of CHARCH-M (1,1) model is positive however, statistically insignificant. This indicates the absence of risk-return trade-off, in which case the higher market risk will not essentially lead to higher market returns. This paper has proposed that an investment in the crypto-currency market is more appropriate for risk-averse investors than risk takers.

Originality/value – The findings of the study will provide investors with necessary information about the bitcoin market price efficiency, hedging effectiveness and risk management.

Keywords Market efficiency, Forecasting, Monetary systems

Paper type Research paper

Introduction

A crypto-currency is a digital asset designed to work as a medium of exchange that uses cryptography to secure its transactions, to control the creation of additional units, and to verify the transfer of assets (Chohan, 2017). Crypto-currencies use decentralized control as
opposed to centralized electronic money and central banking systems (Gipp et al., 2015). The decentralized control of each crypto-currency works through a block-chain that is a public transaction database, functioning as a distributed ledger (Guttmann, 2014). Block-chain has received a significant amount of analysts and press attention over the past few years as this emerging technology holds significant potential (Hileman and Rauchs, 2017). Crypto-currencies were the first application of this technology, and introduced as new set of businesses and vocabulary to the world of payments (Hileman and Rauchs, 2017). A numerous private crypto-currencies have been introduced, whereas innovation of bitcoin currency started operating in January 2009 and is the first decentralised crypto-currency being introduced. However, it did not emerge until more than two years later in April 2011 (Hileman and Rauchs, 2017). Today, there are hundreds of crypto-currencies with market value that are being traded, and thousands of crypto-currencies that have existed at some point. In particular, the bulk of bitcoin currency has been growing faster in the global market circulation since 2009 to reach approximately 16.95 million coins in March 2018 with total market value reached to US$1.093bn (Statista Databased Report, 2018). More importantly, recently a number of central banks started to explore the adoption of crypto-currency and block-chain technologies for retail and large-value payments (Chiu and Koeppl, 2017). For example, the People’s Bank of China aims to develop a nationwide digital currency based on block-chain technology; the Bank of Canada and Monetary Authority of Singapore are studying its usage for interbank payment systems; the Deutsche Bundesbank has developed a preliminary prototype for block-chain-based settlement of financial assets. Many proponents believe that crypto-currency and block-chain technology will have a significant influence on the future development of payment and financial systems (Chiu and Koeppl, 2017). Even though, the crypto-currencies are managed through advanced encryption techniques, many governments and investors still take a cautious approach toward them, this is because of the lack of regulations and consumer protection against fraud, having high cost of mining, lacking of central control, and lacking of recognition. Meanwhile, many banks still do not offer services for crypto-currencies and they refuse to offer services to virtual-currency companies (Schwartzkopff and Levring, 2013; Sidel, 2013; Lee, 2013; and Barrell, 2014).

Many investors expect that in the future, this new technology will have possibilities to drive most of the current market capitalization such as stock market, bond market and money market. This may increase the participants in crypto-currency industry and this is likely to remain the case until a certain measure of price stability and market acceptance is achieved (Musiala, 2015). For instance, during 2017 the crypto-currency market witnessed excessive upward pricing and extensively daily volatility. In particular, the bitcoin currency prices upsurges from US$997.75 in January 2017 to reach US$19,187.78 in December 2017. This represents around 1,823.10 per cent in the market growth and the market still remains subject to unpredictable and extreme fluctuations in prices.

This high volatility may be attributed to how the current crypto-currency model was perceived. By nature it is deflationary because of the fact that it is considered as an investment or speculative asset, but there may be other external aspects that may drive price momentum such as positive media covering, regulators moves and other information. Whereby, in the financial literature it is indicated that information is the fundamental driver of assets pricing and their volatility in the financial market. This information can either be in the form of micro or macro level or both levels (Omokehinde and Abata, 2017). These information can enter the market either symmetrically (linearly) or asymmetrically (non-linearly) and it is expected to be good (positive) or bad (negative) news with serious effects on the volatility of assets returns (Omokehinde and Abata, 2017). According to the efficient
market hypothesis, assets price should fully reflect all available information in the market and then investors can always not beat the market and achieve up normal return (Fama, 1970). The random walk theory also confirmed that price movements of any financial asset will not follow any trends or patterns, and that past price movements cannot be applied as predictors for the future volatility or returns of the assets (Kendall and Hill, 1953). However, in an inefficient market the situation may hold different scenario.

The determinants of the exchange rate volatility for the current fiat money have been extensively examined by many researchers and most of their findings agree that exchange rate volatility can be explained by such macroeconomic policies, namely, inflation, interest rates, money supply, exports and GDP of the country [De Grauwe, (1988), Engel and West, (2005); and Antonakakis and Darby, (2013)]. However, as the crypto-currencies are considered as international currency and decentralized, its exchange rate volatility therefore cannot be explained using such macroeconomic policies of just one country (Cermak, 2017). Thus, the appropriate technique to understand the behaviour of cryptography currencies returns and volatility is to define them in terms of their distribution function. The normality distribution of crypto-currencies returns is considered uncertain and inconsistent if new information does not arrive symmetrically to the market participants, or if investors behave irrationally and do not react linearly to the arrival of new global macroeconomic news. In both situations, the assumptions of efficient market hypothesis will be violated and the estimated residuals of ordinary regression model will be invalid and subsequently the estimated coefficient of the crypto-currency market returns or its price volatility will be measured inaccurately. Further, in real daily life, most of the financial markets are characterized by informational asymmetric, in which there are prospects for asset mispricing or abnormal profit chances. This means that prices of financial assets show volatility clustering behaviour, whereby large changes in prices tend to cluster together, resulting in persistence of the amplitudes of price changes (Cont, 2007). In other word, as stated by Mandelbrot (1963), large changes in assets prices tend to be followed by large changes and small changes in assets prices tend to be followed by small changes. The phenomenon is called volatility clustering and is typically measured by an autoregressive conditional heteroscedasticity ARCH model of Engle (1982).

Many investors realize that financial assets including the new crypto-currency are more volatile and this volatility may consider the main generator and indicator for the market returns. As described by modern portfolio theory (MPT), volatility creates risk associated with the degree of dispersion of returns around the average. Therefore, it is vital for all market participants to have deep understanding on the crypto-currencies market volatility or returns as it is considered as an investment asset rather than a currency for their investment portfolio. Hence, the response of bitcoin currency prices to market information is used in this study as metrics to measure whether crypto-currencies market is symmetric or asymmetric informative. The main objective of the study therefore is to investigate the volatility pattern of bitcoin crypto-currency using symmetric and asymmetric generalised autoregressive conditional heteroscedasticity (GARCH) models. The second objective is to explore whether the phenomena of risk-return trade-off is persistence in crypto-currencies market.

Literature review
Assets volatility is considered as one of the most modern areas for many researchers, academics, investors and market participants. There are several studies investigating the symmetric and asymmetric characteristics of financial asset volatility or returns using different models such of GARCH family models (i.e. GARCH, GARCH-M, The Glosten-Jagannathan-Runkle – generalized autoregressive conditional heteroskedasticity [GJR-
GARCH, Skew-generalized autoregressive conditional heteroskedasticity [SGARCH], exponential GARCH [EGARCH], asymmetric power autoregressive conditional heteroskedastic [APARCH], the Component sGARCH model [csGARCH], the integrated GARCH model [iGARCH], threshold GARCH [TGARCH], nonlinear generalized autoregressive conditional heteroscedasticity [NGARCH], the nonlinear asymmetric GARCH, the absolute value GARCH [AVGARCH] and other GARCH family models. Few studies have been focussing on the volatility of the new digits currency exchange or crypto-currencies market. For example, the most recent study of Chu et al. (2017) examine the volatility of the seven most popular crypto-currencies, namely, Bitcoin, Dash, Litecoin, Monero, Ripple, MaidSafeCoin and Dogecoin, using daily prices over the period of 22 June 2014-17 May 2017. The study used 12 GARCH models to examine the market volatility, which are SGARCH, EGARCH, GJR-GARCH, APARCH, iGARCH, CSGARCH, GARCH, TGARCH, AVGARCH, NGARCH, NAGARCH and ALLGARCH models. The overall result shows that all GARCH models were fitted to each crypto-currency and all the seven crypto-currencies exhibit extreme volatility especially when it comes to their inter-daily prices. The study therefore, suggests that the new digitized currencies investment is more suited for risk-seeking investors looking for a way to invest or enter into technology markets.

Urquhart (2017) examines the volatility of bitcoin currency and shed light on the forecasted ability of GARCH models and ARCH models in the bitcoin market. The result indicates that no evidence of the leverage effect in bitcoin market and that the HAR models are superior in modelling bitcoin currency volatility compared to the traditional GARCH models. Stavroyiannis and Babalos (2017) investigate the dynamic properties of bitcoin and the Standard and Poor’s SP500 index, using different types of econometric methods, including univariate and multivariate GARCH models, and vector autoregressive specifications. Furthermore, the study also examines whether bitcoin currency can be used as a hedging or safe haven instrument in the USA market and explore if the bitcoin currency owns any attributes of gold asset. The findings of the study indicate that bitcoin currency does not hold any of the hedges, diversifiers or safe-haven instruments; rather, it exhibits intrinsic attributes not related to the US market developments. Conversely, Dyhrberg (2016) applies asymmetric GARCH methodology to investigate whether the bitcoin currency has hedging capabilities of gold. The findings indicate that bitcoin currency can be used as a hedging instrument against stocks in the Financial Times Stock Exchange Index and the American dollar in a short term. The study therefore suggests that bitcoin currency can be included as financial instruments to hedge market specific risk.

Bouri et al. (2016) use daily returns on bitcoin currency denominated in US dollar over the period of 18 August 2011-29 April 2016 to examine the relationship between price returns and volatility changes in the bitcoin market. The study found no evidence of an asymmetric return-volatility relation in the bitcoin market for the entire period of the study. However, test was carried out to see if there is a difference in the return–volatility relation before and after the price crash of 2013. The analysis result of the pre-crash period (596 daily observations) and the post-crash period (630 daily observations) indicated a significant inverse relationship between past shocks and volatility before the crash and no significant relationship after crash. Additionally, prior to the price crash of December 2013, positive shocks have increased the conditional volatility more than negative shocks. Chen et al. (2016) applied a variety of GARCH models to examine the volatility of crypto-currency Index (CRIX) family using daily data covering the period of 1 August 2014-6 April 2016. The results of the study indicated that based on the statistical values of the three criteria, namely, log likelihood, Akaike information criterion (AIC) and Bayesian
information criterion (BIC), TGARCH (1, 1) model was found to be the best model for all the CRIX index families. In addition, the results showed that the dynamic conditional correlation (DCC-) GARCH (1,1) found a persistence of volatility clustering and time varying covariance between the three CRIC indices.

Even though a lot of research studies have been conducted in modelling the structure of assets volatility in different financial sectors worldwide only few studies have been focussing on modelling the structure of crypto-currency markets volatility. Furthermore, crypto-currency market still witnesses lack of knowledge of many aspects such as understanding the market informational efficiency and the level of risk that can be accepted for holding an investment in these new digital market currencies. This present study therefore, attempts to contribute to the market through analysing the effect of symmetry and asymmetry information on the bitcoin market volatility and understand the risk return trade-off position.

Data and research methodology
This study used secondary data for daily closing prices of bitcoin currency in US dollar, covering the period from 18 August 2011 to 31 December 2017, whereby, the volatility of bitcoin currency was estimated on return ($r_t$) and the daily returns were calculated using the logarithmic of first difference of daily closing price, which is mathematically presented in the following formula:

$$r_t = \log \left( \frac{P_t}{P_{t-1}} \right)$$

where $r_t$ is the logarithmic daily return on bitcoin currency index for time $t$, $P_t$ is the closing price at time $t$, and $P_{t-1}$ is the corresponding price in the period at time $t-1$.

Preliminary test for the bitcoin prices and its return
Several statistical preliminary tests were conducted to examine the behaviour of bitcoin currency price index before investigating its volatility structure. These include, descriptive statistics (mean, minimum, maximum, and standard deviation), data normality distribution tests (skewness, kurtosis and Jarque–Bera), unit root test, and draw volatility clustering and conducting autoregressive conditional heteroskedasticity (ARCH) test.

In particular, the skewness looks at the distribution balance of the data, whether it is centred (symmetric) or not, whereas values falling outside the range of $-1$ to $+1$ indicate a substantially skewed distribution (Hair et al., 2006). While, kurtosis tests measures the peakedness or flatness of a distribution when compared to the normal distribution. Stock and Watson (2006) recommended that it should have a range not more than $+3.0$. In addition, a widely applied test of normality which is the Jarque–Bera test is applied, which represents the goodness of fit test of whether the sample data have the skewness and kurtosis matching a normal distribution (Jarque and Bera, 1980).

Furthermore, in this study the stationarity of the series for bitcoin return variable was tested using the Augmented Dickey and Fuller (1979) (ADF) and the Phillips and Perron (1988) (PP) unit root test. The ADF and PP unit root test that include both a drift and linear time trend are mathematically presented in the following equations, respectively:

$$\Delta Y_t = \alpha_0 + \alpha_1 t + \gamma Y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta Y_{t-i} + \varepsilon_t$$
\[ \Delta Y_t = \alpha_0 + \alpha_1 t + \gamma Y_{t-1} + \varepsilon_t \]

where, \( \gamma \) represents the variable of bitcoin market return, \( \alpha_i \) and \( \gamma \) are constant terms, \( t \) is the time period, \( \alpha_1 t \) the intercept and time trend that may be added, \( \Delta \) represents the first difference operator, \( \varepsilon_t \) is the white noise residual and \( p \) is the number lagged values. The null hypothesis for both the ADF and the PP unit root test is that: \( H_0: \gamma = 0 \), which denotes that the series has a unit root (the series is not stationary), \( H_1: \gamma \neq 0 \), which denotes alternative hypothesis, i.e. the series is stationary. The study tested the null hypothesis using the critical values reported in Enders (2010).

Finally, it is necessary to examine the presence of heteroscedasticity in residual of the return series before applying the GARCH family methodologies. To this end the study used the Lagrange multiplier (LM) test to examine the ARCH effect, where the null hypothesis of the LM test is that there is no heteroscedasticity presents on the residual (Engle (1982)).

Volatility measurement technique of both symmetric and asymmetric information

The ARCH model introduced by Engle (1982) was the first model effort to measure the financial assets volatility using lagged disturbances. However, it has limitation, where it requires a high ARCH to capture the dynamic behaviour of the volatility. To this end the Generalised Auto-Regressive Conditional Heteroscedasticity (GARCH) model introduced by Bollerslev (1986) allows for a more flexible lag structure. Hence, empirical financial literature shows that the ARCH and the GARCH models are considered as sufficient models in capturing the symmetric volatility clustering of the assets returns. However, their conditional variances fail to respond asymmetrically to the volatility of the financial assets returns. In other words, they failed in modelling the asymmetric information or leverage effect (Alberg et al., 2008). This major weaknesses of the symmetric GARCH models, namely, ARCH and GARCH, have therefore directed to the development of several asymmetric GARCH models such as exponential GARCH (EGARCH) model by Nelson (1991), the asymmetric power ARCH (APGARCH) model by Ding et al. (1993), and the threshold GARCH of Zakoian (1994) (TGARCH), which are the attainment in modelling asymmetric volatility of the return series. Furthermore, there is another limitation in the GARCH family models as Nelson (1991) used the generalized error distribution (GED) to model the innovation of the variance equation. However, the GED does not support the model to fully capture the leptokurtic feature of high frequency financial time series (Miron and Tudor, 2010). To address this issue, Bollerslev (1987), Baillie and Bollerslev (1989) and Beine et al. (2002) have applied the Student’s-t distribution to model the innovation of the variance equation.

For the current study analysis, we used the GARCH (1,1) and GARCH-M (1,1) for the modelling of the symmetric conditional volatility. Furthermore, as in financial market the return of an asset may depend on its risk, therefore, we have to consider the risk effects in the crypto currency market return. To do so, the study applied GARCH-M (1,1) model, whereby, the conditional variance enters the mean equation directly into the GARCH (1,1) model, hence, a positive risk-premium may indicates that data series is positively related to its volatility. On the other hands, the study used EGARCH (1,1), APGARCH and TGARCH (1,1) model for the modelling of the asymmetric volatility in the return series of bitcoin currency. The chosen models understudy are mathematically presented in Table I below.

In addition, the residuals of the estimated models followed the maximum likelihood (ML) estimation to ensure the conditional is normally distributed, which is statically presented by the following equation:
Table I. Symmetric and asymmetric GARCH models specification

<table>
<thead>
<tr>
<th>Equation</th>
<th>GARCH (1,1)</th>
<th>Symmetric information</th>
<th>GARCH-M (1,1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean equation</td>
<td>$r_t = \mu + \varepsilon_t$</td>
<td>Where $r_t$ is the return of the bitcoin currency at time $t$, $\mu$ is the average return and $\varepsilon_t$ is the random innovations with zero mean and constant variance. The parameter $\lambda$ denotes the risk premium, $\sigma$ refers to the conditional standard deviation and $\tau$ denotes the coefficients of the lag returns.</td>
<td></td>
</tr>
<tr>
<td>Variance equation</td>
<td>$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$</td>
<td>Where $\sigma_t^2$ is the conditional variance at time $t$, $\omega$ is the intercept (constant) and $\alpha$ refers to ARCH effect and $\beta$ indicates GARCH effect. $\alpha$ and $\beta$ determine the short-run dynamics of the volatility time series. While $\varepsilon_{t-1}^2$ refers to ARCH term that measures the impact of recent news on volatility. To ensure that $\sigma_t^2$ is positive for all $t$, Bollerslev (1986) enforced these restrictions of $\omega &gt; 0$, $\alpha_i \geq 0$, for $i = 1, 2, \ldots, q$ and $\beta_j \geq 0$ (for $j = 1, 2, \ldots, p$).</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$r_t = \mu + \lambda \sigma_t^2 + \varepsilon_t$</td>
<td>$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$</td>
<td>$r_t = \mu + \lambda \sigma_t^2 + \varepsilon_t$</td>
</tr>
</tbody>
</table>

(continued)
Equation | E-GARCH (1,1) | APARCH (1,1) | Asymmetric information | T-GARCH (1,1) |
--- | --- | --- | --- | --- |
Mean equation | \( r_t = \mu + \varepsilon_t \) | \( r_t = \mu + \varepsilon_t \) | \( r_t = \mu + \varepsilon_t \) |
Variance equation | | | |
\( \ln \left( \sigma_t^2 \right) = \omega + \beta_1 \ln \left( \sigma_{t-1}^2 \right) + \alpha_1 \) | \( \sigma_t^2 = \omega + \alpha_1 (\varepsilon_{t-1})^2 + \beta_1 \sigma_{t-1}^2 \varepsilon_{t-1} \) | \( \sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma d_{t-1} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \) |
\( \left\{ \frac{\varepsilon_{t-1}}{\sigma_{t-1}} - \frac{\pi}{2} \right\} - \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \) | \( = |\varepsilon_{t-1}| - \gamma \varepsilon_{t-1} \) | \( + \beta_1 \sigma_{t-1}^2 \ |

The \( \ln \left( \sigma_t^2 \right) \) is stated for the log of the conditional variance, \( \omega \) is the intercept (constant), \( \alpha \) refers to ARCH effect and \( \beta \) indicates for GARCH effect. \( \delta \) plays the role of a Box-Cox transformation of the conditional standard deviation, \( \gamma \) is referred to the asymmetry or leverage effect parameter and \( \varepsilon_{t-1} \) Lagged error term. Finally, \(|\varepsilon_{t-1}|\) refers to the absolute value of the standardized residuals.

Where, \( \sigma_t^2 \) is the conditional variance at time \( t \), \( \omega \) is the intercept (constant), \( \alpha \) refers to ARCH effect and \( \beta \) indicates GARCH effect. While \( \sigma_{t-1}^2 \) refers to ARCH term that measures the impact of the recent news on volatility. In the above model, the conditional variance is affected differently by both good news \( (\varepsilon_t > 0) \) and bad news \( (\varepsilon_t < 0) \). In which, the good news has an effect on \( \alpha \), whereas the bad news has an effect on \( \alpha + \gamma \). Thus, if \( \gamma \) is significant and positive, negative shocks have a larger effect on \( \sigma_t^2 \) than the positive shocks.
If it is found that the conditional distribution is non-normally distributed, the ML estimators are still consistent and asymptotically normal; the standard error will be inconsistent (Alberg et al., 2008). Thus, the alternative method to address this issue is to re-estimate the GARCH family models using robust standard errors suggested by Bollerslev and Wooldridge (1992), which is known as quasi-maximum likelihood. The estimators as reported by Chu et al. (2017) include “a Gaussian quasi-maximum likelihood estimator for the GARCH (1,1) model [Theorem 3, p. 580, Lumsdaine (1996)]; a stable quasi-maximum likelihood estimator for the EGARCH (1, 1) model [Theorem 6, p. 859, Wintenberger (2013)]; a restricted normal mixture quasi-maximum likelihood estimator for the TGARCH (1, 1) model [Theorem 2.4, p. 1346, Wang and Pan (2014)]; a Laplacian quasi-maximum likelihood estimator for the APARCH (1, 1) model (Theorem 3.3, pp. 457-458, Bardet et al. (2017)”. Finally, the study selects the best model based on the statistical values of the four criteria, namely, ML ration, AIC modelled by Akaike (1974) BIC modelled by Schwarz (1978) and the Hannan–Quinn criterion (HQC) modelled by Hannan and Quinn (1979). The highest the value of ML ratio or the smaller the values of these criteria, the better fit is the model. As final point the study conducted the diagnostic test for all models under study to ensure that the residuals are free from ARCH effect and the error terms are normally distributed to provide evidence that the variance equations of bitcoin market return are well specified.

Findings and discussion
Descriptive statistics: Figure 1 presents the price behaviour of bitcoin currency demonstrated in USA dollars for a seven-year period started from 18 August 2011 to 31 December 2017. During this period the price trend recorded high volatility, whereby the mean price in the interior period was US$880.483, with minimum and maximum values of US$2.2400 and US$19,187.78, respectively.

Furthermore, Table II exhibits the descriptive statistical analysis of the daily market price index and returns of bitcoin currency. It displays that the average daily returns of US $0.0031 with maximum value of US$0.446 and minimum value of US$−0.664. With high market risk as measured by the standard deviation of 0.053, which is about 1,709.67 per cent of its mean showing that the price is so volatile, giving solid signal of price instability in the cryptocurrency market. The normality distribution of the bitcoin market return was measured by skewedness and kurtosis statistic values. In particular, the bitcoin market return distribution was not normally distributed and was skewed to the left with statistical value of −1.40018, which exceeded the rule of thumb of the −1 to +1 (Hair et al., 2006). This indicates that the bitcoin market return is irregular and investors are likely to earn negative returns if the return distribution continues to be skewed to the left in the near future. The kurtosis statistical value stood at 27.541, greater than the rule of thumb of 3.0 as recommended by Stock and Watson (2006). This indicates that the return series is fat tailed and not normally distributed. The overall results of the descriptive statistics behaviour of bitcoin market return is not normally distributed, which may suggest that there may be such chance for speculative business.
Figure 1. Bitcoin price index

Case study of bitcoin currency
Unit root and volatility clustering test results
The closing prices of the bitcoin currency have been converted into daily logarithmic return series to make the series stationary. Table III below displays that both ADF and PP tests provide an evidence of the presence of stationary in the return series, as the P-values of ADF and PP are statically significant at 1 per cent level. In addition, the study graphically estimated the volatility of bitcoin currency return as illustrated in Figure 2. It displays that the return series of bitcoin market return is characterized by Volatility clustering over the period of the study as the period of high volatility followed by period of high volatility for a long period and the period of low volatility followed by period of low volatility for long period as well. This means the return series of bitcoin currency is not constant over time but it is time-varying. To confirm the persistence of volatility clustering in bitcoin market returns, the study used the ARCH-LM test to examine the ARCH effect on the residuals of the return series. The ARCH-LM test result is presented in table III, which indicates the presence of ARCH effects on model residuals. This may indicate that the time series of market return are depended on their own past value (autoregressive), past information (conditional) and exhibit non-constant variance (heteroscedasticity). This is owing to ARCH-LM test statistical value highly significant and the null hypothesis of “no ARCH effect” is rejected at 1 per cent level of significant.

In addition, the study examines the normality distribution of residuals for time series model using the Jarque–Bera test. The Jarque–Bera test value of 58,317.45 and its probability (0.000) provide evidence that the data distribution of bitcoin market return is not normally distributed as its statistical value is highly significant at 1 per cent level of significant. The null hypothesis establishing the model residual is normally distributed is rejected as the P-value is less than the selected significance level (Jarque and Bera, (1980) Figure 3).

The overall results of model diagnostic tests show that the residual behaviour of bitcoin market returns is non-normally distributed and non-free from the auto-correlated and heteroskedastic effect indicate for clustering volatility in the market returns.

Symmetric volatility analysis results
After approving that the bitcoin market return series is characterized by volatility clustering and time-varying in the previous section, the study analysis moves further to determine the best fitted GARCH model that can help in modelling the volatility of return series in the bitcoin market currency. This section therefore discusses the findings obtained by fitting symmetric and asymmetric GARCH models to the return series. Table IV reports the

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Maxi</th>
<th>Mini</th>
<th>SD</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>Jarque–Bera</th>
<th>P-value</th>
<th>No. ob</th>
</tr>
</thead>
<tbody>
<tr>
<td>BTC—price</td>
<td>880.483</td>
<td>19187.78</td>
<td>2,240</td>
<td>2091.050</td>
<td>5.204</td>
<td>34.708</td>
<td>106454.6</td>
<td>0.000</td>
<td>2295</td>
</tr>
<tr>
<td>BTC—return</td>
<td>0.0031</td>
<td>0.446</td>
<td>-0.664</td>
<td>0.053</td>
<td>-1.401</td>
<td>27.541</td>
<td>58317.45</td>
<td>0.000</td>
<td>2294</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF-test</th>
<th>PP test</th>
<th>ARCH-LM test statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>BITCOIN—RETURN</td>
<td>-36.69145***</td>
<td>-48.50225***</td>
<td>F(1,2291) = 176.8995***</td>
</tr>
</tbody>
</table>

Note: *** and ** denotes significant level at 1% and 5% significance respectively
Figure 2.
Volatility in bitcoin return

Case study of bitcoin currency
Figure 3. Normality distribution result in the residuals of time series model.

Series: Residuals
Sample 8/19/2011 12/31/2017
Observations 2294

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>-1.21e-18</td>
</tr>
<tr>
<td>Median</td>
<td>-0.000759</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.442427</td>
</tr>
<tr>
<td>Minimum</td>
<td>-0.667065</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.053157</td>
</tr>
<tr>
<td>Skewness</td>
<td>-1.400181</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>27.54138</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>58317.45</td>
</tr>
<tr>
<td>Probability</td>
<td>0.000000</td>
</tr>
<tr>
<td>Coefficient</td>
<td>Symmetric information</td>
</tr>
<tr>
<td>----------------------</td>
<td>-----------------------</td>
</tr>
<tr>
<td>Mean</td>
<td></td>
</tr>
<tr>
<td>( \mu ) (constant)</td>
<td>0.002269***</td>
</tr>
<tr>
<td>( \lambda )</td>
<td>0.091538</td>
</tr>
<tr>
<td>Risk premium</td>
<td>0.091538</td>
</tr>
<tr>
<td>Variance</td>
<td></td>
</tr>
<tr>
<td>( \omega ) (constant)</td>
<td>0.0000473**</td>
</tr>
<tr>
<td>( \alpha ) (ARCH effect)</td>
<td>0.19048***</td>
</tr>
<tr>
<td>( \beta ) (GARCH effect)</td>
<td>0.819748***</td>
</tr>
<tr>
<td>( \alpha + \beta )</td>
<td>1.010228</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>4195.608</td>
</tr>
<tr>
<td>Akaike info. criterion (AIC)</td>
<td>-3.6544</td>
</tr>
<tr>
<td>Schwarz info. criterion (SIC)</td>
<td>-3.6444</td>
</tr>
<tr>
<td>Hannan–Quinn criterion (HQC)</td>
<td>-3.6507</td>
</tr>
<tr>
<td>ARCH-LM test for heteroscedasticity</td>
<td>0.10818</td>
</tr>
<tr>
<td>ARCH-LM test statistics</td>
<td>0.74224</td>
</tr>
</tbody>
</table>

Note: *** and ** denote significant levels at 1% and 5% significance, respectively.
estimated result of GARCH (1, 1); GARCH-M (1,1); E-GARCH (1,1); APGARCH (1, 1); and TGARCH (1, 1) models. Based on the symmetric model results of GARCH (1,1), it is indicated that the constant (μ) in mean equation is found to be statistically significant at 1 per cent level, and similar results are reported by E-GARCH (1,1), APGARCH (1, 1) and TGARCH (1, 1) models. This indicates that there is an abnormal return in the bitcoin market currency. Moreover, Table IV indicates that the estimated efficient results in conditional variance equation for constant (ω), ARCH (α) and GARCH (β) parameters of the GARCH (1, 1) model are statically significant at 5, 1 and 1 per cent respectively. This confirms the persistent of the volatility in market return. The estimated coefficient result of parameter (β) (0.819748) is greater than the estimated coefficient of parameter (α) (0.19048). This indicates that the market has a memory longer than one period and that volatility is more sensitive to its past values (lagged) than it is to new shock in the market values. In additional the size of the estimated coefficient of the parameters α and β define the volatility in time series (Banumathy and Azhagaiah, 2015). The sum of these coefficients (α + β) stood at 1.010228, which is above unity suggesting that the shock in bitcoin market return will be persisted to many future periods. This finding is supported by Chen et al. (2016) who found the persistence of volatility clustering and time varying in the return series of the three CRIX (crypto-currency index) indices in the market.

In addition, the study investigates the persistence of risk-return trade-off phenomenon in the crypto-currency market by using the GARCH-M (1,1) model as it allows the mean equation of the return series to depend on a function of the conditional variance, and the term to be estimated could be interpreted as the risk premium (Engle et al., 1987). This is because in financial theory the association between risk and returns plays a significant role in drawing the investors’ investment decision. For instance, the capital assets price model theory suggests a linear association between the risk (variance) and the expected returns of a market portfolio. If the risk (the variance) is not constant over time, then the conditional expectation of the market returns is a linear function of the conditional variance (Fama and French, 2004). The result of GARCH-M (1,1) model is reported in Table IV, where the estimated coefficient of conditional variance (λ) in the mean equation is positive but statistically insignificant with the value of 0.091538. This indicates that there is no significant impact of volatility on the expected return, indicating lack of risk-return trade-off phenomenon over the time in crypto-currency markets. This is actually unsteady with risk return trade-off definition that stated a higher risk is associated with greater prospect of higher return and lower risk is associated with a greater possibility of smaller return (Merton, 1973).Thus, it is suggested that investment in crypto-currency market is more suitable for risk-averse investors than risk taker. This finding is inconsistent with the finding of Chu et al. (2017) as they advocated that the new digitized currencies investment is more suited for risk-seeking investors looking for a way to invest or enter into technology markets.

Asymmetric and leverage effects analysis results
The asymmetric and leverage effects have been examined in the current study through the nonlinear asymmetric variance specifications, such as EGARCH (1, 1), APGARCH(1,1) and TGARCH(1,1), using QML distribution assumptions. The coefficient of (γ) parameter that is referred to the asymmetry or leverage effects is found to be statistically insignificant in all cases indicating the absence of the leverage effects or in other words the asymmetry informative does not exist in bitcoin market returns. This finding is consistent with a large body of empirical studies concerning the effect of asymmetric information on the crypto-currencies market returns or volatility such as Dyhrberg (2016); Chen et al. (2016);
Stavroyiannis and Babalos (2017); Bouri et al. (2016); and Chu et al. (2017). This in general means that the bad or good news does not have significant impact at all on volatility or market return in crypto-currencies market. This recommends that bitcoin market price is unpredictable, in which investors cannot achieve above average trading advantages based on past information of the market. This interesting result therefore suggests that bitcoin currency can be used by investors as factual hedging instrument against a market risk specifically during economic turmoil or crisis.

As a final point, for selecting the best fitted model four techniques were utilized namely ML ration, AIC, BIC and HQC criterion. The selection is made based on the highest value of ML ration and the minimum values of AIC, BIC and HQC criterion. Accordingly, the best-fitted models selected was the EGARCH (1,1) with high log likelihood value of 4203.6813 and the low AIC, SIC and HQC values of $-3.65956$, $-3.64676$ and $-3.65470$, respectively. Hence, EGARCH (1,1) model seems to be an adequate depiction of symmetric and asymmetric volatility process for bitcoin market returns. In which the symmetric effect captured by the parameters of ARCH ($\alpha$) of 0.294185, GARCH ($\beta$) of 0.968806 in EGARCH model are statically significant at 1 per cent level and the sum of ($\alpha$ and $\beta$) parameter is 1.262991, which is above the unity confirming that the shock in the return series will persist to many future periods. On the other hand, the asymmetric effect captured by the parameter ($\gamma$) in EGARCH model is negative and statistically insignificant at 1 per cent level provides an evidence of absence in the leverage effect in series return, and the negative sign may disclose that negative shocks (bad news) have more effect on the conditional variance when compared to the positive shocks (good news) but statically still insignificant. In the final stage the study used diagnostic tests of ARCH-LM to check whether the residuals of the specified models show any additional ARCH effect. The results indicate that all the residual of the GARCH models are free from ARCH effect, as the null hypothesis of "no ARCH effect" is accepted at significant level of 5 per cent, which confirms that the variance equations for all volatility specifications in bitcoin market returns are well identified and estimated.

**Conclusion**

This study examined the effect of symmetric and asymmetric information on volatility structure of bitcoin currency daily market returns using different GARCH family models over the period of seven years. The results indicated that the bitcoin market return is linearly affected by symmetric information because the parameters of ARCH ($\alpha$), GARCH ($\beta$) in conditional variance equation are statistically significant at 1 per cent level in all GARCH models. The sum of estimated coefficient of both parameters of ARCH ($\alpha$), GARCH ($\beta$) stood at more than 1 in all cases indicating that the market return or volatility will continue to be unstable for a long future time period. Nevertheless, the bitcoin market return was found insignificant in response to the asymmetric information, which was captured by the coefficient of leverage effect ($\gamma$) neither good nor bad news, indicating the absence of leverage effects. This provides evidence that the bitcoin market return has to some extent a weak form of efficient market, where the price variability could not be predicated using asymmetric information for the short-term speculative investment. Thus, the bitcoin currency could be used as a hedging instrument by many investors during an economic slowdown or financial crisis. Further, the study investigated if the risk-return trade-off opportunity exists in crypto-currencies market using GARCH–M (1,1). The estimated coefficient result of conditional variance or risk premium ($\lambda$) in the mean equation is found to be positive however, statistically insignificant, indicating that higher market risk provided by conditional variance will not lead to higher returns. Thus, it can be concluded that the new digital currencies have the capacity to reserve their place in the financial
market as hedging financial instruments against the market risk and applied as investment assets for portfolio investment strategy.

In fact, crypto-currencies are mainly considered by many market participants and investors as an investment asset rather than a currency (Dyhrberg, 2016). Hence, the crypto-currencies market will continuously be highly speculative and more volatile, as well as susceptible to speculative bubbles, than other currencies (Katsiampa, 2017). Therefore, for further research more efforts need to be taken to understand the volatility structure of the new financial digital assets (crypto-currencies) comparing with other financial assets such as commodity, stocks, bonds, gold and others to draw the prefect portfolio investment diversification strategy.

References


Guttmann, B. (2014), The Bitcoin Bible Gold Edition: All You Need to Know about Bitcoins and More, BoD–Books on Demand, Norderstedt.


**Further reading**


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