The role of media coverage in bubble formation: evidence from the Bitcoin market

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The role of media coverage in bubble formation: Evidence from the Bitcoin market

You can’t value bitcoin because it’s not a value-producing asset...it's a real bubble in that sort of thing.

——Warren Buffett

Abstract

This paper explores the role of media coverage in bubble formation in the Bitcoin market. Three main findings emerge. First, media coverage, regardless of the tone, increases the next day’s Bitcoin returns in the bubble period but not in the non-bubble period. Second, Bitcoin returns can predict media coverage of Bitcoin both in the bubble and non-bubble periods. Finally, there is an insignificant relationship between media coverage and the next day’s Bitcoin’s trading volume in the bubble period but a negative relationship between them in the non-bubble period. Overall, our findings demonstrate that media coverage can act as a driver of Bitcoin returns during bubbles, providing support to Shiller’s argument and advance our understanding of the formation of bubbles and influence of media coverage.

Keywords: media coverage; asset bubbles; cryptocurrencies

1. Introduction

Asset bubbles, posing threats to the notion of rationality and generally causing price distortion as well as resource misallocation, present to be a critical puzzle in financial economics. In his famous book *Irrational Exuberance*, Shiller (2000, p. 95) states, "… news media are fundamental propagators of speculative price movements through their efforts to make news interesting to their audience …" Although Bhattacharya *et al.* (2009) conclude that media hype has limited explanatory power for the internet bubble after examining all news items coming out during 1996-2000, the case could be different in modern times given the movement away from print media and towards social media news. In this paper, we revisit the effect of media coverage on asset bubbles with data from the Bitcoin market.

There has been an ongoing debate about how media coverage impacts the capital market since, at least, the 1990s among academics, practitioners, and policymakers. Initially, news media was considered a convenient tool for transmitting information in the capital market. However, the internet bubble has raised the concern that media play a more complicated role in the capital market. Some scholars (e.g., Shiller, 2000; Tetlock, 2007; Tetlock et al., 2008; Tetlock, 2011) show that in addition to serving as an important player in the information disclosure process that guarantees price efficiency, media can exacerbate investor irrationality, trigger attention cascades, and foster feedback within price changes. Therefore, it is very likely that media coverage facilitates the growth of bubbles.

Shiller (2000) illustrates the process through which media coverage contributes to bubble development with some examples in his book. Specifically, to survive and thrive, media are in fierce competition to attract the public attention, requiring them to find and create stimulating news. Financial markets seem to be a natural cradle for news stories. For one thing, the public generally considers them the big casino and a barometer of the nation's status, which can be utilized by media. For another, financial news can have human interest appeal since it is usually associated with the making or breaking of fortunes. As a result, financial news accounts for a large amount of media content. By either attaching news reports to asset price changes that the public has already observed or reminding the public of past market episodes and the likely trading strategies of other people, news media could foster strong feedback from past price movements to future price movements.

While theoretically intuitive, examining the role of media coverage in determining asset bubbles is empirically challenging. For one thing, other information intermediaries, such as analysts, interact with media (Guest and Kim, 2020), jointly affecting asset prices. For another, despite the repeated occurrence of bubbles and crashes,[1] the dramatic rise and fall in prices for a single asset are relatively scarce. Meanwhile, previous speculative asset bubble episodes were either a one-off or lasting for many years (for a single boom-doom cycle), making it hard to assess the validity of conclusions. The Bitcoin market, on the contrary, offers a useful testing ground for the above investigation. First, it is widely accepted that speculation elicited by the enthusiasm for Blockchain technology mostly accounts for Bitcoin's price, which fits well the characterization of bubbles (Griffin and Shams, 2020). Meanwhile, despite its short history, Bitcoin has survived eight peak-to-trough drawdowns of roughly 70% during the 2013-2021 period, providing a suitable laboratory for studying bubbles. We plot daily returns of Bitcoin in Fig. 1. The large variation in Bitcoin returns is quite evident. Besides, given that official information sources, such as earnings announcements and analyst coverage, are relatively scarce (Xie *et al.*, 2020) for Bitcoin, the impact of media coverage could be easier to identify than in the stock market. Therefore, we explore the effect of media coverage on asset bubbles in the Bitcoin market.

For this purpose, we collect news reports for Bitcoin from Google News during 2012.1-2021.10. The main reason behind using Google News as the data source is that most Bitcoin investors are retail investors and only recently have institutional investors

[1] Perhaps, the most eye-catching bubbles in history are the tulip mania in the 17th century, the Mississippi and South Sea bubbles in the 18th century, the 'Roaring 20s' in the last century, the NASDAQ bubble at the turn of the 21st century, and the real estate boom in major US cities ended in the 2008 global financial crisis.

begun investing in cryptocurrencies. Due to its widespread access and low costs, Google News may become their primary information source against the authoritative press. To identify bubbles, we employ the method proposed by Phillips *et al.* (2015a) and Phillips *et al.* (2015b).[2] This method (often called the PSY method) is well established and outperforms others in terms of size and power when there are multiple bubble episodes in a sample period (Brunnermeier *et al.*, 2020). Based on its statistics, we divide the whole sample period into the bubble and non-bubble periods. Following Tetlock (2007), we adopt a vector autoregressive (VAR) framework to estimate the relationship between media coverage and Bitcoin returns in the bubble and non-bubble periods, respectively. The results show that both positive and negative media coverage is positively related to future Bitcoin returns in the bubble period but there is no statistically significant relationship between positive and negative news coverage and Bitcoin returns during the non-bubble period, supporting Shiller's claim that media coverage can drive the bubble. And the analyses with different methods and alternative measures for bubbles provide similar results.

We further analyze how Bitcoin returns affect media coverage and how media coverage affects Bitcoin's trading volume in different periods. The results suggest that Bitcoin returns could increase the future number of media reports but media coverage's impact on trading volume does not emerge immediately in the bubble period.

Additionally, we also extend the analysis to other cryptocurrencies, news reports written in different languages, and the COVID-19 pandemic. Specifically, given that Ethereum and Litecoin are two leading cryptocurrencies other than Bitcoin, we gather news coverage and trading data for Ethereum and Litecoin and find a positive relationship between media coverage and future returns in the bubble period. Since Japan and Korea have peculiar official languages and cryptocurrency exchanges, we examine the relationship between Bitcoin returns calculated with data from Japanese and Korean exchanges and news reports written in Japanese and Korean. The findings again confirm our hypothesis that media coverage could contribute to the growth of

[2] Since we use the PSY method to detect bubbles and there is no consensus on how to measure Bitcoin's intrinsic value, we define bubbles as the explosive autoregressive behavior in prices in this paper.

bubbles. And the analysis in the COVID-19 pandemic offers evidence that media could better facilitate bubble formation after the outbreak of COVID-19.

Our paper is related to several lines of research. First, a large literature explores how media coverage relates to the behaviors of various market participants. For instance, media coverage can induce investors' trading (Tetlock, 2007; Barber and Odean, 2008; Engelberg and Parsons, 2011; Peress, 2014), predict stock returns (Tetlock *et al.*, 2008; Fang and Peress, 2009), and affect corporate decisions (Dyck *et al.*, 2008; Kuhnen and Niessen, 2012; Dai *et al.*, 2015; Dai *et al.*, 2021). Our study contributes to this line of research by pointing out a potentially bad effect of media coverage, i.e., amplifying investors' irrationality and causing asset bubbles.

Second, our study helps advance the understanding of asset bubbles. Given the large societal costs led by bubbles, both scholars and practitioners devote great efforts to exploring how bubbles come into being. A strand of the literature proposes some market participants that can influence the development of bubbles. In particular, K. Brunnermeier and Nagel (2004) find that the investment of hedge funds does not correct asset prices during the bubble periods as expected. Similar conclusions are reached by Griffin *et al.* (2011), who document that institutional investors drive both the run-up and the collapse of stock prices. Greenwood and Nagel (2009) find that younger managers disproportionately bet on technology stocks and exhibit trend-chasing behavior during the technology bubble, suggesting that inexperienced investors are more likely to buy assets with inflated prices. Andrade *et al.* (2013) verify that analyst coverage can abate the growth of bubbles while Gong *et al.* (2017) analyze the Baosteel call warrant bubble (a derivative in the Chinese financial markets) and show that new investors initiate the bubble and act as the key driving force to sustain the bubble. Running experimental markets with professionals and students, Weitzel *et al.* (2020) further document that professional markets with bubble drivers are susceptible to bubbles, although they are more efficient. We turn our attention to another intermediary (information intermediary to be precise) in the financial markets, i.e., media, and confirm that it can also act as a driver for asset bubbles.

Besides, with the cryptocurrency market as the setting, our study connects to a vast literature on the determinants of cryptocurrency prices. Liu *et al.* (2022) propose that market, size, and momentum factors can be used to predict cryptocurrency returns. Hou *et al.* (2020), Li *et al.* (2021), Wang *et al.* (2019), Liu *et al.* (2020), Zhang and Li (2020), Cong *et al.* (2021), and Zhang and Li (2021) demonstrate that cryptocurrency returns are also related to the limited scalability of Blockchain-technologies in processing transactions, cryptocurrencies' extreme returns, cryptocurrencies' technological sophistication, cryptocurrencies' idiosyncratic volatility, heterogeneous users' transactional demand, safe-haven properties, and cryptocurrencies' liquidity. Motivated by theoretical models, Liu and Tsyvinski (2021) find that network factors that capture users' adoption of cryptocurrencies rather than production factors that represent the costs of cryptocurrency production can affect cryptocurrency returns. Meanwhile, cryptocurrency returns are also associated with investor attention measures (Kristoufek, 2013; Bouoiyour *et al.*, 2014; Bouoiyour and Selmi, 2015; Dastgir *et al.*, 2019; Nasir *et al.*, 2019; Yu *et al.*, 2019; Zhang and Wang, 2020; Guégan and Renault, 2021; Liu and Tsyvinski, 2021) and social media discussions (Mai *et al.*, 2018; Xie *et al.*, 2020). Our findings demonstrate that media coverage also has predictive power on Bitcoin returns during the explosive period.

Our paper differs from studies (e.g., Nasir *et al.*, 2019; Cretarola and Figà-Talamanca, 2020; Enoksen *et al.*, 2020; Zhang *et al.*, 2021) focusing on the Google trend's impact on Bitcoin bubbles in the following two aspects. First, almost all these studies are motivated by the huge price volatility in the Bitcoin market and aim to detect whether there are bubbles and how Google search volume influences the bubbles accordingly. In contrast, the main goal of our paper is to test Shiller's argument regarding media coverage's role in bubble formation. We exploit the Bitcoin market because there are more boom and bust cycles but fewer official information sources in this market. Second, while they use the Google search volume index as their main variable of interest, we employ news reports gathered by Google News. Therefore, our data source and variable construction are also different.

The outline of our paper is as follows. Section 2 describes the data and methodology we used to discern bubbles and measure news coverage. Section 3 analyzes how media coverage is associated with returns and trading volume of Bitcoin in the bubble and non-bubble periods. Section 4 explores the effect of media coverage on returns with different cryptocurrencies and from different regions as well as in the COVID-19 pandemic and shows the robustness of our findings. And Section 5 concludes this paper.

2. Data and methodology

2.1. Bubble measurement

To identify Bitcoin bubbles, we rely on the approach first proposed by Phillips *et al.* (2011) and then modified by Phillips *et al.* (2015a) and Phillips *et al.* (2015b). This approach outperforms other approaches in terms of size and power when multiple bubble episodes occur within a period. This advantage is valuable for our setting because our sample covers many bubble episodes.

In what follows, we briefly outline the testing procedure of the PSY method. The PSY method is a real-time date-stamping strategy for the origination and termination of multiple bubbles and can be considered as an extension of the right-tailed unit root test.[3]

The prototypical model for the right-tailed unit root test is presented below:

$$y_t = dT^{-\omega} + \beta y_{t-1} + \varepsilon_t, \varepsilon_t \sim iid(0, \sigma^2), \tag{1}$$

where d is a constant, T is the sample size, and ω is a parameter that controls the magnitude of the intercept and the drift as $T \to \infty$. The method focuses on the case of $\omega > \frac{1}{2}$, when the drift is small compared to the martingale component of y_t. Under the

[3] The use of the unit root test in detecting bubbles can be traced back to Diba and Grossman (1988), in which the authors proposed testing the no bubble hypothesis by applying standard unit root tests to the stock price series in levels and first-differenced forms. A finding of non-stationarity when the series is in levels but stationarity when the series is in first differences indicates that an explosive rational bubble does not exist. The logic behind the test is that the bubble component of the stock price is generally believed as evolving as an explosive autoregressive process, and an explosive autoregressive process cannot be differenced to stationarity. However, a pitfall with the test is that it fails to effectively distinguish between a stationary process and a periodically collapsing bubble model since patterns of the latter look more like data generated from a unit root or stationary autoregression than a potentially explosive process (Evans, 1991). Taking account of this criticism, Phillips *et al.* (2011) first proposed a new method that relied on recursive right-tailed unit root tests. And our paper utilizes the generalized version of this method (i.e., PSY method) which delivers a consistent real-time date-stamping strategy for the origination and termination of multiple bubbles to determine the bubble and non-bubble periods.

null hypothesis, the process is a unit root ($\beta = 1$); and under the alternative hypothesis, the process is an explosive root ($\beta > 1$).

The above model specification is often complemented with transient dynamics to test exuberance. The recursive approach created by Phillips *et al.* (2015a) involves a rolling window ADF (Augmented Dickey-Fuller) style regression implementation. Specifically, suppose the regression sample starts from the r_1^{th} fraction of the total sample (T) and ends at the r_2^{th} fraction of the sample, where $r_2 = r_1 + r_w$ and r_w is the window size fraction of the regression, ranging from r_0 (i.e., the minimum window width fraction) to 1. The regression model is expressed as:

$$\Delta y_t = \hat{\alpha}_{r_1,r_2} + \hat{\beta}_{r_1,r_2} y_{t-1} + \sum_{i=1}^{k} \hat{\theta}^i_{r_1,r_2} \Delta y_{t-i} + \hat{\varepsilon}_t, \tag{2}$$

where k is the lag order, and y_t is the natural logarithm of the asset price. The number of observations in the regression is $T_w = \lfloor Tr_w \rfloor$, where $\lfloor \cdot \rfloor$ is the floor function. The ADF statistic based on the above regression is denoted as ADF_{r_1,r_2}.

To some degree, the PSY method is a repeated ADF test from regression (2) on subsamples of the price data in a recursive fashion. Specifically, the PSY method not only varies the endpoint of the regression (i.e., r_2) from r_0 (i.e., the minimum window width fraction) to 1, but also allows the starting point r_1 to change from 0 to $r_2 - r_0$. The GSADF statistic (also called generalized supremum ADF) is defined to be the largest ADF statistic in this double recursion over all feasible ranges of r_1 and r_2, i.e.,

$$GSADF(r_0) = sup_{r_1 \in [0, r_2 - r_0]}^{r_2 \in [r_0, 1]} \{ADF_{r_1,r_2}\}. \tag{3}$$

Typically, bubbles occur when the GSADF statistic exceeds the critical value.

The GSADF statistic can also be written as:

$$GSADF(r_0) = sup_{r_2 \in [r_0, 1]} \{BSADF_{r_2}(r_0)\}, \tag{4}$$

where BSADF is the backward sup ADF statistic, defined as $BSADF_{r_2}(r_0) = sup_{r_1 \in [r_0, r_2 - r_0]} \{ADF_{r_1,r_2}\}$. Accordingly, the origination date of a bubble $\lfloor Tr_e \rfloor$ is defined as the first observation whose backward sup ADF statistic exceeds the critical value of the BSADF statistic, where $r_e = sup_{r_2 \in [r_0, 1]} \{BSADF_{r_2}(r_0) >$

$Critical\ value_{r2}\}$. The termination date of a bubble is calculated as the first observation after $\lfloor Tr_e \rfloor + \delta\ log(T)$, whose backward sup ADF statistic falls below the critical value of the BSADF statistic. Phillips *et al.* (2015a) assume that the duration of a bubble should exceed a minimal period represented by $\delta \log(T)$, where δ is a frequency-dependent parameter. We refer to the BSADF statistic as the PSY statistic.

We gather the tick-level trading data (including price and trading volume) of Bitcoin on Bitstamp from January 2012 to October 2021 from Bitcoincharts.com. This is because Bitstamp is one of the most popular exchanges with a high market share and liquidity and has been employed by a series of studies such as Urquhart (2017) and Kalyvas *et al.* (2020).

Financial bubbles and crashes have been recurring phenomena in the Bitcoin market. To identify bubbles, we employ the PSY test, which has been used in the Bitcoin literature to classify bubbles (for instance, Enoksen *et al.*, 2020; Anyfantaki *et al.*, 2021).

Fig.2 plots the BSADF statistic (represented by the dotted line), the natural logarithm of Bitcoin price (represented by the solid line) from January 2012 to October 2021, and the explosive periods (represented by the shaded regions). It is clear that there are many explosive periods.[4] Some of them are quite short, and some of them can last for a long period. Our analysis is conducted within these explosive and non-explosive periods.

2.2. Coverage measurement

As a type of news aggregator, Google News is watching a huge number of news sources worldwide and provides a continuous flow of links to articles from thousands of publishers. Being not only accessed via the Internet but also available as an app on Android and iOS, Google News simplifies the search of news stories and saves

[4] The bubble periods include: 2012.07.16-2012.07.19, 2012.07.21, 2012.07.31-2012.08.18, 2013.01.22-2013.04.14, 2013.04.18-2013.05.01, 2013.11.06-2013.12.15, 2014.10.04-2014.10.05, 2015.01.14, 2015.11.03-2015.11.04, 2016.06.06, 2016.06.11-2016.06.20, 2016.12.23, 2016.12.27-2017.01.04, 2017.05.19-2017.05.26, 2017.05.28-2017.06.24, 2017.06.27-2017.06.28, 2017.08.05-2017.09.13, 2017.09.18, 2017.09.27-2018.02.03, 2018.02.14-2018.03.06, 2018.11.24, 2018.11.26-2018.11.27, 2019.05.11, 2019.05.13-2019.05.16, 2019.05.19, 2019.05.26-2019.05.27, 2019.06.24-2019.06.26, 2019.06.28-2019.06.29, 2020.11.20-2020.11.21, 2020.11.24, 2020.12.17-2020.12.20, 2020.12.22, 2020.12.24-2021.01.20, 2021.02.03, 2021.02.05-2021.02.24, 2021.03.01, and 2021.03.08-2021.03.21. And the rest periods are defined as the non-bubble periods.

considerable time for information acquisition (Calzada and Gil, 2020; Athey *et al.*, 2021). Therefore, it has a large consumer base. Considering that many investors of Bitcoin are amateur investors (especially in the earlier days) who have little access to news reports and are more likely to depend on Google News to read media coverage, Google News could be an appropriate news source for our research question.

To obtain news coverage data of Bitcoin from January 2012 to October 2021, we first search for "Bitcoin" on Google News and then collect all results returned (including the title, source, timestamp, content etc.). Given that the number of news reports (*Newsnum*) on different days is highly skewed,[5] we measure the news coverage for Bitcoin as the natural logarithm of one plus the number of news reports (*Lnewsnum*) each day. To address the concern that the number of news reports increases over time, we follow Da *et al.* (2011) and define the main variable *News*[6] as *Lnews* on a day minus the median of *Lnews* over the past 4 weeks, i.e.,

$$News_t = Lnews_t - \text{Median}[Lnews_{t-1}, Lnews_{t-2}, \ldots Lnews_{t-28}]. \tag{4}$$

Meanwhile, we utilize the Python 3 VADER package[7] to extract sentiment from these news reports. After analyzing a news report's text, this package gives a sentiment compound score based on the ratios of negative and positive words in the report, ranging from -1 (extremely negative) to 1 (extremely positive). Following common practice, we count a news report as a positive one if the sentiment compound score is larger than 0.05; we classify a news report as a negative one if the score is less than -0.05; and we consider a news report a neutral one if the score lies between -0.05 and 0.05. Based on the results, we create two measures. The first one *Posnews* denotes the difference between the natural logarithm of one plus the number of positive news reports on a day (*Lposnewsnum*) and the median of *Lposnewsnum* over the previous 4 weeks. In a similar vein, we refer to *Negnews* as the difference between the natural logarithm of one plus the number of negative news reports on a day (*Lnegnewsnum*) and the median of *Lnegnewsnum* over the previous 4 weeks.

[5] The number of news reports for Bitcoin on a given day ranges from 1 to 53 in our sample.
[6] In fact, *News* measures the abnormal amount of media coverage on a day for Bitcoin. For brevity, when we refer to the amount of media coverage, we are referring to *News* hereafter.
[7] For more information, please visit https://www.nltk.org/ or https://www.nltk.org/api/nltk.sentiment.vader.html#module-nltk.sentiment.vader.

2.3. *Other variables*

The dependent variable in our baseline analysis is the daily Bitcoin returns (*Ret*), which is calculated as follows:

$$Ret_t = ln\left(\frac{P_t}{P_{t-1}}\right), \tag{5}$$

where P_t is the closing price of Bitcoin trading on Bitstamp on day *t*.

According to the previous literature (e.g., Liu and Tsyvinski, 2021), there are some sources of predictability found in daily return data. First, although classic financial theory (e.g., Samuelson, 1965) suggests that prices should roughly follow a random walk with a drift in a complete market without frictions, market microstructure phenomena like bid-ask bounce can harm the purity of the theoretical prediction and cause the genuine or pseudo return autocorrelation. Therefore, we control for the lagged returns of Bitcoin. Also, we follow prior studies (e.g., Mai *et al.* 2018; Enoksen *et al.*, 2020) and incorporate the lagged volume, the lagged transaction volume, and the lagged return volatility to capture liquidity effects and other market frictions. We use the natural logarithm of the dollar trading volume (*Volume*) of Bitcoin on Bitstamp provided by Bitcoincharts.com to control for volume's impact on Bitcoin returns. The transaction volume (*Transaction*) is defined as the natural logarithm of the volume of transfers of Bitcoin between users. For volatility (*Volatility*), we compute it as the sum of the squared intraday returns $r_{t,j}$ at the 5-minute given sampling frequency:

$$Volatility_t = \sum_{j=1}^{m} r_{t,j}^2, \tag{6}$$

where *m* is the number of 5-minute intervals on day *t*.

Inspired by Urquhart (2018) and Liu and Tsyvinski (2021), we measure investor attention for Bitcoin with Google search frequencies. For this purpose, we download the daily Search Volume Index for Bitcoin from Google Trends and include the natural logarithm of google search frequency on a day (*Google*) as a control variable in our analysis.

Given the findings of Liu and Tsyvinski (2021) that the number of active addresses can also predict future Bitcoin returns, we gather address information from

Bitcoincharts.com and control for the natural logarithm of the number of active addresses on a day (*Address*). Finally, to reduce the effect of outliers, we winsorize all variables at the 1% and 99% levels.

2.4. Summary statistics

Table 1 reports the summary statistics of our main variables and their differences between the bubble and non-bubble periods. Regardless of the tone, the average amount of media coverage on a day for Bitcoin in the bubble period is always larger than that in the non-bubble period. On average, the number of positive (negative) news reports for Bitcoin on a given day in the bubble period is 6.2615 (3.3326), while that in the non-bubble period is 5.2687 (2.7583). As for the total number of news reports, there are approximately 17 reports on a typical day in the bubble period and 15 reports on a typical day in the non-bubble period. And the differences between them are all significant, with t-statistics larger than 4.6. Besides, the standard deviation for news measures in the bubble period is also higher than that in the non-bubble period, indicating the great volatility in media coverage amount during the bubble period.

Consistent with the intuition, the mean of daily returns (*Ret*) for Bitcoin in the bubble period is 1.78%, significantly higher than that (0.15%) in the non-bubble period. Also, the standard deviation for *Ret* in the bubble period (0.0707) is also larger than that (0.0398) in the non-bubble period. Likewise, Bitcoin investors tend to trade more and search more in the bubble period than the non-bubble period, and the price volatility of Bitcoin is also higher in the bubble period than that in the non-bubble period.

Additionally, we also present the Pearson correlation coefficients among these variables during the bubble period in Panel A of Table 2 and those during the non-bubble period in Panel B of Table 2. The correlation coefficient between the number of news reports and Bitcoin returns is 0.0635 in Panel A, much higher than that (0.0164) in Panel B, which indicates the positive relationship between news coverage and Bitcoin returns in the bubble period is stronger than that in the non-bubble period. In contrast, it seems that news coverage is more correlated with Bitcoin's trading volume and price volatility in the non-bubble period since the correlation coefficients of *Newsnum* and *Volume* and of *Newsnum* and *Volatility* in the non-bubble period are all larger than those in the bubble period.

3. Baseline findings

3.1. Media coverage effect on Bitcoin returns

Motivated by Tetlock (2007), we employ a VAR framework to investigate how media coverage affects Bitcoin's future returns in different periods. In his VAR model for the relationship between media pessimism and stock returns, Tetlock (2007) includes lags up to 5 days for all variables. However, one of the unique aspects of cryptocurrency trading is that the market is open 7 days a week and is not idle on weekends and national holidays. The lag length determined by using the Schwarz information criterion and Hannan-Quinn information criterion is also 7 days. Therefore, all variables in our model are lagged for 7 days. The return equation for the first VAR can be summarized as

$$Ret_t = a + \beta_1 L7(News_t) + \gamma_1 L7(Ret_t) + \delta_1 L7(Volume_t) + \sigma_1 L7(Transaction_t) + \theta_1 L7(Volatility_t) + \pi_1 L7(Google_t) + \rho_1 L7(Address_t) + \varepsilon_t, \quad (7)$$

where the dependent variable is the daily returns of Bitcoin *Ret*; the main variable of interest is *News*, the daily amount of media coverage for Bitcoin; the control variables include the lagged *Ret*, the lagged *Volume*, the lagged *Transaction*, the lagged *Volatility*, the lagged *Google*, and the lagged *Address*; *L7* is a lag operator which transforms any variable into a row vector consisting of the 7 lags of the variable ($L7(x_t) = [x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4}, x_{t-5}, x_{t-6}, x_{t-7}]$). Following Tetlock (2007), we assume that the disturbance term ε_t in this equation is heteroskedastic across time and the disturbance terms in different equations are independent. Additionally, Newey and West (1987) robust standard errors are utilized to account for any heteroskedasticity and autocorrelation in the residuals up to 7 lags.[8]

Our primary focus is the coefficient estimates of media coverage for Bitcoin *News*, which describes the dependence of Bitcoin returns on media coverage. The results shown in Panel A of Table 3 suggest that Bitcoin returns are significantly related to media coverage to some degree during market exuberance but not in other periods.[9] In particular, a one-standard-deviation increase in media coverage is associated with a 1.88% increase in the next day's Bitcoin returns. Considering that the mean of Bitcoin returns is 1.79%, the impact is of both statistical (with a t-statistic of 4.8519) and economic significance. Another noteworthy finding of Panel A of Table 3 is that the predictive power of media coverage on Bitcoin returns is relatively transient during the explosive period as the coefficient estimates of other lagged *News* are no longer significant at the conventional levels. In contrast, we find no evidence of a significant relationship between media coverage and the Bitcoin return in the non-bubble period since almost all coefficient estimates of *News* (except those of $News_{t-6}$ and $News_{t-7}$) are insignificant.

To better illustrate the impact of media coverage on Bitcoin returns, we present the impulse response functions, which account for the full dynamics of the VAR system. An impulse response function traces the effect of a one-unit standard deviation shock to endogenous variables in the current and subsequent periods. Following common practice, we employ the inverse of the Cholesky decomposition of the residual covariance matrix to orthogonalize the impulses (Roll *et al.*, 2007). Fig. 3 depicts the impulse response functions for *News* based on the estimates of equation (7). The two graphs show the long-run effect on *Ret* of increasing *News* by one standard deviation in the bubble and non-bubble periods. Monte Carlo two-standard error bands (based on 1,000 replications) are provided to gauge the statistical significance of the response.

For the bubble period, the impulse response function increases at first to about 0.017 and then drops to below zero. After about 10 to 20 days, the impulse response

[8] Before delving into the VAR tests, we first check whether the time series of the variables in equation (7) are stationary by using the Augmented Dickey Fuller (ADF) test. The results shown in Table A1 of the appendix suggest that all variables are relatively stationary.

[9] To conserve space, all tables in this paper suppress coefficients of the controls unless otherwise specified.

function converges to zero. This trend suggests that the positive impact of media coverage is not permanent and Bitcoin returns turn back to their long-run equilibrium level within about 10 to 20 days. Regarding the non-bubble period, when the amount of media coverage is independently increased, the Bitcoin returns fluctuate around zero, indicating that the effect of media coverage on the Bitcoin return is very small.

Digging deeper, we replace $L7(News_t)$ in the VAR estimates with $L7(Posnewst)$ and $L7(Negnews_t)$ to examine how positive and negative media coverage is related to the Bitcoin return, respectively. The results are presented in Panel B and Panel C of Table 3. Similar to the findings with media coverage, positive media coverage is also positively associated with the next day's Bitcoin return in the bubble period; however, positive media coverage cannot predict Bitcoin's future returns in the non-bubble period.

Somewhat surprisingly, we also find a statistically significant relationship between negative media coverage and Bitcoin's future returns in the bubble period. Specifically, negative media coverage on day t positively predicts Bitcoin returns on day $t+1$ as the coefficient estimate of $Negnews_{t-1}$ is significantly positive at the 1% levels. As for the non-bubble period, we can see that the coefficient estimate for $Negnews_{t-7}$ is also significantly positive. These results seem consistent with systematic optimism in response to information (Easterwood and Nutt, 1999), i.e., investors (or analysts in the setting of Easterwood and Nutt (1999)) typically underreact to negative information but overreact to positive information. Overall, we find some supportive evidence for Shiller's hypothesis.

3.2. Determinants of Bitcoin media coverage

The above findings prompt an interesting question: can Bitcoin price movements influence media coverage? As discussed earlier, to survive the cruel competition for public attention, media need to create content that is appealing to their audiences and Bitcoin news is often highly read and cited. The narrative of Bitcoin involves inspired cosmopolitan young people, riches, equality, and advanced information technology and generally has many mysterious, impenetrable jargons. The boom and collapse of

Bitcoin prices frequently dominate the headlines. Therefore, we postulate that the market activities of Bitcoin predict the amount of media coverage on Bitcoin. To examine this conjecture, we estimate a VAR model which reverses the link posited in equation (7):

$$\begin{aligned} News_t = a &+ \beta_1 L7(News_t) + \gamma_1 L7(Ret_t) + \delta_1 L7(Volume_t) \\ &+ \sigma_1 L7(Transaction_t) + \theta_1 L7(Volatility_t) \\ &+ \pi_1 L7(Google_t) + \rho_1 L7(Address_t) + \varepsilon_t \end{aligned} \tag{8}$$

where the dependent variable is the daily amount of media coverage for Bitcoin *News*; the main variable of interest is the daily returns of Bitcoin *Ret*; the control variables include the lagged *News*, the lagged *Volume*, the lagged *Transaction*, the lagged *Volatility*, the lagged *Google*, and the lagged *Address*; *L7* is a lag operator which transforms any variable into a row vector consisting of the 7 lags of the variable.

We present the results in Table 4. As expected, the Bitcoin return can predict media coverage of Bitcoin both in the bubble and non-bubble periods, according to Panel A of Table 4. And the magnitude of the coefficient estimate on Ret_{t-1} is not only statistically significant (with t-statistics of 2.1616 in the bubble period and 2.0249 in the non-bubble period) but also economically significant. Specifically, a one-standard-deviation increase in the Bitcoin return is associated with an increase of 0.0663 in news coverage on the next day during the market exuberance, and a one-standard-deviation increase in the Bitcoin return is associated with 0.0188 more news coverage on the next day in other periods. These findings confirm Shiller's claim of media coverage's role in the feedback loop of bubbles. Meanwhile, Bitcoin returns on day *t-6* seems negatively predict the number of news reports in both bubble and non-bubble periods on day *t* as the coefficients estimates of Ret_{t-6} are significantly at the conventional levels. This result implies that media may change their attitudes towards the rise in the Bitcoin price in the long run.

We also repeat this analysis by replacing *News* with positive and negative news coverage and present the results in Panels B and C of Table 4, respectively. Distinguished from the previous findings, Bitcoin returns' influence on the next day's positive or negative media coverage differs for the market condition. In the bubble period, the number of positive media reports on the subsequent day is positively related to Bitcoin returns. However, the coefficient estimate on Ret_{t-1} is insignificant in the case of negative media coverage. In other words, when the return for holding Bitcoin rises, there will be more positive media coverage. As for the non-bubble period, there is no statistically significant correlation between Bitcoin returns and the next day's positive media coverage but a significantly negative relationship between Bitcoin returns and the next day's negative media coverage.

What is more, similar to findings that stocks with more positive news in the past continue to generate more positive news in the future (Wang *et al.*, 2018), we also detect a news momentum phenomenon for Bitcoin. Regardless of the tone of media coverage and market conditions, the coefficient estimates of the news measures on the previous day are significantly positive (except the one for negative media coverage in the bubble period). That is to say, there will be more (positive or negative) news reports about Bitcoin if there are more (positive or negative) news reports about Bitcoin on the prior day.

3.3. Media coverage's effect on Bitcoin trading volume

Furthermore, we analyze the effect of media coverage on market activity from another perspective, i.e., trading volume. The trading volume of Bitcoin could be either positively or negatively related to media coverage, depending on different roles played by media coverage. On the one hand, media coverage could unify people's interpretation of Bitcoin's current performance and shape their expectations for its future development, thereby reducing divergence in investor opinions and trading volume. On the other hand, media coverage could serve as a proxy for investor sentiment (Tetlock, 2007; Tetlock *et al.*, 2008). According to the models proposed by Campbell *et al.* (1993) and DeLong *et al.* (1990), when the absolute value of sentiment is high, liquidity traders will suddenly choose to buy or sell assets, which boosts assets' trading volume.

To see which hypothesis holds in our setting, we modify equation (7) by replacing the dependent variable *Ret* with *Volume* and estimate the following model in the bubble and non-bubble periods:

$$\begin{aligned} Volume_t = a + \beta_1 L7(News_t) + \gamma_1 L7(Ret_t) + \delta_1 L7(Volume_t) \\ + \sigma_1 L7(Transaction_t) + \theta_1 L7(Volatility_t) \\ + \pi_1 L7(Google_t) + \rho_1 L7(Address_t) + \varepsilon_t, \end{aligned} \tag{9}$$

where the dependent variable is the daily trading volume for Bitcoin *Volume*; the main variable of interest is the amount of media coverage for Bitcoin *News*; the control variables include the lagged *Ret*, the lagged *Volume*, the lagged *Transaction*, the lagged *Volatility*, the lagged *Google*, and the lagged *Address*; *L7* is a lag operator which transforms any variable into a row vector consisting of the 7 lags of the variable.

The results are shown in Table 5, with Panels A, B, and C reporting findings with the lagged *News*, the lagged *Posnews*, and the lagged *Negnews* being the main independent variables. Contradictory to the predictions of the above two hypotheses, the coefficient estimate on $News_{t-1}$ as well as those on $Posnews_{t-1}$ and $Negnews_{t-1}$ in the bubble period is insignificant. A plausible interpretation of this finding is that media coverage could both help investors converge in their opinions and induce or reflect investor sentiment. These two effects offset each other, and the net outcome is an insignificant relationship between media coverage and Bitcoin's trading volume on the subsequent day. Additionally, we find the coefficient estimates on $News_{t-2}$ and $Posnews_{t-2}$ are negative and significantly at the 5% level. In other words, news reports released on day *t-2* could reduce investor disagreement. This finding suggests that investors may need some time to fully absorb information in news reports when the market sentiment is high.

Regarding the non-bubble period, Bitcoin's trading volume will be lower when there are more news coverage and positive news coverage on the prior day since the coefficient estimates on $News_{t-1}$ and $Posnews_{t-1}$ are significantly negative. Despite being statistically insignificant, the coefficient estimate of $Negnews_{t-1}$ is also negative, and the one of $Negnews_{t-2}$ is significantly negative at the 1% level. These results indicate that media coverage is more likely to reduce differences in investor opinions rather than stimulating, amplifying, or simply reflecting investor sentiment in the non-bubble period.

4. Additional tests

4.1. *Evidence from other cryptocurrencies*

So far, our analysis on the relationship between media coverage and market activity during the bubble and non-bubble periods is confined to Bitcoin. Although Bitcoin is the most remarkable and representative cryptocurrency, whether our findings can be extended to other cryptocurrencies remains to be a question. To explore how media coverage influences the returns of other cryptocurrencies, we choose another two popular cryptocurrencies with high market share and high liquidity, i.e., Ethereum and Litecoin,[10] and collect their trading and Google News data accordingly.

Ethereum and Litecoin share similar characteristics with Bitcoin. Particularly, a majority of people believe that these cryptocurrencies have no intrinsic value or at least have hard-to-value fundamentals. The surge of interest in these cryptocurrencies is irrational to some extent, and bubbles and crashes keep recurring in their markets. Also, there is no so-called official information source for these two cryptocurrencies, making it easier to extract the effect of media coverage. Intuitively, if media coverage helps boost prices for Bitcoin during market exuberance, the prices of Ethereum and Litecoin should also increase with media coverage in the explosive period. The analysis in Table 3 is replicated for these two cryptocurrencies.

Panels A, B, and C of Table 6 examine how total, positive, and negative media coverage affects returns for Ethereum (in the first half of each panel) and Litecoin (in the last half of each panel). We continue to observe a positive relationship between media coverage and returns for Ethereum and Litecoin in the bubble period. The coefficient estimate for Ethereum on $News_{t-1}$ is 0.0420, significant at the 5% level. As for Litecoin, the coefficient estimate on $News_{t-1}$ is 0.0490, with a t-statistic of 3.0247. A similar story can be told for positive media coverage. The coefficient estimates on

[10] Several studies (Goodell and Goutte, 2021; Meegan *et al.*, 2021) also choose Ethereum and Litecoin as the representatives of cryptocurrencies, excluding Bitcoin.

$Posnews_{t-1}$ are significantly positive for Ethereum and Litecoin. And both magnitudes (0.0437 for Ethereum and 0.0464 for Litecoin) are economically significant. Nevertheless, the impact of negative media coverage on returns differs for these two cryptocurrencies. Specifically, we can see that Ethereum returns are still positively related to the amount of negative media coverage on the prior day at the 1% significance level. In contrast, the coefficient estimate of $Negnews_{t-1}$ for Litecoin is no longer significant, despite being positive.

In the non-bubble period, we find no evidence that media coverage could affect returns of Ethereum and Litecoin on the next day as no coefficient estimate on media coverage measures in the subsequent day is statistically significant. Moreover, only three coefficient estimates on lagged media coverage measures (i.e., those of $News_{t-6}$ and $Posnews_{t-6}$ for Ethereum and that of $Negnews_{t-3}$ for Litecoin) are significant at the conventional levels. The results are also similar to those in Table 3.

Overall, our findings that media coverage could help increase prices during the bubble period hold for other cryptocurrencies.

4.2. A multi-region analysis

In this subsection, we extend our research to Bitcoin traded in other regions and news coverage written in other languages.

Bitcoin can be traded globally, and many nonintegrated exchanges for Bitcoin exist in parallel across countries. According to Makarov and Schoar (2020), most of these exchanges operate like exchanges in traditional equity markets, i.e., investors can submit the buy and sell orders, and then the exchange clears all traders based on a centralized order book. However, a prominent difference between the Bitcoin market and the equity market is that there is no provision to ensure investors receive the best price when executing trades, resulting in large and recurring deviations in Bitcoin prices across exchanges (i.e., market segmentation).

At the same time, Google News is a worldwide news aggregator. It offers links not only to news stories written in English but also to stories written in other languages such as Chinese, Japanese, and Korean. Considering traders in Japan (South Korea) are likely to read news reports written in Japanese (Korean) and buy or sell Bitcoin on their local exchange and in their local currency, we further analyze whether the role of media coverage in Bitcoin bubble development holds for Bitcoin traded on exchanges in Japan or Korea. To do so, we obtain news stories written in Japanese and Korean by searching for "Bitcoin" in Japanese and Korean.[11] We also use the Google search frequencies for Bitcoin in Japan and South Korea to calculate *Google*. At the same time, we also download trading data on exchanges of bitFlyer in Japan and Korbit in South Korea from Bitcoincharts.com and use the PSY method to identify bubbles. If media coverage does contribute to bubble development, we should observe the positive relationship again between media coverage written in Japanese and Korean and the next day's Bitcoin returns calculated with the price data of the corresponding exchanges during market exuberance.

Table 7 provides the results of the above tests, with Panel A showing results from Japan and Panel B showing results from Korea. As reported in Panel A, the coefficient estimate on $News_{t-1}$ remains to be significantly positive in the bubble period and insignificant in the non-bubble period, implying that media coverage plays a role in boosting Bitcoin bubbles in Japan. Similarly, we also detect a significantly positive relationship between media coverage and Bitcoin returns during the bubble period but a significantly negative relationship between media coverage and Bitcoin returns not during the non-bubble period in South Korea. These results indicate that our conclusion applies to Bitcoin traded in regional exchanges and media coverage written in languages other than English, further confirming Shiller's claim.

4.3. Coronavirus pandemic analysis

The COVID-19 pandemic has upended modern life. According to the statistics provided by the John Hopkins University Coronavirus Resource Center, by the end of February 2022, there were approximately 430 million reported cases and 6 million

[11] Bitcoin is"ビットコイン" in Japanese and "비트코인" in Korean.

deaths. The rapid spread of COVID-19 has not only posed unprecedented stress to the healthcare systems but also caused extreme disruptions to economic activities (Augustin *et al.*, 2022), changing business and individual attitudes to the future as well as their investment behaviors. How does the COVID-19 pandemic affect the role of media coverage in bubble formation?

To provide an answer, we separate all bubble and non-bubble periods into those before and after January 2020, i.e., the outbreak of the COVID-19 pandemic, and repeat the VAR analysis in these periods accordingly. Table 8 provides the results, with Panel A reporting the relationship between media coverage and Bitcoin returns before the COVID-19 pandemic and Panel B reporting those after the COVID-19 pandemic. Despite the fact that Bitcoin returns are positively related to the amount of media coverage on the prior day in bubble periods before and after the COVID-19 pandemic, the magnitude of this relationship differs. Specifically, the coefficient estimate on $News_{t-1}$ in Panel A is 0.0242, with a t-statistic of 3.5072, while that in Panel B is 0.0360, with a t-statistic of 3.5644. In other words, the positive relationship between media coverage and Bitcoin returns becomes stronger after the COVID-19 pandemic. This could be due to the implementation of lockdown policies. According to a report from Forbes in March 2020,[12] total Internet hits surged by between 50% and 70% as millions of people chose to go online under lockdown. Consequently, news reports transmitted through Internet may play a more important role in shaping investors' expectations and decisions. Meanwhile, consistent with results in Table 3, there is no significant relationship between media coverage and Bitcoin returns in the short run in the non-bubble period, irrespective of the COVID-19.[13]

4.4. Alternative measures for bubbles

While the aforementioned results provide solid evidence for the role of media coverage in bubble growth, a reasonable concern is that the way we detect bubbles

[12] For more information, please visit https://www.forbes.com/sites/markbeech/2020/03/25/covid-19-pushes-up-internet-use-70-streaming-more-than-12-first-figures-reveal/?sh=4273c44e3104.
[13] We also investigate how media coverage influences Bitcoin returns in the market downturns. The results are presented in Table A2 in the appendix.

affects our conclusions. To respond to this concern, we conduct some robustness checks.

In the first two panels of Table 9, we follow Enoksen *et al.* (2020) and use two measures derived from the PSY statistic to define bubbles. Specifically, we first employ the PSY statistic itself (*PSY*), i.e., the supremum of the estimated ADF statistic BSADF, as the bubble measure. The second measure is a dummy variable (*Bubdum*) which equals one when the BSADF statistic is above the generated 95% asymptotic critical value and zero otherwise. And then, we regress *PSY* or *Bubdum* on the lagged media coverage measures as well as other control variables included in equation (7). It is obvious that our main finding, i.e., media coverage helps the growth of Bitcoin bubbles, still holds with these two measures.

In the above analysis, we do not take fundamentals into consideration when employing the PSY method to detect bubbles. In the following test, we examine whether our main conclusions change after considering the fundamental value of Bitcoin. So far, no consensus has been reached on how to measure the intrinsic value of Bitcoin. However, some scholars, such as Hayes (2019), find that the intrinsic value of Bitcoin could be related to the marginal cost of producing one bitcoin. This is because mining for bitcoins involves a great amount of electricity, which imposes costs on miners. And according to the economic theory, the product's price should move towards its marginal cost of production if all producers make the same product in a competitive market. Meanwhile, Bhambhwani *et al.* (2019) show that the computing power captures the trustworthiness of the blockchain, thereby determining the value of mineable cryptocurrencies. Motivated by these findings, we use Cambridge Bitcoin Electricity Consumption Index (CBECI) to measure the power usage of mining for bitcoins as well as Bitcoin fundamentals. And then, we re-define bubble periods with the price-to-power-usage ratio (*PP*) and replace *Ret* with *PP* to re-conduct the VAR analysis. The results are shown in Panel C of Table 9. The coefficient estimate of $News_{t-1}$ in the first column is 0.0264, significant at the 5% level, indicating the price-to-power-usage ratio on the next day is positively related to the amount of news coverage in the bubble period. And again, we detect no significant relationship between media coverage and the next day's price-to-power-usage ratio in the non-bubble period.

Collectively, the results suggest that our conclusions do not depend on how bubbles are measured.[14]

5. Conclusions

Financial bubbles have held a fascination for economists and historians for centuries (e.g., Abreu and Brunnermeier, 2003; K. Brunnermeier and Nagel, 2004; Griffin *et al*., 2011; Greenwood and Nagel, 2009). This is in part due to the difficulties in explaining human behaviors in bubble episodes and in part due to the devastating side effects of price collapses following bubbles. Although Shiller's claim that media coverage could contribute to bubble development is famous, to date, little empirical analysis confirms it. In the paper, we take the task with Bitcoin data. Compared with the traditional asset markets, there is no official information source that could blur media coverage's effect. Also, despite its short history, Bitcoin has gone through several boom-bust cycles.

Using the bubble detection method proposed by Phillips *et al.* (2015a), we classify our sample period from January 2012 to October 2021 into the bubble and non-bubble periods. We also collect news data from Google News. Doing the VAR analysis in the bubble and non-bubble periods, respectively, we find that Bitcoin returns on the next day are positively related to media coverage (no matter positive or negative) in the bubble period and no significant relationship between media coverage and Bitcoin returns in the non-bubble period, demonstrating Shiller's claim. Besides, we also find that our conclusions can be extended to other cryptocurrencies, Bitcoin trading in non-English speaking countries, and the COVID-19 period and are robust to alternative measures for bubbles.

With the aforementioned findings, our paper advances the existing understanding of media coverage's role in capital markets and the drivers of Bitcoin prices.

[14] In addition, we also conduct some robustness checks to show that our results do not depend on the measurement of media coverage and model specifications. The results are reported in Tables A3, A4, and A5 in the appendix.

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