Economics Bulletin

Volume 40, Issue 3

Can intraday public information explain Bitcoin Returns and Volatility? A PGARCH-Based Approach.

Kais Tissaoui
University of Hail,Saudi Arabia . The IFG & FSEGT, University of Tunis El Manar, Tunisia

Taha Zaghdoudi
University of Hail,Saudi Arabia. LAREQUAD & FSEGT, University of Tunis El Manar, Tunisia.

Khaled issa Alfreahat
University of Hail, Community College,Saudi Arabia.

Abstract

This paper examines two competing hypotheses, that is, mixture of distribution hypothesis (MDH) and sequential information arrival hypothesis (SIAH) in the cryptocurrency market using high-frequency data. Specifically, we attempt to test the explanatory power of intraday public information arrival for Bitcoin returns and volatility over the period from January 1, 2019 to May 16, 2019. Based on AR (2)-PGARCH (1.1. δ), the empirical results reveal the following: First, we find more evidence to support the MDH than the SIAH since the current trading volume participates to absorb the persistence of Bitcoin volatility stronger than the lagged trading volume. Second, solid evidence of the instantaneous effect of intraday trading volume on intraday Bitcoin returns is verified more than the lagged effect, which supports the MDH rather than the SIAH.

This research has been funded by Scientific Research Deanship at University of Ha'il- Saudi Arabia through Project number RG-191337
Citation: Kais Tissaoui and Taha Zaghdoudi and Khaled issa Alfreahat, (2020) ''Can intraday public information explain Bitcoin Returns and Volatility? A PGARCH-Based Approach. '', *Economics Bulletin*, Volume 40, Issue 3, pages 2085-2092
Contact: Kais Tissaoui - kaistissaoui@yahoo.fr, Taha Zaghdoudi - zedtaha@gmail.com, Khaled issa Alfreahat - khaled.alfreahat@gmail.com.
Submitted: March 28, 2020. **Published:** August 08, 2020.

1. Introduction:

The information flow in the stock market has been highlighted by many theoreticians and practitioners. In the extant literature, many financial academics have extensively studied theoretically and empirically the linkage between trading volume, stock returns, and return volatility in the equity markets in line with two main theoretical hypotheses: (i) The mixture of distribution hypothesis (MDH) (Andersen, 1996; Bohl and Henke, 2003; Boubaker and Beljid, 2011; Celik, 2013; Choi et al., 2012; Clark, 1973; Epps and Epps, 1976; Lamoureux and Lastrapes, 1990; Mahajan and Singh, 2009; Naik and Padhi, 2014; Najand and Yung, 1991; Park, 2010; Sampath and Garg, 2019; Shen et al. 2018) states that there is an instantaneous association between trading volume, stock return, and return volatility. This suggests that, at the same time, all traders collect the same quantities of public information, and hence the move of stock returns and trading volume to optimal equilibrium is direct. Therefore, the lagged trading volume does not contribute to explain or forecast the current stock returns or the current return volatility, and vice versa.
(ii) The sequential information arrival hypothesis (SIAH) (Copeland, 1976; Jennings et al., 1981; Lee and Rui, 2000; Le and Zurbruegg, 2010; Mougoué and Aggarwal, 2011; Sampath and Garg, 2019; Shen et al., 2018; Tissaoui and Aloui, 2011; Tissaoui and Aloui, 2014) proposes that the new information flow in the stock market is not received by all traders at the same time. Therefore, an intermediate equilibrium is attained. As soon as all traders have taken advantage of the new information, a final equilibrium is accomplished. This indicates that the lagged trading volume contributes to explain or forecast, the current stock returns or the current return volatility, respectively, and vice versa, and there is no instantaneous interaction between them. Nevertheless, we are not aware of any similar analysis for Bitcoin and other cryptocurrency markets based on intraday data samples. Thus, this paper conducts a research examining the effects of information arrival on the Bitcoin market since the literature is paying increased attention to Bitcoin as an electronic payment system as well as a trading financial asset and a new instrument in portfolio management (Kristoufek, 2014).

Thus, analysing the research on the Bitcoin market highlights that the majority of papers have focused on the main factors of several specificities of Bitcoin, such as price volatility (Aalborg et al., 2019; Baek and Elbeck, 2015; Bouri et al., 2017), speculative bubbles (Cheah and Fry, 2015), inefficiency (Bariviera, 2017; Nadarajah and Chu, 2017; Tiwari et al., 2018), price discovery (Brandvold et al., 2015; Bouoiyour et al., 2016; Blau, 2018), informed trading (Feng et al., 2018; Wang et al., 2019), and Bitcoin returns (Baur et al., 2019).

This paper aims to fill this gap in the research by providing much more extensive evidence on the explanatory power of intraday public information arrival for Bitcoin returns and volatility since daily observations are unable to take into account the intraday information diffused in the stock market. As far as we know, this research is unique as it is the first research to examine the dynamic effect of intraday information flow on both the first and second moments of stock return distributions by using a Power GARCH (PGARCH) of Ding, Granger, and Engle (1993), which requires the estimation of the power parameter. This enables us to determine the nature of information arrival in cryptocurrency markets. The rest of the paper is organized as follows:

Section 2 describes the data. The methodology is proposed in Section 3. Section 4 presents the analysis and results, and Section 5 concludes the paper.

2. Data

The sample data examined in this research were collected from cryptodatadownload.com. The time period ranges from January 1, 2019, to May 16, 2019. All the data were downloaded as minute values, for a total of 187233 observations. Overall, we use two intraday series: a volume series and a close price series. From these intraday series, a 5-minute interval return and trading volume are constructed. Return time series, in 5-minute intervals t, are calculated as follows:

$$R_t = 100 \times Ln(\frac{Close_t}{Close_{t-1}})$$

where $Close_t, Close_{t-1}$ represent the last value on interval t and the last value on interval t–1, respectively. The trading volume (V_t) represents the sum of Bitcoin quantities traded in interval t.

Table 1 reports the descriptive statistics of intraday stock returns and intraday trading volumes. From this table, we observe that all high-frequency series have a non-normal distribution because the statistics values of the Jarque–Bera test are significant at 1% for all variables. Moreover, the Skewness statistics differ from 0 for all series. This indicates that the distributions of all series are asymmetrical. Furthermore, the Kurtosis statistics are superior to 3, meaning that the distribution of all series has fatter tails. For the stationary characteristics, the unit-root tests (PP and ADF tests) presented in Table 1 indicate that the null hypothesis of the existence of a unit root is rejected for all series. This implies that our data is suitable for no engender-spurious results.

Table 1: Descriptive statistics and Unit-root tests

Variables	R_t	V_t
Max	2.223	1073.53
Min	-2.115	0.000
Std. Dev.	0.078	28.491
Skewness	-0.332	12.518
Kurtosis	131.97	250.371
Jarque-Bera Test	25956996***	96456596***
PP Test	-200.13***	-187.506***
ADF Test	-141.66***	-42.690***
Observations	37447	37447

***Statistical significance at 1% level

3. Empirical methodology

In this section, we apply a PGARCH (p, q,$\boldsymbol{\delta}$) model proposed by Ding, Granger, and Engle (1993). This model is appropriate for data like our sample, as it permits us to consider the asymmetry, volatility persistence, and the influence of asymmetric shock on volatility. This type of uni-variate ARCH model is flexible, since it allows the introduction of other exogenous variables to explain the dependent variable. Therefore, in equation variance, we use the conditional standard deviation instead of the conditional variance. In this description, we add the parameter γ_k to reflect the asymmetric effect of news on volatility and δ as a power parameter.

Thus, our first step here is to determine the conditional mean equation for our Bitcoin return series. To achieve this, we use the autoregressive process (AR (k)) as follows:

$$r_t = \omega + \sum_{i=1}^{k} \varphi_i \, r_{t-1} \quad (1)$$

where φ_i measures the effect of lagged values of Bitcoin return.

In the second step, we formulate the conditional variance equation in the PGARCH (p.q. **δ)** process as follows:

$$h_t^{\delta} = \alpha_0 + \sum_{i=1}^{p} \alpha_i \left(|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i}\right)^{\delta} + \sum_{j=1}^{q} \beta_j \, \sigma_{t-j}^{\delta} + \varepsilon_t \quad (2)$$

α_i represents the effect of the passed error term, and β_j represents the effect of lagged conditional variance. γ_k is the coefficient of the leverage effect. δ represents a power parameter having a positive value (the parameter will be estimated in lieu of imposing). δ>0 indicates that a negative shock has a higher significant effect on conditional volatility than a positive shock. In our study, all identification tests and selection criteria show that the Bitcoin return series follows an AR (2)-PGARCH (1.1. **δ**) specification.

4. Empirical results

4.1. Original specifications

This section highlights the results of our analysis of the estimation of the original specification. Panel A of Table 2 reports the regression coefficients for Eqs.(1) and (2). We observe that all coefficients of the mean and variance equations are significant. More specifically, negative $\boldsymbol{\varphi_1}$ and $\boldsymbol{\varphi_2}$ measuring the lagged values of Bitcoin returns are important since they indicate that the passed information set relating to Bitcoin returns participates in diminishing the actual Bitcoin return. Furthermore, the empirical evidence proved that α_1 and β_1 are significant and positive, just like the asymmetry coefficient γ_k. The persistence of volatility measured by the sum of ($\boldsymbol{\alpha_1}$ +$\boldsymbol{\beta_1}$+1/2 γ_1) shows that there is a volatility clustering on the Bitcoin market. In other words, there will be a strong persistence of Bitcoin return volatility over time and a significant leverage effect. This finding is supported by the positive and significant values of the power parameter δ_1. This also implies that negative shocks have a greater effect on actual volatility than positive shocks. From a financial perspective, this indicates that the uncertainty in the Bitcoin market is extensively explained over time by the previous information set on the Bitcoin risk.

4.2. Augmented specification: Mixture distribution hypothesis test

As explained above, the MDH supposes that a public information content on current trading volume (V_t) can be used to explain or forecast, respectively, the actual values of returns or return volatility, and vice versa. Empirically, such public information can be exploited to build a better model describing the intraday dynamics of our data. Our approach consists of adding the actual Bitcoin trading volume simultaneously to the conditional mean equation ((V_t) will have the coefficient $\boldsymbol{\theta_1}$) and in the conditional variance equation ((V_t) will have the coefficient $\boldsymbol{\omega_1}$). Therefore, our objective is to validate the MDH or No. Panel B of Table 2 contains the regression coefficients of the augmented specifications. For the relationship in mean, we illustrate that all coefficients measuring the lagged values of Bitcoin returns are significant and negative. The same results apply to the coefficient of trading volume (V_t). This achievement implies that the public information flow has a negative effect on returns in the cryptocurrency market, meaning that the mixture-of-distribution hypothesis is verified in the first-order moment.

From the variance equation estimates, all coefficients are significant and positive. Additionally, the coefficient $\boldsymbol{\theta_1}$ measuring the effect of the trading volume on Bitcoin volatility is positive and significant. Furthermore, the inclusion of trading volume in the conditional variance equation decreases the persistence of Bitcoin return volatility. We remark that the sum of the coefficients of persistence ($\boldsymbol{\alpha_1}$ +$\boldsymbol{\beta_1}$+1/2 γ_1) declines compared to the sum of these coefficients calculated from the original specifications. It seems surprising to discover that the new value is 0.799 (less than 0.9). Hence, the current trading volume represents a significant source of the persistence of Bitcoin volatility in the cryptocurrency market. This highlights that the persistence of return volatility is practically absorbed by the current trading volume. This is also supported by the decrease in the power parameter δ_1 from 1.732 in the original specification to 1.343 in the augmented specification, meaning that the power of lagged volatility has been reduced in favour of an increase in the current trading volume effect. In addition, the paper supports the mixture-of-distribution hypothesis in the second-order moment. Moreover, Table 2 highlights an improvement in the incremental explanatory power manifested by an increase in the maximum likelihood values after the inclusion of external variables in the original specifications (from 56584.78, original specification to 62987.48, augmented specification).

4.3. Augmented specification: Sequential information arrival hypothesis test

There is clear evidence that the MDH is verified in the cryptocurrency market. The next step highlights the estimated results from the application of AR (2)-PGARCH (1.1. $\boldsymbol{\delta}$) examining the SIAH. The test of this hypothesis is crucial since the authors in the microstructure theory proved that the use of current trading volume generates the problem of simultaneity bias. The way to deal with this limit[1] is to include the lagged trading volume in both the conditional mean equation ((V_{t-1}) will have the coefficient $\boldsymbol{\theta_1}$) and the conditional variance equation ((V_{t-1}) will have the coefficient $\boldsymbol{\omega_1}$). Such a proposal is appropriate with the sequential information arrival hypothesis (SIAH).

Therefore, panel C of Table 2 displays the regression evidence of the augmented specifications. For the interaction in mean, we demonstrate that all coefficients measuring the lagged values of Bitcoin returns are significant and negative. The coefficient of lagged trading volume (V_{t-1}) is negative and insignificant. This result indicates that information arrival in a sequential fashion

[1] The trading volume might itself be partly influenced by stock return volatility (Lee and Rui, 2002; Mestel et al., 2003; Tissaoui and Aloui, 2011)

has no effect on Bitcoin returns in the cryptocurrency market. Thus, the sequential information arrival hypothesis (SIAH) is not proven in the first-order moment.

We now consider the parameter estimates of the variance equation. We still see that all coefficients are significant and positive. Nonetheless, it is surprising to note that the results determined from the specification augmented by lagged trading volume are similar to those of the original specification rather than as indicated in the findings of the specification augmented by current trading volume. In more detail, we observe that the coefficient $\boldsymbol{\theta_1}$ measuring the influence of lagged trading volume on Bitcoin volatility is positive and significant. Despite this effect, the persistence of Bitcoin return volatility remains strong since the sum of the coefficients of persistence ($\boldsymbol{\alpha_1}$ +$\boldsymbol{\beta_1}$+1/2 γ_1) has a value of 1.081. This value exceeds 1.00 and is close to the value estimated from the original specification (1.088). However, it is superior to the value determined from the variance equation augmented by the current trading volume. This shows that the lagged trading volume represents no significant source of the persistence of Bitcoin volatility in the cryptocurrency market. Hence, we report that the persistence of volatility is not reduced by the inclusion of the lagged trading volume in the conditional variance equation.

Moreover, Panel C in Table 2 indicates that the power parameter δ_1 (1.723) is superior to that estimated for the augmented specification by the current trading volume (1.343), but is close to the value of the original specification (1.732). This highlights that the lagged trading volume contains useful information explaining the current Bitcoin volatility lowly, but does not allow a reduction in the persistence of Bitcoin volatility in the cryptocurrency market. Therefore, we confirm the sequential flow of information in the cryptocurrency market. This flow, however, is not considered as a source of persistence of volatility in this type of market. Overall, this implies that the sequential information arrival hypothesis (SIAH) is not strongly corroborated in the second-order moment.

.

Table 2: Regressions results

	Parameters	Original Specification Panel A	Augmented Specification by (V_t) Panel B	Augmented Specification by (V_{t-1}) Panel C
Conditional Mean	ω	-8.12E-05	0.0016	-0.0001
	(p-value)	(0.617)	(0.000)***	0.4891
	φ_1	-0.054	-0.068	-0.053
	(p-value)	(0.000)***	(0.000)***	(0.000)***
	φ_2	-0.073	-0.054	-0.073
	(p-value)	(0.000)***	(0.000)***	(0.000)***
	θ_1		-0.0001	7.67E-06
	(p-value)		(0.000)***	0.4269
Conditional Variance	α_0	0.0006	0.002	0.0006
	(p-value)	(0.000)***	(0.000)***)	(0.000)***
	α_1	0.343	0.292	0.338
	(p-value)	(0.000)***	(0.000)***	(0.000)***
	β_1	0.710	0.436	0.708
	(p-value)	(0.000)***	(0.000)***	(0.000)***
	γ_1	0.069	0.127	0.069
	(p-value)	(0.000)***	(0.000)***	(0.000)***
	δ	1.732	1.343	1.723
	(p-value)	(0.000)***	(0.000)***	(0.000)***
	ω_1		0.0005	0.0000043
	(p-value)		(0.000)***	(0.000)***
	$\alpha_1 + \beta_1 + 1/2\ \gamma_1$	1.088	0.792	1.081
Log likelihood		56584.78	62987.48	56590
Observations		37447	37447	37447

***Statistical significance at 1% level

5. Conclusion:

Using a different methodological approach to prior studies, this research focused on the Bitcoin trading volume and its effect on both Bitcoin return and Bitcoin volatility using high-frequency data. Based on AR (2)-PGARCH (1.1. **δ**) framework, we test two competing hypotheses, MDH and SIAH, in the cryptocurrency market. The main finding indicates that the MDH is strongly confirmed in the first and second-order moments, unlike the SIAH. The results also show that the current trading volume represents a significant source of Bitcoin volatility persistence. However, the results demonstrate an insignificant effect of lagged trading volume as sequential information flow on the persistence of Bitcoin volatility. Overall, our study is important for investors in the cryptocurrency market since it allows them to take into account the interconnections between trading volume and return, and between trading volume and volatility in order to construct their portfolios. In addition, our results provide the opportunity for these investors to understand that they must actively exploit the public information to best effect and in an instantaneous manner in order to accomplish the transactions.

Acknowledgement:

This research has been funded by Scientific Research Deanship at University of Ha'il- Saudi Arabia through Project number RG-191337

References:

Aalborg, H.A., Molnár, P., De Vries, J.E., 2019. What can explain the price, volatility and trading volume of BitCoin? Finance Research Letters 29, 255-265. https://doi.org/10.1016/j.frl.2018.08.010

Andersen, T., 1996. Return volatility and trading volume: An information flow interpretation of stochastic volatility. Journal of Finance 51, 169–204. https://doi.org/10.1111/j.1540-6261.1996.tb05206.x

Baek, C., Elbeck, M.A., 2015. Bitcoins as an investment or speculative vehicle? A first look. Applied Economics Letters 22 (1), 30–34. https://doi.org/10.1080/13504851.2014.916379

Bariviera, A. F., 2017. The inefficiency of Bitcoin revisited: A dynamic approach. Economics Letters 161, 1– https://doi.org/10.1016/j.econlet.2017.09.013

Baur, D.G., Hong, K., Lee, A.D., 2018. BitCoin: Medium of exchange or speculative assets? Journal of International Financial Markets, Institutions and Money 54, 177-189. https://doi.org/10.1016/j.intfin.2017.12.004

Blau, B. M., 2018. Price dynamics and speculative trading in Bitcoin. Research in International Business and Finance 43, 15–21. https://doi.org/10.1016/j.ribaf.2017.07.183

Bohl, M. T., Henke, H., 2003. Trading volume and stock market activity: The Polish Case. International Review of Financial Analysis 12, 513–525. https://doi.org/10.1016/S1057-5219(03)00066-8

Boubaker, A., Beljid, M., 2011. The empirical relationship between stock returns volatility and trading volume: Evidence on the Tunis stock market. International Journal of Management Science and Engineering Management 6, 374–381. https://doi.org/10.1080/17509653.2011.10671186

Bouoiyour, J., Selmi, R. Tiwari, A., 2015. Is bitcoin business income or speculative foolery? New ideas through an improved frequency domain analysis. Annals of Financial Economics 10, 1550002. https://doi.org/10.1142/S2010495215500025

Bouraoui,T.,2019. The drivers of Bitcoin trading volume in selected emerging countries. The Quarterly Review of Economics and Finance. In presshttps://doi.org/10.1016/j.qref.2019.07.003

Bouri, E., Azzi, G., Dyhrberg, A.H., 2017. On the return–volatility relationship in the Bitcoin market around the price crash of 2013. Economics: The Open-Access, Open-Assessment E-Journal, 11 (2017-2): 1—16. https://doi.org/10.5018/economics-ejournal.ja.2017-2

Brandvold, M., Moln´ar, P., Vagstad, K., Vagstad, O.C.A., 2015. Price discovery on Bitcoin exchanges. Journal of International Financial Markets, Institutions & Money 36, 18–35. https://doi.org/10.1016/j.intfin.2015.02.010

Celik, S., 2013. New evidence on the relation between trading volume and volatility. Business and Economic Research. 3 (1), 176–186. https://doi.org/10.5296/ber.v3i1.3222

Cheah, E.-T., Fry, J., 2015. Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. Economics Letters 130, 32–36. https://doi.org/10.1016/j.econlet.2015.02.029

Clark, P. K., 1973. A subordinated stochastic process model with finite variance for speculative prices. Econometrica. 41, 135–156. https://doi.org/10.2307/1913889

Copeland, T., 1976. A model of asset trading under the assumption of sequential information arrival. Journal of Finance. 31, 1149–1168. https://doi.org/10.1111/j.1540-6261.1976.tb01966.x

Darrat, A., Rahman, S., Zhong, M., 2003. Intraday trading volume and return volatility of the DJIA stocks: A note. Journal of Banking & Finance. 27, 2035–2043. https://doi.org/10.1016/S0378-4266(02)00321-7

Epps, T., Epps, E., 1976. The stochastic dependence of security price changes and transaction volumes: Implications for the mixture of distributions hypothesis. Econometrica. 44, 305–321. https://doi.org/10.2307/1912726

Feng, W., Wang, Y., Zhang, Z., 2018. Informed trading in the bitcoin market. Finance Research Letters. 26, 63 – 70. https://doi.org/10.1016/j.frl.2017.11.009

Jennings, R., Starks, L., Fellingham, J., 1981. An equilibrium model of asset trading with sequential information arrival. Journal of Finance, 36, 143–161. https://doi.org/10.1111/j.1540-6261.1981.tb03540.x

Kristoufek, L., 2015. What Are the Main Drivers of the Bitcoin Price? Evidence from Wavelet Coherence Analysis. PLoS ONE 10(4): e0123923. https://doi.org/10.1371/journal.pone.0123923

Lamoureux, C. G., Lastrapes, W. D., 1990. Heteroskedasticity in stock return data volume versus GARCH effects. Journal of Finance. 45, 221–229. https://doi.org/10.1111/j.1540-6261.1990.tb05088.x

Le, V., Zurbruegg, R., 2010.The role of trading volume in volatility forecasting. J Int Finan Mark Inst Money. 20(5), 533–555. https://doi.org/10.1016/j.intfin.2010.07.003

Lee, B. S., Rui, O. M., 2002. The dynamic relationship between stock returns and trading volume: Domestic and cross-country evidence. Journal of Banking and Finance, 26, 51–78. https://doi.org/10.1016/S0378-4266(00)00173-4

Mougoué, M., Aggarwal, R., 2011. Trading volume and exchange rate volatility: evidence for the sequential arrival of information hypothesis. J Bank Finance. 35(10), 2690–2703. https://doi.org/10.1016/j.jbankfin.2011.02.028

Nadarajah, S. Chu, J., 2017. On the inefficiency of Bitcoin. Economics Letters. 150, 6 – 9. https://doi.org/10.1016/j.econlet.2016.10.033

Najand, M., Yung, K., 1991. A GARCH examination of the relationship between volume and price variability in futures markets. Journal of Futures Markets. 11, 613–621. https://doi.org/10.1002/fut.3990110509

Park, B-J ., 2010. Surprising information, the MDH, and the relationship between volatility and trading volume. J Financ Mark. 13(3),344–366. https://doi.org/10.1016/j.finmar.2010.02.001

Sampath, A., Garg, P.,2018. Contemporaneous and Causal Relationship between Returns and Volumes: Evidence from Nifty Futures. International Review of Finance.19 (3), 653-664. https://doi.org/10.1111/irfi.12175

Shen D, Li X, Zhang,W., 2018. Baidu news information flow and return volatility: evidence for the Sequential Information Arrival Hypothesis. Econ Model. 69,127–133. https://doi.org/10.1016/j.econmod.2017.09.012

Tissaoui, K., Aloui, C., 2011. Information flow between stock return and trading volume: the Tunisian stock market. International Journal of Financial Services Management. 5, 52–82. https://doi.org/10.1504/IJFSM.2011.038328

Tissaoui, K., Aloui,C.,2014. Public and private information: Lessons from the emerging Tunisian stock market. International Journal of Management Science and Engineering Management.9(1),48-77. https://doi.org/10.1080/17509653.2013.858898

Tiwari, A.K., Jana, R.K., Das, D., Roubaud, D., 2018. Informational efficiency of Bitcoin—an extension. Econ Lett. 163,106–109. https://doi.org/10.1016/j.econlet.2017.12.006

Wang, P., Zhang, W., Li, X., Shen, D., 2019. Trading volume and return volatility of Bitcoin market: Evidence for the sequential information arrival hypothesis. J. Econ. Interact. Coord. 14, 377–418.https://doi.org/10.1007/s11403-019-00250-9