Published in Slovak Republic
European Journal of Economic Studies
Has been issued since 2012.
E-ISSN: 2305-6282
2019, 8(1): 77-84

DOI: 10.13187/es.2019.1.77
www.ejournal2.com

The Leverage Effect and Information Flow Interpretation for Speculative Bitcoin Prices: Bitcoin Volume vs ARCH Effect

Chamil W. Senarathne [a, *]

[a] School of Economics, Wuhan University of Technology, China

Abstract

This paper examines the leverage effect and the information flow interpretation of heteroskedasticity – from a sample of daily Bitcoin return data from 3/19/2016 to 7/24/2018 – using the framework of Lamoureux and Lastrapes (1990). The results show that the Bitcoin return variance cannot be effectively explained by GARCH (1, 1), GJR-GARCH or EGARCH models given the stationarity of variance of return. The leverage effect is not observed by the estimate of EGARCH model. ARCH effect vanishes and the coefficient becomes highly statistically insignificant when the volume—as a mixing variable—is included in the conditional variance equation of IGARCH model. These findings suggest that the Bitcoin price changes are generated from an independent stochastic price increment process of which the increments are subordinated to stationary ARCH errors. As such, the Bitcoin can be classified as a class of speculative assets in the cryptocurrency exchange.

Keywords: bitcoin, information flow, EGARCH, stationary ARCH, volume.

1. Introduction

Until 2009, a little was known about carrying out a commercial transaction over the Internet (i.e. electronic communication network) without a trusted party. A virtual affiliated paper by Nakamoto, 2008 proposes an electronic payment system based on cryptographic proof which creates a highly efficient electronic marketplace for goods and services. The central idea of the paper has been further developed and implemented in January 2009. Since then, economic agents could carry out settlement of commercial transactions on this platform anonymously without going through financial intermediaries. Bitcoin as a virtual currency has grown significantly over the past few years and are quoted against a number of national currencies of the world. Equilibrium Bitcoin price changes quoted against national currencies of different countries may contain valuable information about the demand and supply. As presented in Figure 1, USD Bitcoin price changes have been subject to high volatility and volume trades over the last three years. A. Urquhart finds that the price and volume of Bitcoin tend to cluster together—which implies that—the large errors are followed by large errors and vice versa (Urquhart, 2017: 145). These clusters of price changes are likely to persist over a long run (Kurihara, Fukushima, 2018: 8). This suggests that the variance of this market price (i.e. Bitcoin price) may change over time and can be predicted by the past forecast errors in the sense of R.F. Engle (Engle, 1982: 987).

* Corresponding author
E-mail addresses: chamil@whut.edu.cn (C.W. Senarathne)

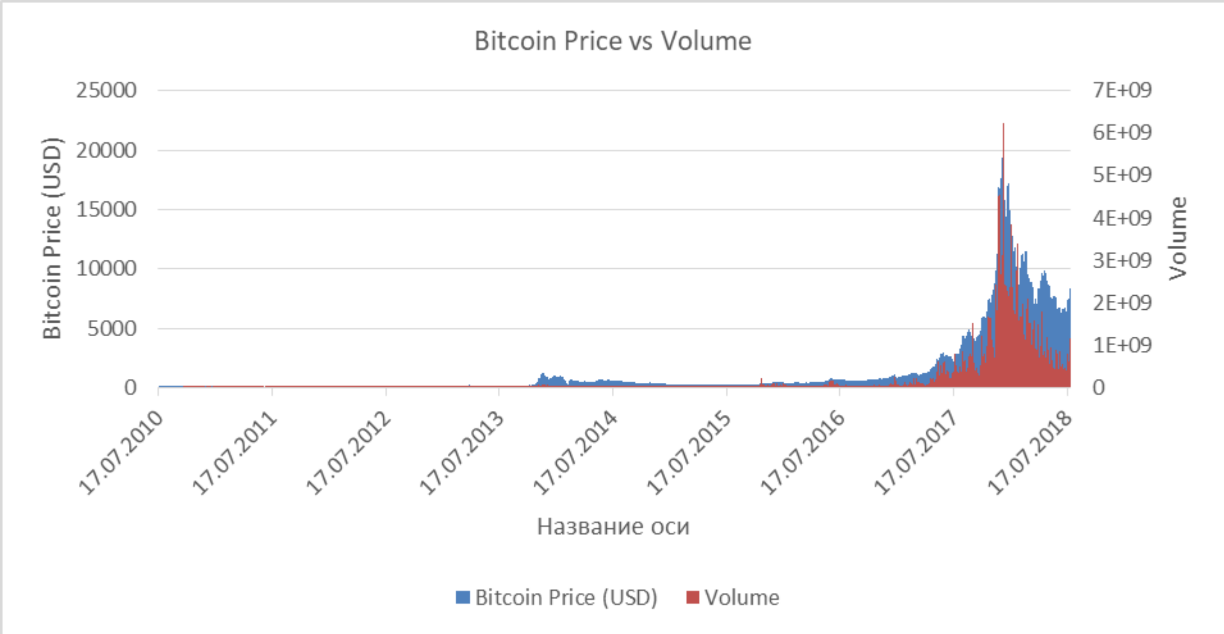

Fig. 1. Bitcoin Price vs. Volume

Trades carried out through electronic communication networks (ECN) offer a number of advantages. M. Balcilar examines the competitive advantages for an equity trader trading through ECNs and Nasdaq market makers, and find that it offers the advantages of anonymity and speed of execution (Barclay et al., 2003: 2637). They also find that the trades carried out though ECNs are more informed than trades carried out through market makers—traders often carry out trades through ECNs when trading volumes and return volatility are high*. The scholars such as M. Buchholz, L. Kristoufek, D. van Wijk, show that the Bitcoin price is determined by (*i*) supply-demand interactions, (*ii*) Bitcoin's attractiveness for investors and (*iii*) the global macroeconomic and financial developments, respectively (Buchholz et al., 2012: 312; Kristoufek, 2013: 3415; van Wijk, 2013). What factually drives the Bitcoin price has however been debated among recent scholars. Using Empirical Mode Decomposition techniques, M. Buchholz, M demonstrates that the price of Bitcoin is driven by the long-term fundamentals rather than the speculative behavior of investors (Bouoiyour., 2016: 843). Contrarily, Buchholz et al., 2012: 312; Grinberg, 2012: 159; Kristoufek, 2013: 3415; Ciaian et al., 2016: 1799; Glaser et al., 2014; Yermack, 2015:31; Baek, Elbeck, 2015: 30; Cheah, Fry 2015: 32; Bouoiyour, Selmi 2015: 449; Dyhrberg, 2016: 85; Baur et al., 2018: 177 show that the Bitcoin is a speculative asset† rather than a currency or long-term investment. Unlike other exchange instruments, the Bitcoin price is not determined by the underlying value of an asset (e.g. futures). Hence, it is difficult to ascertain as to how the Bitcoin price evolves over time.

On the other hand, a number of scholars attempt to understand the predictability of Bitcoin price. M. Balcilar employs a non-parametric causality-in-quantiles test to identify any causal relationship between trading volume, volatility and returns, and find that the volume is useful in forecasting return but not the volatility of Bitcoin (Balcilar et al., 2017: 64). They however detect nonlinearity and structural breaks in the return and volume. S. Nadarajah, J. Chu test Bitcoin returns for random walk behavior (under Efficient Market Hypothesis (EMH)) and find that it does not follow the rules of EMH (Nadarajah, Chu, 2017: 6)‡. A. Urquhart uses battery of tests to study the informational efficiency of Bitcoin market and finds that the market is a weak form inefficient (Urquhart, 2016: 80). However, A.F. Bariviera, A.K. Tiwari find the existence of efficient conditions in the Bitcoin market (Bariviera, 2017: 1; Tiwari, 2018: 106). P. Ciaian et al. find that the

* They also show a permanent price impact of trades in different venues and revelation of private information of traders.
† Some identify it as a speculative asset while others as a speculative bubble.
‡ However, the power transformation tests reveal that the Bitcoin market is efficient.

attractiveness of Bitcoin for investors and users has a significant impact on the price discovery (Ciaian et al 2016: 1799).

Although there has been a voluminous literature on the efficiency and drivers of Bitcoin price, only a handful of scholars have studied about the speculative behavior of Bitcoin prices and volume using a common framework (e.g. Lamoureux, Lastrapes, 1990: 221)[*]. The objective of this paper is to examine the leverage effect in the Bitcoin market and the impact of information flow attached to Bitcoin trading volume[†] on equilibrium price formation in the speculative USD Bitcoin quotes, using the framework of C.G. Lamoureux, W.D. Lastrapes (Lamoureux, Lastrapes, 1990: 221). The paper is organized as follows. Section 2 provides the methodological framework. Section 3 describes data set including its empirical properties. Section 4 discusses the findings and section 5 provides the concluding remarks.

2. Theoretical Specification

Following Lamoureux, Lastrapes, 1990: 221; Sharma et al., 1996: 337; Choi et al 2012: 584 and Zhang et al., 2014:70 define δ_{mt} denote the m^{th} intraday equilibrium market price increment[‡] in day t summed up over a daily data horizon.

$$\varepsilon_t = \sum_{m=1}^{n_t} \delta_{mt} \tag{1}$$

Where n_t is a stochastic random variable (i.e. the mixing variable) which reflects the aggregate amount of new information arrival at the Bitcoin market. Assume that the new information arrival process is sequential rather than simultaneous[§] which could be expressed as;

$$n_t = \theta_0 + b(L)n_{t-1} + \Phi_t, \quad n_t \geq 0 \qquad (2),$$

Where n_t is serially correlated and the evolution to the mixing variable is accounted for by the lag polynomial operator $b(L)$ of order q and Φ_t, is a non-negative random error with zero mean and unit variance. In the sense of C.G. Lamoureux, W.D. Lastrapes assume that ε_t is subordinated to δ_m, so that $\Omega = E(\varepsilon_t^2|n_t)$ where Ω is the persistence of conditional variance estimated by an EGARCH[**] model. Since the mixture model is invoked, $\Omega = \sigma^2 n_t$ and $\varepsilon_t|\ n_t \sim N(0, \sigma^2 n_t)$ (Lamoureux, Lastrapes, 1990: 221).

For the variance estimation in the sense of D.B. Nelson, the following specification which accounts for asymmetric effect of innovations on volatility is given (Nelson, 1991: 347),

$$R_t = \mu_{t-1} + \varepsilon_t, \tag{3}$$
$$\varepsilon_t \backslash (\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots\ldots) \sim N(0, h_t), \tag{4}$$
$$\ln(\sigma_t^2) = \omega + \eta \ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \tag{5}$$

where ω is a constant and σ_t^2 is the conditional variance at time t. η is the coefficient of prior period's volatility or the coefficient corresponds to ARCH and γ is the coefficient applicable to leverage effect in the Bitcoin market, if applicable. α is the coefficient of long-term volatility or the GARCH coefficient. The coefficient γ is expected to be negative and statistically significant, if a negative shock has a greater impact on volatility than the positive shocks of the same magnitude. Under the null hypothesis of Bitcoin market price change variance is characterized by the type of Asymmetric GARCH model (i.e. EGARCH) described above, the coefficient γ should be negative

[*] See e.g. Naik et al., 2018: 99. This paper extends their sampling period.
[†] Exchanges against USD.
[‡] A random variable from a stationary price change process (see also Senarathne, Jayasinghe, 2017: 1; Senarathne, Jianguo 2018; Senarathne, 2018; Senarathne, 2019 for a similar preposition).
[§] Such postulation is in line with Copeland, 1976: 1149 and Smirlock, Starks, 1988: 31.
[**] Exponential generalized autoregressive conditional heteroskedasticity.

and statistically significant and the sum of EGARCH coefficients (except intercept term) should be less than unity.

If the null hypothesis is accepted, the time dependence of Bitcoin volume in the rate of new information arrival at the market is tested by introducing the Bitcoin volume* V_{t-1} into the conditional variance equation (5) as,

$$\varepsilon_t \backslash (V_{t-1}, \varepsilon_{t-1}, \varepsilon_{t-2}, \ldots..) \sim N(0, h_t), \tag{6}$$

$$\ln(\sigma_t^2) = \omega + \eta \ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] + \lambda V_{t-1} \tag{7}$$

If the null hypothesis is rejected, the time dependence is tested by estimating an Integrated GARCH Model (mean specification and distributional assumptions of errors remain same) as;

$$a_t = \sigma_t \varepsilon_t \tag{8}$$

$$\sigma_t^2 = \varphi + \beta_1 \sigma_{t-1}^2 + (1 - \beta_1) a_{t-1}^2 \tag{9}$$

Where, the condition $1 > \beta_1 > 0$ usually prevails and the impact of volatility shocks $\zeta_{t-i} = a_{t-i}^2 - \sigma_{t-i}^2$ for $i > 0$ on σ_t^2 is assumed to persist over time,† in which, the information set is relevant for the forecasts of the conditional variance.

The Bitcoin volume V_t is included in the variance equation (9) as,

$$\sigma_t^2 = \varphi + \beta_1 \sigma_{t-1}^2 + (1 - \beta_1) a_{t-1}^2 + \psi V_{t-1} \tag{10}$$

If volume is a manifestation of time dependence in the rate of new information arrival at the Bitcoin market, the coefficient β_1 of the IGARCH model‡ should be negligible when accounting for uneven flow of information arrival under serial correlation in the presence of ARCH in the IGARCH.

3. Data and Empirical Results

Daily USD Bitcoin price quotes (BTC-USD) and volume data are obtained from Yahoo webpage§ covering a sampling period from 3/19/2016 to 7/24/2018. This period reflects the first and the largest clustering of price changes (See Figure 1) in the Bitcoin market. The descriptive statistics of the sample data are as follows.

* In order to eliminate possible simultaneity bias, lag volume is considered as Lamoureux, Lastrapes, 1990: 221 suggest.
† See Tsay, 2005.
‡ Especially, the ARCH effect in the sense of Lamoureux, Lastrapes, 1990: 221
§ Available at https://finance.yahoo.com/quote/BTC-USD/history?p=BTC-USD

Table 1. Empirical Description of the Sample Data

Variable	Mean	Median	Max.	Min.	JB	ADF	LM	Q (36)
R_t	0.0044	0.0034	0.2556	-0.1724	611.53	-29.26	47.13	22.45
V_t	4.6E+08	1.8E+08	6.3E+09	7.4E+06	6591.61	-1.84	NA	9837.1

Source: Author's estimation
Notes:
1. JB – Jarque–Bera test statistic for normality. Under null hypothesis for normality, critical value of χ2 (2) distribution at 5 % significance level is 5.99.
2. ADF- Augmented Dickey–Fuller test statistic for stationarity of data for maximum 18 lags. Under null hypothesis for data having unit root, the critical value at 5 % significance level is -2.87.
3. LM is the LM is the ARCH LM test statistic for number of observations multiplied by the R-squared value for 3 lags. Under null hypothesis, critical value of χ2 (3) distribution at 5 % significance level is 7.815 (OLS equation $R_t = c + \varepsilon_t$.).
4. Q (20) is the Ljung-Box Q statistic for serial correlation upto 20 lags, in the margin debt values. Under the null hypothesis for no serial correlation, the critical value of χ2(20) distribution at 5 % significance level is 31.41.
5. * Statistically significant at 5 % and *** Statistically significant at 10 %.

Bitcoin return and volume data are highly nonnormal as the test statistic exceeds the critical value of 5.99 under Jarque–Bera test. Although the volume series is nonstationary, the return distribution is stationary as null hypothesis of data having a unit root is rejected at 5 percent significance level under Augmented Dickey–Fuller test. ARCH effect in return data exists for 3 lags under ARCH-LM test. The test statistic exceeds the critical value of 7.815 at $\chi 2$ (3) distribution at 5 percent significance level. However, Ljung-Box Q statistic for serial correlation upto 20 lags accepts the null hypothesis of no serial correlation as the test statistic is below the critical value of 31.41. However, volume series is highly serially correlated.

The coefficients ω, η, and α of EGARCH model are statistically significant at 5 percent significance level. However, the coefficient γ applicable to leverage effect is negative but highly statistically insignificant. As such, the leverage effect does not appear to have been presented in the Bitcoin market for the period considered. Leverage effect often observes in financial markets with diversifiable individual firms, where the information flow on both market factors (e.g. market risk premia (Bollerslev et al., 2011: 31) and firm-specific factors (e.g. financial leverage (Figlewski, Wang 2000) are presented. Index specific leverage effect can be observed when the volatility of individual stocks is greater than index volatility (Bouchaud et al., 2001)*. As such, the Bitcoin market is not characterized by such distinguishable features.

* Observed mostly in the case of investor panic.

Table 2. Maximum Likelihood Estimation of GARCH Models

EGRCH	ω	t-stat	η	t-stat	γ	t-stat	α	t-stat	$(\eta+\gamma+\alpha)$
$\ln(\sigma_t^2)$without V_t	-0.5714*	-3.1391	0.3618*	3.6078	-0.0175	-0.2503	0.9506*	48.21	1.2948
IGARCH	β_1	t-stat	$(1-\beta_1)$	t-stat	ψ	t-stat	NA	NA	$((\beta_1+(1-\beta_1))$
σ_t^2 without V_t	0.0756*	3.4579	0.9244*	42.28	NA	NA	NA	NA	1.0000
σ_t^2 with V_t	0.0019	0.8317	0.9981*	444.97	6.6E-14*	2.9453	NA	NA	1.0000

Source: Author's estimation
Notes:
1. * Statistically significant at 5 % assuming returns are conditionally normally distributed. ** Statistically significant at 10 %.
2. The coefficients are estimated using the methods described by Bollerslev and Wooldridge (1992) for obtaining quasi-maximum likelihood (QML) covariances and robust standard errors.
3. Residual diagnostics of EGARCH (without volume)—Wald coefficient restriction results for null hypotheses $\eta = 0$ and $\alpha+\eta = 0$ are 13.01* (F-stat) and 235.71* (F-stat) respectively; Akaike info criterion (-3.79); Log likelihood (1633.32); Durbin-Watson stat (1.98); ARCH-LM test for Obs*R-squared (4.77) Ljung-Box Q statistic (25.12); Jarque–Bera test statistic (533.04*)
4. Residual diagnostics of IGARCH (without volume)— Wald coefficient restriction results for null hypotheses $\beta_1 = 0$ is 11.95* (F-stat); Akaike info criterion (-3.70); Log likelihood (1591.91); Durbin-Watson stat (1.98); ARCH-LM test for Obs*R-squared (17.34*) Ljung-Box Q statistic (24.12). Jarque–Bera test statistic (822.45*).

On the other hand, the coefficients η, γ and α of EGARCH – summing up to greater than one – is an indication of a stationary GARCH process* which may not fit the time series data well. The symmetric effect† of information arrival on volatility is therefore lumped up into the intercept term ω which is negative and statistically significant at 5 percent significance level. Note that the estimates of GARCH (1, 1) and GJR-GARCH model (not reported) produced results with same issue. Hence, the natural choice would be to consider an Integrated GARCH model which would suit the nature of the time series behavior of Bitcoin data. Both ARCH and GARCH terms as measured by β_1 and $(1-\beta_1)$ are positive and statistically significant as estimated by equation (9) of the IGARCH model. However, the ARCH effect vanishes and becomes highly statistically insignificant at 5 percent significance level, when the volume is introduced into the conditional variance equation of IGARCH as in (10) above‡. This provides strong evidence for the hypothesis that the ARCH residual variance is a reflection of time dependence in the rate of information arrival at the Bitcoin market. Thus, the behavior of Bitcoin price changes is speculative—as a standalone asset class§ in the cryptocurrency market could exhibit—where the equilibrium price is determined by an independent stochastic price increment process under stationary ARCH-type of residual heteroskedasticity (see especially Nelson, 1990: 318).

4. Conclusion

The current literature is ambiguous as to whether the Bitcoin price change behavior is speculative and only a handful of scholars attempt to identify the mixed distribution properties of Bitcoin price changes. An examination on the type of heteroscedasticity in Bitcoin return data would help identify the price change behavior of Bitcoin market. The framework of C.G. Lamoureux, W.D. Lastrapes offers a more realistic methodology for resolving this puzzle (Lamoureux, Lastrapes, 1990: 221).

The leverage effect cannot be observed in the Bitcoin market during the sampling period** as estimated by the EGARCH model and, as such, the nature of data cannot be explained by an

* Which may well be characterized by a deterministic increment (i.e. a liner trend) in the conditional volatility (See Kontonikas, 2004: 525)
† Due to stationarity of variance.
‡ See Lamoureux, Lastrapes, 1990: 221).
§ I.e. a single instrument.
** I.e. the period with the largest cluster

asymmetric GARCH process in the presence of stationarity of conditional variance. When interpreted with reference to information arrival hypothesis in the presence of ARCH*, Bitcoin price formation process could well be characterized by a stochastic process with independent increments, driven by the information content of past (lagged) volume data (i.e. the mixing variable)†. The form of persistence of new information arrival is therefore a reflection of stationary ARCH variance type of heteroscedasticity in the Bitcoin return data. These findings provide evidence for the argument that Bitcoin price changes are speculative as they are likely to be generated from stochastic and stationary variance process.

5. Acknowledgements

The author would like to thank the Editor-in-Chief, Vidishcheva Evgeniya and the Deputy Editor-in-Chief, Rajović Goran. The author would like to thank Violetta Molchanova for pleasant editorial support. All remaining errors are the author's responsibility.

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* As estimated by an IGARCH model.

† I.e. conformity with mixture of distribution hypothesis of Clark (1973)

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