



Does investor sentiment on social media provide robust information for Bitcoin returns predictability?

Dominique Guégan, Thomas Renault

► To cite this version:

Dominique Guégan, Thomas Renault. Does investor sentiment on social media provide robust information for Bitcoin returns predictability?. Finance Research Letters, 2021, 38, pp.101494. <10.1016/j.frl.2020.101494>. <hal-03205154>

HAL Id: hal-03205154

<https://hal.science/hal-03205154v1>

Submitted on 13 Feb 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons CC BY-NC 4.0 - Attribution - Non-commercial use - International License

Does investor sentiment on social media provide robust information for Bitcoin returns predictability ?

¹, Dominique Guégan^{a,b}, and Thomas Renault^{*a}

^aUniversité Paris 1 Panthéon Sorbonne (CES, LabEx Refi), Paris, France.

^bCa' Foscari University, Venezia, Italie

Wednesday 26th February, 2020

Abstract

We use a dataset of approximately one million messages sent on StockTwits to explore the relationship between investor sentiment on social media and intraday Bitcoin returns. We find a statistically significant relationship between investor sentiment and Bitcoin returns for frequencies of up to 15 minutes. For lower frequencies, the relation disappears. We also find that the impact of sentiment on returns is concentrated on the period around the Bitcoin bubble. However, the magnitude of the effect is rather small making it impossible for a trader to make economic profits by trading on the information published on social media.

Keywords: Cryptocurrency, Bitcoin, Investor Sentiment, Investor Attention, Market Efficiency, Social Media, StockTwits.

JEL classification: G12, G14.

*Electronic address: thomas.renault@univ-paris1.fr; Corresponding author: Thomas Renault. CES Sorbonne - Université Paris 1 Panthéon-Sorbonne, Maison des Sciences Économiques. 106-112, boulevard de l'Hôpital 75013 Paris.

Does investor sentiment on social media provide robust information for Bitcoin returns predictability ?

Abstract

We use a dataset of approximately one million messages sent on StockTwits to explore the relationship between investor sentiment on social media and intraday Bitcoin returns. We find a statistically significant relationship between investor sentiment and Bitcoin returns for frequencies of up to 15 minutes. For lower frequencies, the relation disappears. We also find that the impact of sentiment on returns is concentrated on the period around the Bitcoin bubble. However, the magnitude of the effect is rather small making it impossible for a trader to make economic profits by trading on the information published on social media.

Keywords: Cryptocurrency, Bitcoin, Investor Sentiment, Investor Attention, Market Efficiency, Social Media, StockTwits.

JEL classification: G12, G14.

1 Introduction

In 2018 and 2019, a total of 98 articles containing the keyword *Bitcoin* were published in Finance Research Letters. This growing academic interest in this subject follows the frenzy of individual investors since the 2017-2018 Bitcoin bubble, during which the price of the Bitcoin rose from \$1,500 to nearly \$20,000 in just a few months. For researchers, the Bitcoin market is indeed particularly interesting because of its structure and the abundance of available data. The strong presence of individual investors, arbitrage opportunities between platforms, weak regulation, lack of fundamental value and high price volatility make the Bitcoin market an ideal place to study market efficiency.

Recent papers have explored which variables affect Bitcoin's returns focusing mainly on stock market returns, exchange rates, gold prices, central bank interest rates, internet search queries, and economic policy uncertainty (Panagiotidis et al. 2018, Demir et al. 2018, Aalborg et al. 2019, Dastgir et al. 2019, Poyser 2019). In this paper, we explore a novel source of data – social media messages sent on the platform StockTwits - to answer a key question regarding the Bitcoin market: what is the role played by investor sentiment in the price dynamics process. This issue has important implications for academics working on the efficient market hypothesis, but also for investors trying to beat the market and for regulators wanting to better understand the drivers of this volatile market to protect unsophisticated traders. We provide empirical evidence on this question by analyzing if investor sentiment on social media contains robust information for Bitcoin returns predictability at various time-frequency (1 minute to 24 hours).

When it was created in 2009, and until the end of 2014, the Bitcoin market was very illiquid and little known to investors. During this period, Urquhart (2016) and Bariviera (2017), among others, have investigated the efficiency of the Bitcoin market by analyzing if past information predicts future returns. They find that Bitcoin returns were auto-correlated and, based on these findings, conclude that the Bitcoin market was inefficient at that time. But since 2015, the increase of trading volume, the arrival of new and more informed traders and the increase in (social) media coverage have led to higher attention towards this new asset and create a change in the structure of the Bitcoin market. Recent academic papers found that, in the more recent period, and contrary to previous findings, the Bitcoin market is efficient (Tiwari et al. 2018, Grobys & Sapkota 2019), even at the high-frequency level

Sensoy (2019). Similar results have been found when considering proxies of investor attention by using data from social media and Google Search (Urquhart 2018, Shen et al. 2019): past information do not forecast returns in the recent period.

To explore the relationship between investor sentiment and Bitcoin returns, and following the methodology of Renault (2017), we extract all messages about the Bitcoin sent by individual users and traders on the largest social network for finance: StockTwits. From a database of 988,622 messages sent between 2017 and 2019, we construct investor sentiment indicators - at various frequencies from 1 minute to 24 hours - by computing the average sentiment of messages posted on StockTwits during each time interval. We also construct a measure of investor attention by considering the number of messages sent on StockTwits during a given time interval.

Our contributions are the following. First, using multivariate regressions and Granger causality tests, we find that investor sentiment allows us to predict the evolution of returns, but only for high frequencies (up to 15 minutes). Market efficiency varies with sampling frequency, consistent with Aslan & Sensoy (2019). The predictability disappears after 15 minutes, in line with some previous literature results on the efficiency of the Bitcoin market at the daily level. Second, splitting our sample into a pre-bubble and post-bubble period, we find that the impact of sentiment on returns is concentrated on the period including the Bitcoin bubble. This result is consistent with the presence of irrational sentiment-driven noise traders during this period (De Long et al. 1990).

Last, we observe that considering reasonable transaction costs makes it impossible to generate abnormal profits by implementing a trading strategy based on investor sentiment. Due to limits to arbitrage, the time to execute orders and the difficulty to short the Bitcoin, the implementation of a strategy based on investor sentiment is very complex. Thus, we cannot conclude from our results that the Bitcoin market is inefficient at the intraday level. This market remains highly unpredictable.

The paper is structured as follows. Section 2 describes the two types of data used all along with the papers. Section 3 presents the methodology. Section 4 analyses the results considering the whole sample and two subsamples. Section 5 concludes.

2 Data

We use two types of data: trade data to compute intraday BTC–USD returns and StockTwits data to measure investor sentiment and investor attention.

2.1 Bitcoin price data

We download complete historical Bitcoin trade data on www.bitcoincharts.com¹. We consider BTC–USD exchange rate from the US-based cryptocurrency exchange Kraken, as in Dyhrberg et al. (2018), one of the leading cryptocurrency exchange platform in the world. From trade data, we construct BTC–USD exchange rate time series at various frequencies: 1min, 2min, 5min, 15min, 30 min, 1 hour, 2 hours, 6 hours, 12 hours and 24 hours.² As in Baur et al. (2019), we do not find any evidence of time-of-day or day-of-week returns anomalies when considering data up to 2019.³

2.2 StockTwits messages

StockTwits is a microblogging platform where users can share ideas and opinions about the stock market. Since its creation in 2008, more than 180 million have been sent on the platform by a total of more than 100,000 users. For researchers in finance and computing science, StockTwits is a very valuable source of data as users can use a toggle button to self-classify their messages as bullish (positive) or bearish (negative) before posting a message on the platform. Data from StockTwits have been used, among others, by Oliveira et al. (2017), Mahmoudi et al. (2018) and Cookson & Niessner (2019).⁴

We use the StockTwits API to download all data related to the Bitcoin since the creation of the website in 2008. However, before July 2017 and the introduction of a specific symbology for cryptocurrencies on the StockTwits website⁵, the number of messages related to

¹ <http://api.bitcoincharts.com/v1/csv/>

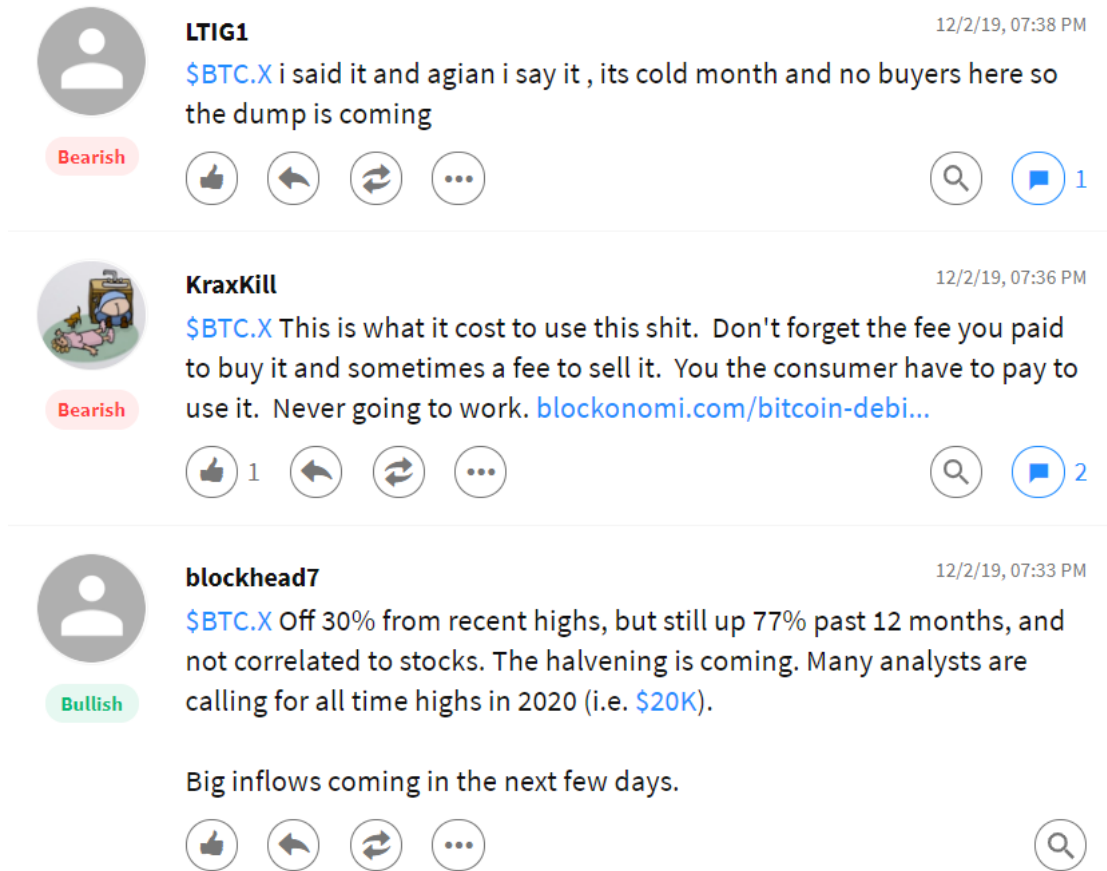
² Comparing daily returns based on data from Coinbase with daily returns derived from data from CoinMarketCap.com (as in Caporale & Plastun (2018)), we find a correlation of 0.9816.

³ Replicating Caporale & Plastun (2018), we find a day of the week effect on Monday for the period 2013-2017. However, the anomaly seems to have disappeared on the period 2017-2019.

⁴ Users on StockTwits might also use the platform to release false or misleading information to affect cryptocurrencies prices (see Li et al. (2019) for an example of the use of the encrypted messaging app “Telegram” for pump-and-dump schemes.)

⁵ “StockTwits Adds Streams and Symbology for 100+ Cryptocurrencies and Tokens” - July 2017 [StockTwits Blog]

Figure 1: Screenshot of the StockTwits website



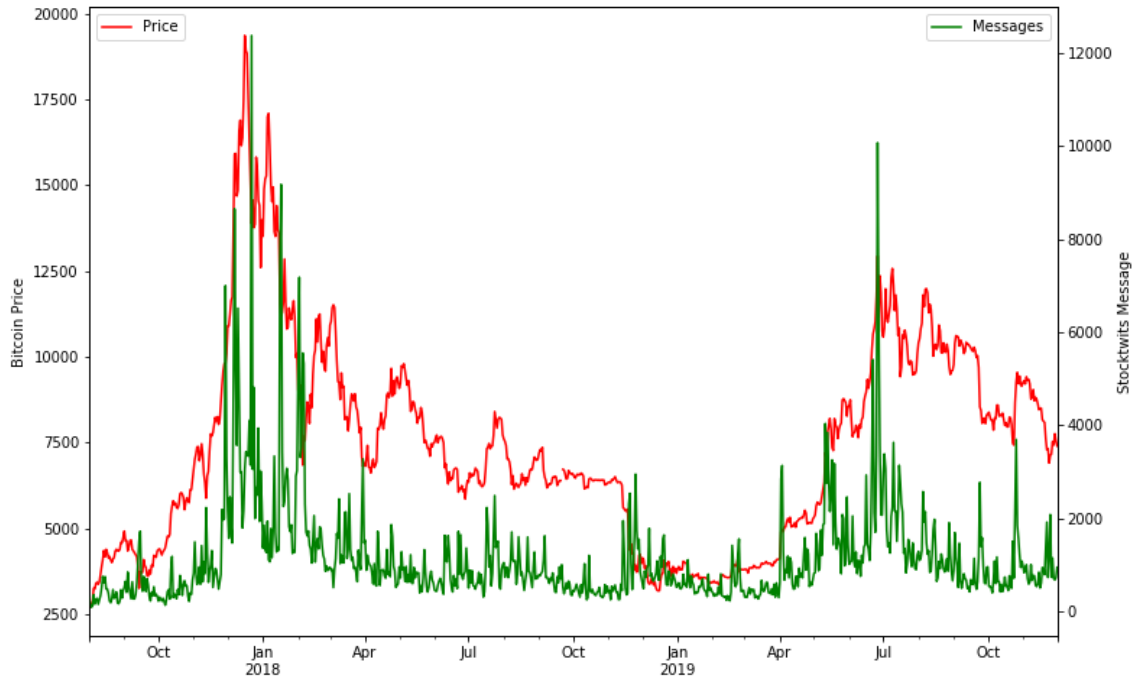
Note: Figure 1 presents a screenshot of the StockTwits website (<https://stocktwits.com/symbol/BTC.X>) made on December 3, 2019.

Bitcoin and other cryptocurrencies was very low. As we are considering intraday intervals, and in order to have a sufficient number of messages per time interval, we focus our analysis on the period from August 1st, 2017 to December 1st, 2019. We end up with a database of 988,622 messages. Figure 1 shows an example of three messages: two messages classified as negative (Bearish tag) and one message classified as positive (Bullish tag).

The correlation between the daily number of messages sent on StockTwits and Bitcoin prices is high (0.61). Figure 2 illustrates the relationship between the number of messages and Bitcoin prices during the 2017-2019 period at a daily frequency.

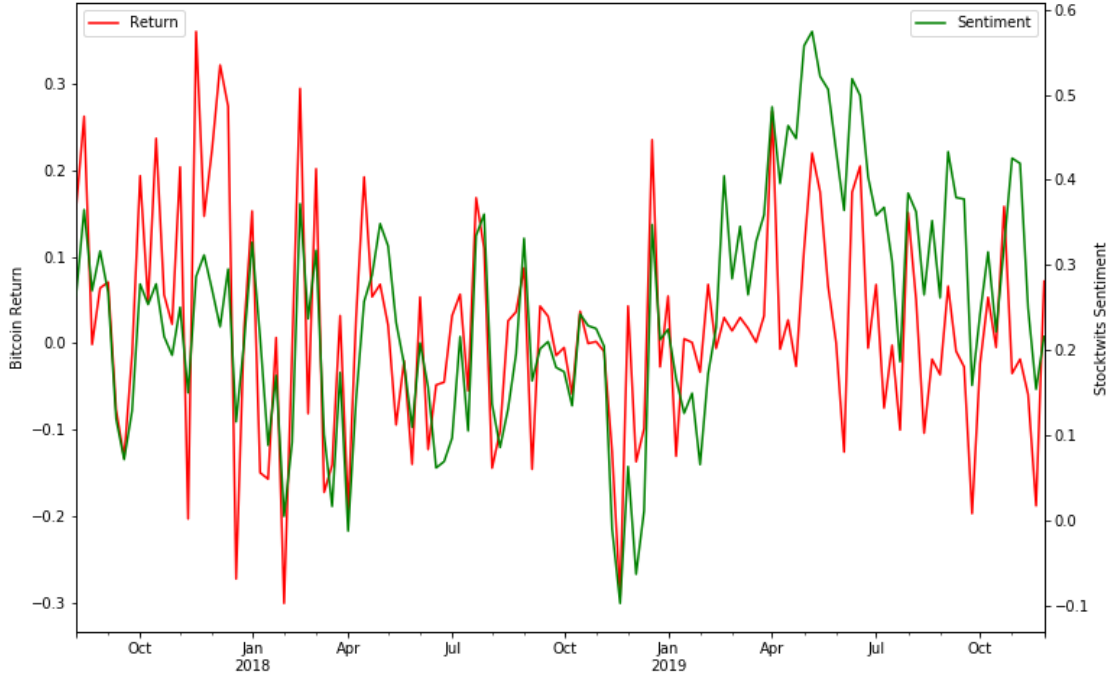
We compute investor sentiment by considering the average (declared) sentiment of mes-

Figure 2: Bitcoin prices and StockTwits activity



Note: Figure 2 presents the evolution of the BTC–USD exchange and the number of messages sent on StockTwits about the Bitcoin at a daily frequency from August 2017 to December 2019. The BTC–USD exchange data are based on Kraken trade data, considering the price of the last trade.

Figure 3: Bitcoin returns and StockTwits sentiment



Note: Figure 3 presents the evolution of the BTC–USD exchange rate and the sentiment of messages sent on StockTwits about the Bitcoin at a weekly frequency, from August 2017 to December 2019. The BTC–USD exchange data are based on Kraken trade data, considering the price of the last trade.

sages published on StockTwits on a given time interval. We also find that the correlation between Bitcoin returns and investor sentiment is important (0.45). Figure 3 illustrates this relationship.

3 Methodology

To shed light on the causality link behind the correlation illustrated in the previous Section, we conduct both OLS regressions and Granger causality tests. Our methodology is very similar to the one used by Kim & Kim (2014) on the relation between stock returns and sentiment on Internet message boards (Yahoo! Finance) and the one used by Shen et al.

(2019) on the relation between Twitter activity (message volume) and Bitcoin returns.

We denote R_t the returns of the cryptocurrency (BTC). We define investor sentiment, S_t , as the difference between the number of bullish (positive) messages and the number of bearish (negative) messages divided by the total number of messages sent during the time interval. By construction, S_t is equal to -1 if all messages are negative, to +1 if all messages are positive, and to 0 if the same number of positive and negative messages have been sent during the time interval considered. We consider the following equation to test price predictability using both past returns and past sentiment:

$$R_t = \alpha + \beta_1 R_{t-1} + \beta_2 S_{t-1} + \epsilon_t \quad (1)$$

We run the previous regressions for t equal 1 minute to t equal 24 hours. We also consider a potential reverse causality – i.e., that returns Granger causes investor sentiment – by conducting Granger causality tests.

As a robustness check, we introduce the total number of messages as a proxy for investor attention. We define M_t as the natural logarithm of the number of messages plus one. We solve the following equation,

$$R_t = \alpha + \beta_1 R_{t-1} + \beta_2 S_{t-1} + \beta_3 M_{t-1} + \epsilon_t \quad (2)$$

in order to take this proxy into account in our analysis.

4 Results

We first consider the full sample period (August 2017 - December 2019) by including only the investor sentiment variable. Then, we add investor attention. Last, we present our results for the two sample periods (bubble, August 2017 - April 2018, and post-bubble, May 2018 - December 2019).

Table 1: Investor sentiment and Returns - Full Sample (Equation 1)

Frequency	β_1	β_2	Adjusted R^2	Number of observations	Returns causes Sentiment	Sentiment causes Returns
1 min	-0.1355***	0.0035***	1.841	1228320	***	***
2 min	-0.0572***	0.0040***	0.332	614160	***	***
5 min	-0.0143*	0.0047***	0.023	245664	***	***
15 min	-0.0081	0.0087**	0.006	81888	***	*
30 min	-0.0061	0.0060	0.000	40944	***	
1 hour	-0.0319**	0.0352	0.088	20472	***	
2 hours	-0.0728***	0.1432*	0.479	10236	***	**
6 hours	-0.0473*	0.3590	0.153	3412	***	
12 hours	0.0803*	-0.0997	0.498	1706	***	
24 hours	-0.0326	1.7117	0.050	853	*	

Note: Table 1 presents the estimation of the equation $R_t = \alpha + \beta_1 R_{t-1} + \beta_2 S_{t-1} + \epsilon_t$. Standard errors are computed using White's heteroskedasticity robust standard errors. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. For the Granger causality test, the superscripts ***, **, and * indicate that the null hypothesis that the first variable Granger causes the second variable is rejected at the 1%, 5%, and 10% levels. An empty cell indicates that the first variable Granger does not cause the second variable

4.1 Investor sentiment - Full Sample

Table 1 presents the estimations of the coefficients β_1 and β_2 in equation (1) for different frequencies, from 1 minute data to 24 hour.

Looking at column 3 in Table 1, we observe that the value of the coefficient β_2 (investor sentiment) is statistically significant for frequencies up to 15 minutes. As in Sensoy (2019), we observe that the higher the frequency, the lower the pricing efficiency is. Investor sentiment also Granger causes Bitcoin returns for the same frequencies (column 7). The value of the coefficient is however rather small. An increase of 1 of the investor sentiment (i.e, from neutral to positive) leads to an increase of the Bitcoin returns by 0.0035% to 0.0087%. When we consider five-minute data, we find that Bitcoin returns are on average equal to -0.0035% when the investor sentiment on the previous period was negative, and equal to +0.0025% when the investor sentiment on the previous period was positive. While statistically significant, the size of the effect is too small to make economic profits – after transaction costs – by trading on investor sentiment.

Table 2: Sentiment, Volume and Returns - Full Sample (Equation 2)

Frequency	β_1	β_2	β_3	Adjusted R^2	Number of observations
1 min	-0.1355***	0.0033***	0.0007	1.841	1228320
2 min	-0.0572***	0.0038***	0.0005	0.322	614160
5 min	-0.0143**	0.0040***	0.0023*	0.027	245664
15 min	-0.0083	0.0077**	0.0052*	0.015	81888
30 min	-0.0063	0.0043	0.0085	0.009	40944
1 hour	-0.0320**	0.0327	0.0011	0.24	20472
2 hours	-0.0727***	0.1381*	0.0153	0.479	10236
6 hours	-0.0471*	0.3521	0.0171	0.128	3412
12 hours	0.0802**	-0.0873	-0.0296	0.446	1706
24 hours	-0.0332	1.7473	-0.0848	-0.047	853

Note: Table 2 presents the estimation of the equation $R_t = \alpha + \beta_1 R_{t-1} + \beta_2 S_{t-1} + \beta_3 M_{t-1} + \epsilon_t$. Standard errors are computed using White's heteroskedasticity robust standard errors. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

As in Kim & Kim (2014) and Renault (2019), we also find that returns Granger causes sentiment (column 6). This result seems logical as StockTwits' users often use social media to discuss and comment past price developments, which implies a causality from returns to sentiment. We also find, for time intervals between 1 minute and 15 minutes, that returns in time t are negatively related to returns at $t+1$ (β_1 in column 2). As the size of the β_1 coefficient is the highest for high frequencies (1 minute), we believe that the negative returns autocorrelation we observed is mainly driven by a bid-ask bounce at the intraday level as in Heston et al. (2010). When we consider 24 hours time interval, past returns do not affect current returns, consistent with previous research who find that the Bitcoin market is efficient at a daily frequency (Urquhart 2016, 2018).

4.2 Investor sentiment and investor attention

Table 2 presents the estimation of the coefficients β_1 (returns), β_2 (investor sentiment) and β_3 (investor attention) of the equation (2) for different frequencies.

Looking at the value of the coefficient β_3 , we observe that the number of messages is not significant for most frequencies. At a daily frequency, and as in Shen et al. (2019) and Urquhart (2018), we do not find any statistically significant relationship between investor

Table 3: Bubble and post-bubble regressions results

Panel A : August 2017 to April 2018					
Frequency	β_1	β_2	β_3	Adjusted R^2	Number of observations
2 min	-0.0996***	0.0147***	-0.0008	1.017	439200
15 min	0.0010	0.0338**	0.0047	0.014	23424
2 hours	-0.0911***	0.2367	0.0065	0.661	2928

Panel B : May 2018 to December 2018					
Frequency	β_1	β_2	β_3	Adjusted R^2	Number of observations
2 min	0.0017	0.0003	0.0010	0.002	439200
15 min	-0.0224	0.0010	0.0058*	0.059	58560
2 hours	-0.0522**	0.1083	0.0206	0.248	7320

Note: Table 3 presents the estimation of the equation $R_t = \alpha + \beta_1 R_{t-1} + \beta_2 S_{t-1} + \beta_3 M_{t-1} + \epsilon_t$ on two periods: the Bitcoin bubble period and the post Bitcoin bubble period. Standard errors are computed using White's heteroskedasticity robust standard errors. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

attention and Bitcoin returns. Thus, adding investor attention to the equation does not affect the relation between investor sentiment and stock returns.

4.3 Bubble and post-bubble periods

To consider a potential change in the behaviors of investors before and after the Bitcoin bubble in December 2017, we also run the regression (2) for two subperiods: the Bitcoin bubble period (August 2017 to March 2018) and the post Bitcoin bubble period (April 2018 to December 2019). Table 3 presents those results.

We find that during the bubble period, as in the full sample, the estimate of the β_2 coefficient (investor sentiment) is statistically significant. Furthermore, the size of this estimate for β_2 is more than three times higher on the Bitcoin bubble period compared to the full sample period, consistent with the presence of irrational sentiment-driven noise traders during this period (De Long et al. 1990). However, in the post Bitcoin bubble period, we do not find any significant relationship between investor sentiment and Bitcoin returns. The effect on investor sentiment on stock returns is thus concentrated on the bubble period.

Last, as our indicator mostly capture the sentiment of investor located in the US and as Kraken is a US-based cryptocurrency platform, we re-run the previous regressions by (1) restricting our analysis to the US daytime hour and (2) removing all time intervals during which no tweets were sent. We confirm that our results are robust to the removal of those periods.

5 Conclusion

This paper contributes to the discussions on the efficiency of the Bitcoin market and on the determinants of Bitcoin returns by exploring the relationship - at various time-frequency - between investor sentiment on social media and the evolution of the price of Bitcoin. While previous papers focus either on returns predictability from past returns at the intraday frequency (Aslan & Sensoy 2019, Sensoy 2019), or on returns predictability from past information published on social media at a daily frequency (Urquhart 2018, Shen et al. 2019), we combine both approaches: an intraday analysis of the relation between investor sentiment on social media and Bitcoin returns.

We find, for high frequencies up to 15 minutes, that the sentiment of messages sent on StockTwits about the Bitcoin during a period $t-1$ has a statistically significant and positive effect on return in t . This effect is concentrated on the bubble period (August 2017 to April 2018) consistent with the presence of irrational sentiment-driven noise traders during this period. At lower frequency (daily), we do not find any significant relationship consistent with previous results on the literature on the efficiency of the market at a daily frequency.

However, it is important to note that while the coefficient of the investor sentiment variable is statistically significant for high-frequency periods, considering reasonable transaction costs makes it impossible to generate abnormal profits by trading on the information derived from social media data. The Bitcoin market remains highly unpredictable and volatile. In that regard, the regulator's role is to warn unsophisticated traders who wish to enter this market and who may be influenced by false promises of gains.

While we focus on the relation between Bitcoin returns and investor sentiment, we believe that further research could focus on (1) the relation between investor sentiment and realized volatility at the intraday level, (2) the impact of political or regulatory events on sentiment

and returns, and (3) the relation between investor sentiment and other cryptocurrencies returns.

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.
- Aslan, A. & Sensoy, A. (2019), ‘Intraday efficiency-frequency nexus in the cryptocurrency markets’, *Finance Research Letters* .
- Bariviera, A. F. (2017), ‘The inefficiency of Bitcoin revisited: A dynamic approach’, *Economics Letters* **161**, 1–4.
- Baur, D. G., Cahill, D., Godfrey, K. & Liu, Z. F. (2019), ‘Bitcoin time-of-day, day-of-week and month-of-year effects in returns and trading volume’, *Finance Research Letters* **31**, 78–92.
- Caporale, G. M. & Plastun, A. (2018), ‘The day of the week effect in the cryptocurrency market’, *Finance Research Letters* .
- Cookson, J. A. & Niessner, M. (2019), ‘Why don’t we agree? Evidence from a social network of investors’, *The Journal of Finance* **Forthcoming**.
- Dastgir, S., Demir, E., Downing, G., Gozgor, G. & Lau, C. K. M. (2019), ‘The causal relationship between bitcoin attention and bitcoin returns: Evidence from the copula-based granger causality test’, *Finance Research Letters* **28**, 160–164.
- De Long, J. B., Shleifer, A., Summers, L. H. & Waldmann, R. J. (1990), ‘Noise trader risk in financial markets’, *Journal of political Economy* **98**(4), 703–738.
- Demir, E., Gozgor, G., Lau, C. K. M. & Vigne, S. A. (2018), ‘Does economic policy uncertainty predict the bitcoin returns? an empirical investigation’, *Finance Research Letters* **26**, 145–149.
- Dyhrberg, A. H., Foley, S. & Svec, J. (2018), ‘How investible is Bitcoin? Analyzing the liquidity and transaction costs of Bitcoin markets’, *Economics Letters* **171**, 140–143.
- Grobys, K. & Sapkota, N. (2019), ‘Cryptocurrencies and momentum’, *Economics Letters* **180**, 6–10.
- Heston, S. L., Korajczyk, R. A. & Sadka, R. (2010), ‘Intraday patterns in the cross-section of stock returns’, *The Journal of Finance* **65**(4), 1369–1407.

- Kim, S.-H. & Kim, D. (2014), ‘Investor sentiment from internet message postings and the predictability of stock returns’, *Journal of Economic Behavior & Organization* **107**, 708–729.
- Li, T., Shin, D. & Wang, B. (2019), ‘Cryptocurrency pump-and-dump schemes’, *Available at SSRN 3267041* .
- Mahmoudi, N., Docherty, P. & Moscato, P. (2018), ‘Deep neural networks understand investors better’, *Decision Support Systems* .
- Oliveira, N., Cortez, P. & Areal, N. (2017), ‘The impact of microblogging data for stock market prediction: Using Twitter to predict returns, volatility, trading volume and survey sentiment indices’, *Expert Systems with Applications* **73**, 125–144.
- Panagiotidis, T., Stengos, T. & Vravosinos, O. (2018), ‘On the determinants of bitcoin returns: A lasso approach’, *Finance Research Letters* **27**, 235–240.
- Poyser, O. (2019), ‘Exploring the dynamics of bitcoin’s price: a bayesian structural time series approach’, *Eurasian Economic Review* **9**(1), 29–60.
- Renault, T. (2017), ‘Intraday online investor sentiment and return patterns in the US stock market’, *Journal of Banking & Finance* **84**, 25–40.
- Renault, T. (2019), ‘Sentiment analysis and machine learning in finance: a comparison of methods and models on one million messages’, *Digital Finance* pp. 1–13.
- Sensoy, A. (2019), ‘The inefficiency of Bitcoin revisited: A high-frequency analysis with alternative currencies’, *Finance Research Letters* **28**, 68–73.
- Shen, D., Urquhart, A. & Wang, P. (2019), ‘Does Twitter predict Bitcoin?’, *Economics Letters* **174**, 118–122.
- Tiwari, A. K., Jana, R., Das, D. & Roubaud, D. (2018), ‘Informational efficiency of Bitcoin—an extension’, *Economics Letters* **163**, 106–109.
- Urquhart, A. (2016), ‘The inefficiency of Bitcoin’, *Economics Letters* **148**, 80–82.
- Urquhart, A. (2018), ‘What causes the attention of Bitcoin?’, *Economics Letters* **166**, 40–44.