

**FINANCIAL TWITTER SENTIMENT ON BITCOIN RETURN AND HIGH-FREQUENCY VOLATILITY**

*Xiang Gao, Weige Huang, and Hua Wang*

**Abstract.** This paper studies how sentiment affect Bitcoin pricing by examining, at an hourly frequency, the linkage between sentiment of finance-related Twitter messages and return as well as the volatility of Bitcoin as a financial asset. On the one hand, there was calculated the return from minute-level Bitcoin exchange quotes and use of both rolling variance and high-minus-low price to proxy for Bitcoin volatility per each trading hour. On the other hand, the mood signals from tweets were extracted based on a list of positive, negative, and uncertain words according to the Loughran-McDonald finance-specific dictionary. These signals were translated by categorizing each tweet into one of three sentiments, namely, bullish, bearish, and null. Then the total number of tweets were adopted in each category over one hour and their differences as potential Bitcoin price predictors. The empirical results indicate that after controlling a list of lagged returns and volatilities, stronger bullish sentiment significantly foreshadows higher Bitcoin return and volatility over the time range of 24 hours. While bearish and neutral financial Twitter sentiments have no such consistent performance, the difference between bullish and bearish ratings can improve prediction consistency. Overall, this research results add to the growing Bitcoin literature by demonstrating that the Bitcoin pricing mechanism can be partially revealed by the momentum on sentiment in social media networks, justifying a sentimental appetite for cryptocurrency investment.

**Keywords:** Bitcoin, cryptocurrency, sentiment, Twitter, social media, volatility

**JEL Classification:** G12, G14, G15

**Authors:****Xiang Gao**

Shanghai Business School, 2271 West Zhong Shan Road, Shanghai, China, 200235

E-mail: [gaoxiang@sbs.edu.cn](mailto:gaoxiang@sbs.edu.cn)

<https://orcid.org/0000-0003-4914-557X>

**Weige Huang (Corresponding Author)**

Zhongnan University of Economics and Law, 182 Nanhu Avenue, Wuhan, China, 430073

E-mail: [weige\\_huang@zuel.edu.cn](mailto:weige_huang@zuel.edu.cn)

<https://orcid.org/0000-0002-0615-3302>

**Hua Wang**

Shenzhen Technology University, 3002 Lantian Road, Shenzhen, China, 518118

E-mail: [wanghua@sztu.edu.cn](mailto:wanghua@sztu.edu.cn)

<https://orcid.org/0000-0001-5186-4165>

**Citation:** Gao, X., Huang, W., & Wang, H. (2021). Financial Twitter Sentiment on Bitcoin Return and High-Frequency Volatility. *Virtual Economics*. 4(1), 7-18. [https://doi.org/10.34021/ve.2021.04.01\(1\)](https://doi.org/10.34021/ve.2021.04.01(1))

Received: January 2, 2021. Revised: January 7, 2021. Accepted: January 10, 2021.

© Author(s) 2021. Licensed under the [Creative Commons License - Attribution 4.0 International \(CC BY 4.0\)](https://creativecommons.org/licenses/by/4.0/)

## 1. Introduction

It has been a long time since social networks came into people's life. Social networks are everywhere in everyday life and they are now attracting a huge amount of attention, not only of the social network users but also of financial investors in various fields. A large number of researchers believe that the public mood or sentiment expressed in social media is related to financial markets. In the past, De Long et al. (1990) investigated investor sentiment and suggested that different types of investors such as rational investors could make a profit from the market by exploiting the investor sentiments. Audrino et al. (2020) analyse the impact of sentiment and attention variables on the stock market volatility by using dataset that combines social media, news articles, information consumption, and the study shows that attention and sentiment variables are able to improve volatility forecasts significantly. Thus, professional investors could exploit the behavior of retail investors who use social media platforms as channels to obtain information about securities' potential performance.

Twitter, which is a very popular Micro-blogging forum, has been used to extract a proxy for investor sentiment. For instance, Affuso et al. (2018) examine the impact of investor sentiment and geography on stock returns and conclude that Twitter sentiment is among important factors that can have an impact on stock returns and negative tweets have a larger impact than positive tweets. Bollen et al. (2011) derive different types of moods from Twitter messages and indicate that predictions of the stock indices can be refined through the study of information. Twitter sentiments and activity, the latter measured as the number of Tweets in a certain time interval, are available to investors through commercial data providers. Chen et al. (2014) found that social media represent one way for the investors to access information in equity markets.

Broadstock et al. (2019) used Twitter messages to construct sentiment measures, and their results showed that stocks reacted to both firm specific and market wide sentiment which meant that sentiment from social media provided the pricing influence against the stock market. Sprenger et al. (2014) studied how twitter sentiment related with the stock-related characteristics and investigated the trading characteristics of the listed stocks and their related tweets in the social media, finding the volume of tweets to be related to the trading volume of the corresponding stocks. Besides, Bukovina (2016) studied the investor sentiment obtained from social media and applied to the behavior finance area. All the studies mentioned above highlight the critical connection between the daily financial market and social media data. Nevertheless, most of the studies conduct analyses only considering stock market domain.

Bitcoin as a new popular investment alternative has one of the highest market capitalizations and is the leading cryptocurrency in the digital asset space. Bitcoin has quite outperformed some asset classes, and due to increasing speculation, it is now gradually becoming not only one of the highest traded digital assets across the world but also an important financial asset for alternative investments. There is a considerable amount of media attention to BitCoin investments. For instance, Dyhrberg (2016) and Dastgir et al. (2019) studied how media

attention might affect the trading in Bitcoins. Philippas et al. (2019) took the investigation of how the increasing media attention in social networks may affect the trace jumps in Bitcoin trading.

Nevertheless, there exists a growing literature on how to obtain the sentimental signals from Twitter, and how to use the sentimental signals to predict Bitcoin price and volatility. This paper adds to the literature on Bitcoin by examining the link between sentiment on Twitter and Bitcoin returns and volatility. This research proposes a novel perspective of linking the sentimental signals from Twitter with Bitcoin price and volatility prediction in high-frequency. Each tweet is categorized into bullish, bearish, and neutral sentiment according to well-accepted financial market dictionaries and algorithms. This paper takes an intraday perspective and considers hourly Bitcoin return and price changes as the subject of study. Two main objectives emerge: (i) assessing the impact of Twitter investor sentiment on Bitcoin return and volatility and (ii) propose a novel channel for forecasting Bitcoin performance at hourly intervals.

## 2. Literature Review

This paper is related to two strands of literature. Firstly, it adds to a large body of literature attempting to identify determinants of Bitcoin as an alternative investment tool. Being the most successful application of blockchain technology, numerous research such as Carrick (2016), Bouri et al. (2017), and Gandal et al. (2018) has shown that Bitcoin contains speculation, complementary-currency, and diversification characteristics resembling an investable asset class.

Previous research has studied the relationship among the price return of Bitcoin with the performance of other markets or economic indicators. For instance, Kristoufek (2015) studied the relation among the price return of Bitcoin with the performance of stock equity and fixed income markets. Panagiotidis et al. (2018) studied the relationship among the price return of Bitcoin with the major economic indicators such as unemployment rates. Hakim da Neves (2020) & Nasir et al. (2019) studied the relation among the price return of Bitcoin with social factors such as online search intensity. Nevertheless, the effect of social media sentiment on the Bitcoin market is largely overlooked due to their remoteness in the long run. The present paper argues the existence of a high-frequency intraday connection between the two. Many forecasting models (Sun et al., 2020) are also utilized in the attempt to capture the price trend of cryptocurrencies.

However, these factors do not adequately explain the daily returns of Bitcoin on a continuous intraday basis, and Balciilar et al. (2017) argue that the high-frequency fluctuations are more likely to be affected by the noise and momentum in the markets rather than the fundamental characteristics. Besides, Catania et al. (2019) study the high-frequency data of the social media data and conclude that the high-frequency social media data have high importance for the market movement. In line with studies emphasizing the importance of high-frequency data, this article aims to investigate whether high-frequency Twitter sentiment information is

related to contemporaneous Bitcoin returns and volatility. Moreover, the question is posed whether such relationships can be used to predict the overnight or next day's Bitcoin return and price variations.

Secondly, the paper is also complementary to the literature about the predictability of Twitter sentiment on the financial markets. Bollen et al. (2011) conclude that the predictions of the stock indices can be refined through the study of information. Groß-Klußmann et al. (2019) examine the relation between signals derived from the unstructured social media text data and financial market developments in a long-term time range and conclude that there is relationship between the social media text data and financial market performance. Gu & Kurov (2020) find that the information content of Twitter sentiment of an individual company can predict the future returns of the underlying stock. However, it is still little known about whether such Twitter opinions can reveal pricing information and volatility expectation for asset class Bitcoin. This paper shows that the sentiment signals on tweets at a high frequency are not able to predict returns on stock markets.

### 3. Data and Methodology

The purpose of this research is to explore the sentiment information contained in tweets and exploit it to predict Bitcoin price and volatility. To attain the goal, this section first introduces the data treatment and then presents the methodology employed to investigate Bitcoin predictability.

The textual data used consists of finance- and economics-related Twitter posts automatically downloaded by Gulacsy, D. (2019) using Java Twitter streaming API from June 24th, 2019 to August 12th, 2019 in real-time. To construct dictionary-based sentiment measures, two documents are employed in categorizing each tweet into one of the three types of sentiments--bullish, bearish, and null (i.e., neither bullish nor bearish). The first document comes from the positive and negative word lists published by Loughran & McDonald (2011). The second document considers the stock market opinion lexicon created using diverse statistical measures and a large set of labeled messages from StockTwits (Nuno et al., 2016). Finally, the notation "bullish" ("bearish") is used to represent the total number of bullish (bearish) tweets posted in an hour. Similarly, "null" is used to denote the hourly count of Twitter posts which are neither categorized as the bullish or bearish sentiment. There is also constructed a sentiment premium statistic "BMB" by letting bullish tweet number minus bearish tweet number. The logic is to capture the average range from optimistic to pessimistic moods on social media platforms.

There are employed intraday high-frequency trading records from the Bitstamp exchange in minute intervals. Raw data fields contain timestamps expressed in UNIX time, minute-to-minute updates of OHLC (open, high, low, and close) prices, and a weighted Bitcoin price. To match with the Tweet sample, there are aggregated minute-frequency Bitcoin variables to the hourly level. In specific, hourly OHLC prices are their respective minute counterparts in an hour's time range. Regarding the weighted price quotes, the average across all minute values

is taken. There are two prediction targets: return and volatility. The Bitcoin return target is the simple return of holding Bitcoin for every hour evaluated at weighted price quotes. Another is the hourly volatility of Bitcoin prices. Bitcoin volatility target is measured by both a variance, which is computed on the basis of hourly prices over the previous 24 hours in a rolling way and an “HML” indicator, which is simply the hour’s low Bitcoin price subtracted from the same hour’s high. All these Bitcoin pricing statistics are scaled into a consistent order of magnitude (Table 1).

**Table 1.** Summary statistics

Hourly Variable	Min	Mean	Median	Max	Std. Dev.
Bitcoin Return	-0.08385	-0.00007	0.00031	0.09074	0.01176
Bitcoin Volatility	0.00323	0.01056	-0.00984	0.03082	0.00532
Bitcoin High Minus Low Price	28	175	138	1989	141
No. of Bullish Tweets	10	83	78	253	30
No. of Bearish Tweets	1	37	34	102	18
No. of Null Sentiment Posts	19	382	333	1322	174
Bullish Minus Bearish Tweets	-22	46	44	182	24

*Note:* The web-crawled Twitter posts are real-time from June 24<sup>th</sup>, 2019 to August 12<sup>th</sup>, 2019. The total number of tweets studied in this paper accounts for 550,661 with 91,158 Bullish ones, 40,371 Bearish ones, and 419,132 Nulls.

*Source:* developed by the authors.

Table 1 lists the summary statistics of our main variables. The empirical methodology follows the next specification:

$$Bitcoin_{t+\tau} = \alpha + \beta Sentiment_t + \gamma Null_t + \eta_1 R_{t-1} + \eta_2 R_{t-2} + \eta_3 R_{t-3} + \eta_{12} R_{t-12} + \theta_1 V_{t-1} + \theta_2 V_{t-2} + \theta_3 V_{t-3} + \theta_{12} V_{t-12} + \varepsilon_t \quad (1)$$

where  $Bitcoin_{t+\tau}$  is the target variable of either a return or volatility proxy with  $\tau$  setting at a range of time points up to 24 hours ahead of the current hour. Let  $Sentiment_t$  be a chosen measure of informative Twitter sentiment measure. The number of tweets with null emotions are controlled so that strong emotions about investment can be captured without disturbances from irrelevant social media fever. By acknowledging the autocorrelation or momentum effect inherent in financial asset pricing, several lagged returns and volatilities are also included in the above regression. It is expected to estimate a statistically significant  $\beta$  coefficient, and a positive estimate before the bullish sentiment would imply that an optimistic mood in social networks leads to higher levels of Bitcoin hourly return and volatility. However, it is suspected that, for a longer sample period, this short-run over-reaction will cause post drift back to the long-run pricing trend of Bitcoin assets.

#### 4. Results and Discussion

Table 2 shows the results of regressing hourly Bitcoin returns, 24-hour rolling variance, and high-minus-low price on the three types of sentiments. As can be seen, bullish sentiment is strongly associated with Bitcoin returns and volatility in the high-frequency dimension. In specific, after controlling for a list of returns and volatilities lagged by 1, 2, 3, and 12 hours, a stronger bullish sentiment significantly foreshadows higher Bitcoin return and volatility contemporaneously. Though not statistically significant, the number of tweets with bearish sentiment tends to be negatively correlated with the contemporaneous return. And without controlling other variables, the number of tweets with bearish sentiment is able to predict negatively the volatility with the magnitude of similar size as the number of tweets with the bullish sentiment (-0.72 vs. 0.74). It is also noted that the number of tweets with bullish sentiment is consistently able to positively predict the difference between high and low prices (HML). It is interesting to note that, although not statistically significant, the number of tweets with bearish sentiment seems to negatively predict HML without controlling other variables, but positively forecast HML after controlling other variables.

**Table 2.** Bullish/bearish sentiment and contemporaneous Bitcoin return and volatility

Dep. Var. is:	Return		Volatility			
			Variance		HML	
	(1)	(2)	(3)	(4)	(5)	(6)
Bullish	0.36** (0.16)	0.38** (0.17)	0.04*** (0.01)	0.04*** (0.01)	1.03*** (0.17)	1.09*** (0.17)
Bearish	-0.15 (0.26)	-0.21 (0.27)	0.03 (0.02)	0.03 (0.02)	0.48* (0.28)	0.43 (0.28)
Null	-0.02 (0.03)	-0.01 (0.03)	-0.01*** (0.002)	-0.01*** (0.002)	-0.11*** (0.03)	-0.11*** (0.03)
Lagged Returns	Yes	Yes	No	Yes	No	Yes
Lagged Variances	No	Yes	Yes	Yes	Yes	Yes
Constant	-18.57* (10.60)	-11.87 (12.99)	0.29 (1.03)	0.29 (1.03)	-6.26 (13.28)	-7.85 (13.17)
No. of Obs.	1,119	1,096	1,096	1,096	1,096	1,096

Note: The coefficients are scaled up by 10,000, and heteroscedasticity robust standard errors are in parentheses. \* p<0.1; \*\* p<0.05; \*\*\* p<0.01.

Source: developed by the authors.

Given the results from Table 2 (i.e., the number of tweets with bullish and bearish sentiment seems to oppositely predict return, volatility, and HML), it makes sense to construct a single variable which is the difference between the number of twitters with the bullish and bearish sentiment in order to capture a “real” bullish sentiment in the entire sentiment environment in an hour. In Table 3, the step is taken to re-run the regression exercises in Table 2 by replacing the bullish and bearish sentiment with their difference as a potential forecasting variable. It is

found that, while bearish and vacant financial Twitter sentiments have no comparable consistent performance with the bullish sentiment, the BMB ratings can improve concurrent prediction consistency at the cost of the degree of statistical significance. It should be noticed that the magnitudes of the BMB power on predicting return are similar between with and without controlling other variables (0.32 vs. 0.36). That said, the power is quite robust. On the contrary, the prediction power of BMB on volatility is much weakened after controlling the other variables (0.74 vs. 0.03) although both are statistically significant. It is found that without controlling variables, null is weakly and statistically correlated with volatility. A final observation is that BMB stays consistently positively correlated with HML, though the prediction size is halved after controlling for other variables.

Tables 2 and 3 examine the contemporaneous relationship between sentiment and Bitcoin assets. Table 4 explores whether the sentiment can predict future return and volatility. More specifically, BMB is used to predict future return, volatility, and HML in 2, 6, 12, and 24 hours. Table 3 summarizes the predictive power of BMB for Bitcoin return and volatility in the next 2 to 24 hours. Except for the 24-hour return, all other prediction targets are statistically and positively associated with the sentiment premium predictor at least at the 5% significance level. Specifically, BMB negatively predicts return half-day. It means that if the sentiment is bullish-dominant, the price is likely to decrease in the next 12 hours. However, BMB fails to statistically foreshadow Bitcoin prices in the next 24 hours. Also, it is noted that the BMB are positively correlated with future volatility in the next 12 hours and the sizes are similar with 24 hours. The BMB can also positively predict HML in the next 12 and 24 hours though the strength of predictive power seems to be weakened across time. Based on results on volatility and HML, it can be concluded that the market uncertainty will increase when the sentiment in Twitter is bullish.

**Table 3.** Sentiment premium and contemporaneous Bitcoin return and volatility

Dep. Var. is:	Return		Volatility			
			Variance		HML	
	(1)	(2)	(3)	(4)	(5)	(6)
BMB	0.33** (0.15)	0.36** (0.17)	0.03** (0.01)	0.03** (0.01)	0.81** (0.17)	0.87*** (0.17)
Null	-0.002 (0.02)	0.0004 (0.02)	-0.002 (0.002)	-0.002 (0.002)	-0.02 (0.02)	-0.01 (0.02)
Lagged Returns	Yes	Yes	No	Yes	No	Yes
Lagged Variances	No	Yes	Yes	Yes	Yes	Yes
Constant	-14.63 (9.50)	-8.31 (11.89)	1.72* (0.95)	1.69* (0.95)	24.59** (12,34)	23.03* (12.25)
No. of Obs.	1,119	1,096	1,096	1,096	1,096	1,096

Note: The coefficients are scaled up by 10,000, and heteroscedasticity robust standard errors are in parentheses. \* p<0.1; \*\* p<0.05; \*\*\* p<0.01.

Source: developed by the authors.

This paper also checks if the sentiment on Twitter used in this research can predict stock returns in the U.S. market. More specifically, treatment variables are used in this research to predict returns in stock market indices. The indices include the entire market and markets with large-, middle-, and micro-size stocks. Generally, it is found that the sentiment shown on our dataset is not able to predict stock market returns. That is, by setting the stock market returns and volatility as a benchmark, at the hour-frequency level, there is not found supportive evidence that the Twitter sentiment indices used in this paper can predict hourly aggregate stock returns and volatility. This implies that the high-frequency Twitter sentiment might only have pricing power in volatile and digital asset markets. Investors in the traditional stock market are relatively immune to very short-time sentiment movements. A further step is to explore why sentiment extracted from Twitter displays Bitcoin orientation.

**Table 4.** Sentiment premium predicts next 2 to 24 hours Bitcoin return and volatility

<i>Panel A</i>	<b>Return</b>	<b>Return</b>	<b>Variance</b>	<b>Variance</b>	<b>HML</b>	<b>HML</b>
<b>Dep. Var. is:</b>	<b>forward2</b>	<b>forward6</b>	<b>forward2</b>	<b>forward6</b>	<b>forward2</b>	<b>forward6</b>
	(1)	(2)	(3)	(4)	(5)	(6)
BMB	-0.16 (0.16)	-0.25 (0.16)	0.09*** (0.02)	0.18*** (0.03)	0.99*** (0.17)	1.06*** (0.18)
Null	0.03 (0.02)	0.03 (0.02)	-0.01*** (0.003)	-0.01*** (0.004)	-0.03 (0.02)	-0.06*** (0.02)
Lagged Returns & Variances	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-7.18 (11.90)	-4.62 (11.90)	5.80*** (1.61)	13.68*** (2.41)	32.57*** (12.44)	52.69*** (12.70)
No. of Obs.	1,094	1,090	1,084	1,072	1,084	1,072

  

<i>Panel B</i>	<b>Return</b>	<b>Return</b>	<b>Variance</b>	<b>Variance</b>	<b>HML</b>	<b>HML</b>
<b>Dep. Var. is:</b>	<b>forward12</b>	<b>forward24</b>	<b>forward12</b>	<b>forward24</b>	<b>forward12</b>	<b>forward24</b>
BMB	-0.50*** (0.16)	-0.09 (0.16)	0.30*** (0.04)	0.37*** (0.06)	0.90*** (0.18)	0.79*** (0.16)
Null	0.04* (0.02)	0.03 (0.02)	-0.02*** (0.01)	-0.03*** (0.01)	-0.11*** (0.02)	-0.04*** (0.02)
Lagged Returns & Variances	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.30** (11.71)	-8.52 (11.46)	26.83*** (3.20)	46.65*** (4.31)	90.99*** (12.90)	74.88*** (11.50)
No. of Obs.	1,084	1,072	1,084	1,072	1,084	1,072

Note: The coefficients are scaled up by 10,000, and heteroscedasticity robust standard errors are in parentheses. \* p<0.1; \*\* p<0.05; \*\*\* p<0.01.

Source: developed by the authors.

To sum up, it is found that the number of tweets with bullish sentiment leads both the contemporaneous and future Bitcoin return as well as volatility. The more is the bullish sentiment shown in Twitter, the higher are the present prices and the lower are the future

prices in Bitcoin. And the stronger is the bullish sentiment, the higher is the degree of uncertainty in current and future Bitcoin prices.

## 5. Conclusions

In the financial world, the investors need to reduce volatility, and one way is to diversify the portfolio with alternative assets displaying superior hedge characteristics. This research proposes Bitcoin as an alternative investment. Bitcoin, as a new popular investment alternative, has one of the highest market capitalizations and is the leading cryptocurrency in the digital asset space. It is also imperative for investors to examine drivers of Bitcoin price movements and volatility. This paper adds to the growing literature of Bitcoin by examining the link between sentiment on Twitter and Bitcoin returns and volatility. A novel way is offered to obtain the sentimental signals from Twitter to predict Bitcoin price and volatility. Each tweet is categorized into one of three sentiments which are bullish, bearish, and null. The empirical results indicate that sentiment from Twitter (e.g., bullish sentiments) can predict Bitcoin returns and volatility, namely, a 1% increase in the different of optimistic and pessimistic tweets lead to 0.3%-0.4% raise in Bitcoin return at the same time and a similar size of increase in Bitcoin variance in the next day.

Thus, it can be concluded that Bitcoin prices are partially predicted by momentum on social media sentiment in social networks, justifying a sentimental appetite. This finding is important for investors who are interested in getting social media sentiment information as an alternative investment judgment. For future investigations, it will be interesting to investigate how to combine the sentiment prediction with the other pricing prediction methods such as technical analytical methods, fundamental analysis, and prediction based on time series and machine learning. It will be also intriguing to decipher the information contained in textual messages that specifically talk about investment in cryptocurrency rather than the broader financial markets. Furthermore, it would be of great interest to weigh each tweet differently according to some measures such as the number of “likes”, of words in each tweet, of retweets and who writes the tweet when constructing the sentiment indices.

## 6. Author Contributions

All authors contributed equally.

## 7. Acknowledgements

We are grateful to the two anonymous referees.

## 8. Conflicts of Interest

The authors declare no conflict of interest.

## References

- Affuso, E., & Lahtinen, K. (2018). Social Media Sentiment and Market Behavior. *Empirical Economics*, 57, 105-127. <https://doi.org/10.1007/s00181-018-1430-y>
- Audrino, J., Sigrist, F., & Ballinari, D. (2020). The Impact of Sentiment and Attention Measures on Stock Market Volatility. *International Journal of Forecasting*, 36, 334-357. <https://doi.org/10.1016/j.ijforecast.2019.05.010>
- Balcilar, M., Bouri, E., Gupta, R., & Roubaud, D. (2017). Can Volume Predict Bitcoin Returns and Volatility? A quantiles-based approach. *Economic Modelling*, 64, 74-81. <https://doi.org/10.1016/j.econmod.2017.03.019>
- Barber, B.M., Odean, T., & Zhu, N. (2008). Do Retail Trades Move Markets? *The Review of Financial Studies*, 22(1), 151-186. <https://doi.org/10.1093/rfs/hhn035>
- Bollen, J., Mao, H., & Zheng, X. (2011). Twitter Mood Predicts the Stock Market. *Journal of Computational Science*, 2, 1-8. <https://doi.org/10.1016/j.jocs.2010.12.007>
- Bouri, E., Molnar, P., Azzi, G., Roubaud, D., & Hagfors, L.I. (2017). On the Hedge and Safe Haven Properties of Bitcoin: Is it Really More Than a Diversifier? *Finance Research Letters*, 20, 192-198. <https://doi.org/10.1016/j.frl.2016.09.025>
- Broadstock, D., & Zhang, D. (2019). Social-Media and Intraday Stock Returns: The Pricing Power of Sentiment. *Finance Research Letters*, 30, 116-123. <https://doi.org/10.1016/j.frl.2019.03.030>
- Bukovina, J. (2016). Social Media Big Data and Capital Markets – An Overview. *Journal of Behavioral and Experimental Finance*, 11, 18-26. <https://doi.org/10.1016/j.jbef.2016.06.002>
- Carrick, J. (2016). Bitcoin as a Complement to Emerging Market Currencies. *Emerging Markets Finance and Trade*, 52(10), 2321-2334. <https://doi.org/10.1080/1540496X.2016.1193002>
- Catania, L., & Sandholdt, M. (2019). Bitcoin at High Frequency. *Journal of Risk and Financial Management*, 12(1), 36. <https://doi.org/10.3390/jrfm12010036>
- Chen, H., De, P., Hu, Y.J., & Hwang, B.-H. (2014). Wisdom of Crowds: The Value of Stock Opinions Transmitted Through Social Media. *The Review of Financial Studies*, 27(5), 1367-1403. <https://doi.org/10.1093/rfs/hhu001>
- 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. <https://doi.org/10.1016/j.frl.2018.04.019>
- 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. <https://doi.org/10.1086/261703>
- Dyhrberg, A.H. (2016). Bitcoin, Gold and the Dollar – A GARCH Volatility Analysis. *Finance Research Letters*, 16, 85-92. <https://doi.org/10.1016/j.frl.2015.10.008>
- Gandal, N., Hamrick, J.T., Moore, T., & Oberman, T. (2018). Price Manipulation in the Bitcoin Ecosystem. *Journal of Monetary Economics*, 95, 86-96. <https://doi.org/10.1016/j.jmoneco.2017.12.004>

- Groß-Klußmann, A., König, S., & Ebner, M. (2019). Buzzwords Build Momentum: Global Financial Twitter Sentiment and the Aggregate Stock Market. *Expert Systems with Applications*, 136(1), 171-186. <https://doi.org/10.1016/j.eswa.2019.06.027>
- Gu, C., & Kurov, A. (2020) Informational Role of Social Media: Evidence from Twitter Sentiment. *Journal of Banking and Finance*, 121, 105969. <https://doi.org/10.1016/j.jbankfin.2020.105969>
- Gulacsy, D. (2019). *Twitter Investor Sentiment Analysis Dataset, Version 2*. Retrieved on April 17, 2020 from <https://www.kaggle.com/dominikgulacsy/twitter-investor-sentiment-analysis-dataset>.
- Hakim das Neves, R. (2020). Bitcoin Pricing: Impact of Attractiveness Variables. *Financial Innovation*, 6, 21. <https://doi.org/10.1186/s40854-020-00176-3>
- 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>
- Loughran, T., & McDonald, B. (2011). When is a Liability not a Liability? Textual Analysis, Dictionaries, and 10-Ks. *The Journal of Finance*, 66(1), 35-65. <https://doi.org/10.1111/j.1540-6261.2010.01625.x>
- Nasir, M.A., Huynh, T.L.D., Nguyen, S.P., & Duong, D. (2019). Forecasting Cryptocurrency Returns and Volume Using Search Engines. *Financial Innovation*, 5, 2. <https://doi.org/10.1186/s40854-018-0119-8>
- Nuno, O., Cortez, P., & Areal, N. (2016). Stock Market Sentiment Lexicon Acquisition Using Microblogging Data and Statistical Measures. *Decision Support Systems*, 85, 62-73. <https://doi.org/10.1016/j.dss.2016.02.013>
- Panagiotidis, T., Stengos, T., & Vravosinos, O. (2018). On the Determinants of Bitcoin Returns: A LASSO approach. *Finance Research Letters*, 27, 235-240. <https://doi.org/10.1016/j.frl.2018.03.016>
- Philippas, D., Rjiba H., Guesmi, K., & Goutte, S. (2019). Media attention and Bitcoin prices. *Finance Research Letters*, 30, 37-43. <https://doi.org/10.1016/j.frl.2019.03.031>
- Sprenger, T.O., Tumasjan, A., Sandner, P.G., & Welpe, I.M. (2014). Tweets and trades: The Information Content of Stock Microblogs. *European Financial Management*, 20(5), 926-957. <https://doi.org/10.1111/j.1468-036X.2013.12007.x>
- Sun, X., Liu, M., & Sima, Z. (2020). A Novel Cryptocurrency Price Trend Forecasting Model Based on LightGBM. *Finance Research Letters*, 32, 101084. <https://doi.org/10.1016/j.frl.2018.12.032>