# The Content Matters: The Impact of Blockchain and Bitcoin Disclosure on Stock Performance

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*Abstract:* In this paper, we investigate the stock performance of firms that mention bitcoin, blockchain, or cryptocurrency (BCB) in their 10-K filing. Specifically, we hypothesize that the link observed in the literature between these stocks and bitcoin return is due to both assets separately comoving with relevant news events. To test this hypothesis, we perform textual analysis on both the firms' 10-K filing around the mention of BCB and news stories related to BCB released over the next calendar year. We indeed find that the stock returns and bitcoin return only have a statistically significant relationship on days when the news story content is highly similar to the 10-K content. We also find that these stocks have a stronger reaction when the news story is negatively worded. Trading volume is also significantly higher on the days with a similar news story, suggesting that investors are aware of the link.

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# 1. Introduction

With the recent surge in the prevalence of cryptocurrencies and blockchain, there has also been a surge in research in this area.[1] Publicly traded firms have also started to increase their exposure to cryptocurrencies and blockchain.[2] Thus, Cheng et al. (2019) look at firms' 8-K disclosures where blockchain, cryptocurrency, or bitcoin[3] (which we will refer to as BCB hereafter) are mentioned. The authors investigate the type of disclosures and the firms that disclose these activities, and they find an immediate and positive investor response, which then reverses after about a month. Cahill et al. (2020) find a large positive investor reaction on the 8-K announcement day for firms that disclose blockchain investments. The authors also find the puzzling result that these firms react to bitcoin performance, which should be separate from the blockchain technology. Autore et al. (2020) also find a significant short-term stock price reaction to blockchain disclosure.

The previously mentioned studies also arrive at different conclusions as to whether the stocks that disclose BCB exposure/investment/adoption (hereafter, the BCB stocks) comove with bitcoin price, depending on the sample of stocks. Cheng et al. (2019) find that an equal-weighted portfolio of the stocks that disclose BCB in their 8-K filing comove with bitcoin. However, Cahill et al. (2020) find that a larger sample of stocks mentioned in news headlines (rather than financial disclosures), along with the mention of blockchain, does not comove with bitcoin. We attempt to resolve this discrepancy by investigating, in a systematic manner, whether U.S. stocks with some exposure to BCB comove with bitcoin.

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[1] According to Akyildrim et al. (2020a), 135 and 467 publications in 2017 and 2018 were related to cryptocurrency research, respectively.
[2] See for example, Cheng et al. (2019), Jain & Jain (2019), Cahill et al. (2020), Autore et al. (2020), Sharma et al. (2020), and Akyildirim et al. (2020b).
[3] We follow the convention of using Bitcoin to refer to the system, and bitcoin to refer to the unit of account.

However, the scope of our study goes beyond resolving this discrepancy in the literature. We also aim to investigate *when* these stocks react to bitcoin movements, or rather, under what conditions. We posit that the BCB stocks may not react to every bitcoin price shift but rather may only react to relevant and salient news related to BCB. While there may be some level of "bitcoin mania" that drives these stocks' prices, there are several factors that are likely to limit this relationship. First, the companies may not be directly exposed to bitcoin, but rather to some other currency or to blockchain only. Second, the disclosure could mention bitcoin as a threat rather than an investment opportunity. Finally, bitcoin itself is very volatile, with many days of large price movements, so investors may only react at certain times. To proxy for the events that the stocks may *actually* react to, we use news stories in the Wall Street Journal (WSJ) and New York Times (NYTimes) that mention BCB. We use 10-K disclosures to select our stocks, and we perform textual analysis on both the 10-K disclosure (around the mention of BCB) and the news story. Using 10-K disclosures (rather than name changes or 8-K disclosures as others in the literature use) should provide a sample of firms that are not merely disclosing speculative BCB activity, which is why Autore et al. (2020) use 10-K disclosures as a measure of "credible" investments in blockchain. The textual analysis allows us to create a cosine similarity score for the 10-K report and the news story, which gives us a measure of how similar the wordings of the two are. We argue that this would help resolve the three points above, as we would only expect stock prices to move when the news is relevant to the company's BCB disclosure. We also argue that the stocks would only react to bitcoin price movements on days when there is relevant news (i.e., related to the 10-K disclosure) that the market would integrate into the stock's price. Thus, we would expect the stock prices and bitcoin to show more significant co-movement on days with relevant news.

To provide further context, we also analyze the sentiment of the news story and create a measure of the positive versus negative wording. It is not clear if negative news should matter more than positive ones, but we nonetheless investigate whether the BCB stock prices react more to negative or positive news stories and if this news sentiment affects the stock price and bitcoin co-movement.

We also aim to extend the literature in the following ways: 1) We extend the existing studies to a longer horizon (the calendar year after the 10-K filing). The studies previously mentioned focus on the short-term market reaction to some announcements related to BCB, whereas we focus on the longer-term performance of the stocks after the disclosure and what affects that performance. 2) We include bitcoin and cryptocurrency in addition to blockchain disclosures, similar to Cheng et al. (2019). 3) We investigate whether these stocks react to cryptocurrency and blockchain shocks and, perhaps most importantly, what type of shocks. We include cryptocurrency disclosures in order to increase robustness, and since cryptocurrencies (especially bitcoin) and blockchain are so closely linked, with both are rising in popularity. We use 10-K filings from 2013 to 2018; thus, we use returns from 2014 to 2019.

To preview the results, we find evidence that the relationship between bitcoin price and the BCB stock prices is dependent upon the similarity score. While we find that our sample of stocks has a significantly higher average return on days with a high bitcoin return (compared to days with a low bitcoin return), once we control for the news similarity, we find no significant difference. In an attempt to confirm whether investors are indeed paying attention to both the 10-K content and the news content, we also report the average trading volume for the days of these events. We find that trading volume is significantly higher on the same days in which the returns are significantly higher, suggesting that investors are trading on these events (while potentially ruling out an illiquidity explanation). Thus, we find evidence in support of our main hypothesis, but we also find that both large bitcoin price movements *and* relevant news must be present for there to be a statistically significant difference in the stocks' returns.

In our empirical analysis, we examine the average return of our BCB stocks on the following days: days of high (above the 70th percentile) bitcoin return, days of low (below the 30th percentile) bitcoin return, days of news stories with a positive tone/sentiment, days of news stories with a negative tone/sentiment, days of similar news stories (similarity score above the median), days of less similar news stories (similarity score below the median), and days of no news stories and medium bitcoin return for comparison. We also perform two-way and three-way sorts (e.g., days of high bitcoin return and similar news stories) and report the average returns for those days. We find the following pattern: the BCB stocks have significantly higher average returns on days of high bitcoin return and similar news stories (compared to low bitcoin return days and less similar news stories). Our two-way sorts show that a similar news story must be present for the bitcoin-BCB stock relationship to hold. This could explain the finding of Cahill et al. (2020) that firms disclosing a blockchain investment react to bitcoin performance, even though the two are separate entities. We find that the bitcoin price movement must coincide with news that would be similar to what the firm mentioned in their disclosure. However, we do include firms that disclose/mention cryptocurrency as well, so our results are not directly comparable to those of Cahill et al. For robustness, we regress the raw returns and risk-adjusted returns on bitcoin return, similarity score, news sentiment, and other control variables. Our general results hold in this setting in that the interaction between similarity score and bitcoin return dominates the other factors. We find that a stock's liquidity matters here as well.

As to the effect of news story sentiment, we find that the BCB stocks have a higher return on positive news story days compared to negative news story days, but the difference is not statistically significant. However, the impact of the news story sentiment becomes clear when bitcoin movements and the similarity score are included. We find that the BCB stocks have very low (highly negative) average returns on days of both negative news and low bitcoin returns, and these average stock returns are significantly lower than days of both negative news and high bitcoin return. This difference is even more extreme when the news story is similar in content to the 10-K disclosure. However, on positive news story days, there is no significant difference in the stocks' returns when bitcoin return is low versus high. Thus, the stocks, in general, have a higher return on days with positive news stories. However, the reaction to relevant news and bitcoin movements is much more pronounced when the news sentiment is negative.

The rest of the paper proceeds as follows: Section 2 reviews the relevant literature and gives some background to bitcoin (and cryptocurrencies in general) and blockchain. Section 3 details our data and methodology used and defines the variables used. The results are provided in Section 4. Section 5 concludes.

## 2. Literature Review and Hypotheses

This study is related to a nascent but growing literature that examines the impact of blockchain and digital currency adoption on firm and stock performance (Cheng et al., 2019). The research interest in BCB follows bitcoin's rise in popularity among individuals and corporations and the attention to blockchain, its underlying technology (Grant, 2017; Tapscott & Tapscott, 2017; Carson et al., 2018; Schmidt & Wagner, 2019; Culpan, 2020). Nakamoto (2008) introduced[4] the concept of Bitcoin as "a peer-to-peer electronic cash system." It refers to both the cryptocurrency

[4] Narayanan & Clark (2017) claim that many of the ideas and technologies that led to the invention of Bitcoin were based on the earlier academic literature, and Nakamoto's true innovation is the way these components are combined.

and the payment system that verifies and stores the digital currency transactions or blockchain. There is substantial uncertainty regarding the ultimate use and success of blockchain technology and cryptocurrencies. They are touted by many as disruptive technologies that can disintermediate established financial institutions and reduce transaction costs (e.g., Tapscott & Tapscott, 2017; Stevens, 2017). On the other hand, others consider blockchain and cryptocurrency markets over-hyped and destined to failure (e.g., Roubini, 2018).

There are multiple emerging strands of literature on BCB.[5] Several studies focus on how blockchain works and the mechanism and implications of cryptocurrency markets (e.g., Böhme et al., 2015; Yermack, 2017; Abadi & Brunnermeier, 2018; Raskin & Yermack, 2018; Cong & He, 2019; Easley et al., 2019; Catalini & Gans, 2020; Cong et al., 2021a; Saleh, 2021). For example, Böhme et al. (2015) examine the Bitcoin ecosystem in its early days and provide insights regarding the future of digital currencies as financial assets and their risk, regulatory challenges, and monetary policy implications.[6] Yermack (2017) explores the corporate governance implications of blockchain and contends that the technology can alter the relative power of managers and shareholders in favor of shareholders by introducing more transparency to management actions and greater liquidity to the market.

Cong & He (2019) focus on an important feature of blockchain technology, namely, decentralized consensus, which facilitates the creation and execution of smart contracts. They build a theoretical model to show that these features of blockchain can reduce information asymmetry and improve consumer welfare. On the other hand, blockchain could promote collusion between sellers;

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[5] A few studies attempt to provide a comprehensive review of the BCB literature. For example, see Yli-Huumo et al., 2016, Corbet et al., 2019, and Akar & Akar, 2020.
[6] The total market capitalization of Bitcoin has grown from $3.5 billion in March 2015, as reported by Böhme et al. (2015), to more than one trillion dollars as of March 2021 (*Source:* www.blockchain.com).

therefore, blockchain technology's successful application requires carefully-designed protocols and appropriate antitrust policies. Catalini & Gans (2020) claim that blockchain technology can reduce the costs of running a decentralized marketplace, specifically, the verification and networking costs. Consequently, it can lead to more innovation and competition. In contrast, Abadi & Brunnermeier (2018) identify a "blockchain trilemma"; that is, the distributed ledger cannot simultaneously achieve correctness, decentralization, and cost-efficiency. Overall, this literature identifies crucial aspects of BCB and the social and economic implications of their adaptation.

Other studies examine the Initial Coin Offerings (ICOs) and asset pricing properties of cryptocurrencies (e.g., Urquhart, 2016; Liu & Tsyvinski, 2018; Catalini & Gans, 2018; Brauneis & Mestel, 2018; Corbet et al., 2018; Hu et al., 2019; Makarov & Schoar, 2020; Sockin & Xiong, 2020; Howell et al., 2020; Cong et al., 2021b). For example, Urquhart (2016) uses the daily closing price of bitcoin (in U.S. dollars) from August 2010 through July 2016 to investigate the efficiency of the bitcoin market. The results reveal that although bitcoin returns were inefficient over the period, the efficiency has improved in later years. Liu & Tsyvinski (2018) examine the determinants of returns for three major cryptocurrencies: Bitcoin, Ripple, and Ethereum. They show that cryptocurrency prices are not driven by common risk factors, such as stock and bond market returns, macroeconomic variables, currency exchange rates, and commodity prices. Instead, they are driven by factors such as momentum in the cryptocurrency markets and investor attention (measured by, for example, the change in the number of Google searches for each digital currency).

Similarly, Corbet et al. (2018) study the relationship between the return of three popular cryptocurrencies (Bitcoin, Ripple, and Litecoin) and other financial assets in the 2013-2017 period. They also find that the returns on different cryptocurrencies are highly correlated but disconnected from other assets. Finally, Howell et al. (2020) investigate the emerging phenomenon of Initial Coin Offerings (ICO). They analyze more than 1,500 ICOs, which raised a combined capital of $12.9 billion from 2014 to 2018, to identify their major real-world success factors. They show that an ICO's outcome depends on factors such as issuer characteristics, including experience and credible commitment, voluntary disclosures, and the successful listing of the ICO tokens. Overall, this subset of the literature highlights the rapid rise of cryptocurrencies as an alternative asset class.

Another group of studies focuses on the role of cryptocurrencies as a medium of exchange and their bubble dynamics (e.g., Baek & Elbeck, 2015; Cheah & Fry, 2015; Cheung et al., 2015; Brandvold et al., 2015; Fry & Cheah, 2016; Blau, 2018; Ammous, 2018; Baur et al., 2018; Gandal et al., 2018; White et al., 2020). Baek & Elbeck (2015) examine the bitcoin market in the initial years, i.e., from July 2010 to February 2014, and conclude that it is highly speculative. Similarly, Cheah & Fry (2015) conclude that bitcoin has zero fundamental value and, hence, highly susceptible to price bubbles. In more recent studies, Baur et al. (2018) and White et al. (2020) show that bitcoin mainly resembles a technology-based product or a speculative investment rather than a currency. Finally, Gandal et al. (2018) report that the unprecedented rise in bitcoin's value in late 2013 (from $150 to more than $1,000) was likely caused by market manipulation. Overall, despite the recent institutional endorsements and rise in the value of bitcoin and other digital currencies,[7] the literature cast doubt on their viability as a medium of exchange or store of value.

[7] For example, in October 2020, PayPal Holdings, Inc announced that it will enable its users in the United States to buy, hold, and sell four major cryptocurrencies (PayPal, 2020). Similarly, in its 10-K filing to the Securities and Exchange Commission (SEC) for the fiscal year of 2020, Tesla, Inc. reported that it has bought $1.5 billion worth of bitcoins and plan to accept bitcoin as payment. In March 13, 2021, the price of one bitcoin surpassed $60,000 before dropping the next day.

### 2.1. The Impact of BCB Adoption and Name Change on Stock Performance

More relevant to our paper, multiple recent studies investigate the effect of BCB adoption (Cheng et al., 2019; Cahill et al., 2020; Autore et al., 2020; Yen & Wang, 2021) and BCB-related name change (Jain & Jain, 2019; Sharma et al., 2020; Akyildirim et al., 2020a; 2020b) on stock prices and returns. Cheng et al. (2019) explore the market reaction to public firms' 8-K disclosures that mention BCB for the first time between November 2013 and May 2018. They show that the timing of the disclosures mirrors the rise in bitcoin price and Google searches. They further split their sample of 82 unique firms to speculative and existing disclosures and show that the market initially reacts positively to speculative disclosures, especially when bitcoin returns are positive. However, the reaction largely reverses within 30 days of the disclosure. They argue that investors could be willing to pay a high price for stocks of firms exposed to BCB due to the limited supply of such stocks.

Cahill et al. (2020) investigate the market reaction to blockchain-related announcements of 713 firms across 45 countries between November 2016 and December 2018. They find that the average abnormal return on the announcement day is 5.3% in their sample. Additionally, U.S. and smaller firms experience higher announcement abnormal returns compared to non-U.S. and larger firms. Similar to Cheng et al. (2019), they break their sample into speculative and non-speculative announcements and report that non-speculative (i.e., more committed) announcements are associated with lower abnormal returns. Interestingly, although they only focus on blockchain-related news, they report that the observed abnormal returns are linked to bitcoin returns, likely because investors confuse bitcoin- and blockchain-related investments. Moreover, the correlations between the firms' stock returns and bitcoin returns increase after the announcements. Finally, they find that buying and holding the stocks in their sample results in positive and significant alphas, which are strongest in 2017.

Autore et al. (2020) investigate the shareholder value creation associated with the adoption of blockchain technology, i.e., the first announcement of a firm's investment in blockchain. Using 249 news announcements, they report an initial positive market reaction of 13%, on average. However, contrary to Cheng et al. (2019) and Cahill et al. (2020), they find that more credible announcements, i.e., the ones related to investments in an "Advanced" stage or followed by the inclusion of the term "blockchain" in the following 10-Q or 10-K filing, are associated with higher initial stock returns and little or no reversal in the next three months. Overall, these studies document the impact of BCB investments on stock performance. However, they primarily focus on the market reaction around the investment news and provide mixed evidence on the shareholder reaction to credible vs. speculative announcements.

In a recent study, Yen & Wang (2021) examine the effect of BCB disclosures in the 10-K filings on the stock price three months after the fiscal year-end. They use textual analysis, specifically, the latent Dirichlet allocation (LDA) method, to group disclosures into multiple topics. They find that only disclosures about the solutions and risk factors of blockchain technology positively affect the market value of the stock. On the other hand, they report that bitcoin- and cryptocurrency-related disclosures have a marginal or negative effect on the stock price.

Investors' attention to bitcoin has prompted many companies to change their names by incorporating one of the BCB keywords. For example, in December 2017, the Long Island Iced Tea Corp changed its name to the Long Blockchain Corp. The company's stock price increased by 300% in one day (Shapira & Leinz, 2017). Accordingly, several studies investigate the implications of a BCB-related name change. Jain & Jain (2019), using a sample of ten companies, find that the name change is associated with significant positive abnormal returns for two months. However, the returns reverse from positive to negative within two to five months after the event. Sharma et al. (2020), based on a sample of 52 firms, also find a positive and significant effect on the stock returns after the inclusion of blockchain or cryptocurrency in the company's name. They show that the observed positive abnormal returns remain strong even 50 days after the announcement and cannot be explained by common industry factors. Finally, using a sample of 82 name-change announcements across 13 countries, Akyildirim et al. (2020b) show that firms use blockchain-related name changes to benefit from a "crypto-exuberant" stock market premium. However, such practices hurt the firms' profitability and financial leverage.

We argue that even though studies show that many firms, with highly speculative motives, attempt to ride the bitcoin and blockchain "mania" (Cheng et al., 2019; Akyildirim et al., 2020a), adoption of such radical technologies, if credible, could lead to strong financial performance and high growth for adopting firms (Srinivasan et al., 2002).

## 2.2. Hypotheses and Research Questions

As we discuss in the previous section, there is mixed evidence on the impact of BCB adoption on stock performance. Although most studies point to such investments' speculative nature, there is an indication that the announcement of credible investment blockchain technology leads to a favorable and sustained stock market reaction (Autore et al., 2020). We attempt to extend this nascent literature by investigating the implications of BCB investment for stock performance beyond the announcement effect.

The content of the financial reports, i.e., the 10-K filings, can be used to identify credible BCB activity. Corporate disclosures, e.g., through the SEC filings, provide important information to investors and can strongly impact firm value and stock performance (Jiao, 2011). Therefore, unlike name changes, public relations, or 8-K reports, BCB activity disclosures in the 10-K filing suggest more commitment from the firm. Following the disclosure, the company's stock price could become more correlated with bitcoin price (Cahill et al., 2020) and react to bitcoin price movements or news about BCB. It is well-established that the stock price is influenced by macroeconomic news or news about the firm (Birz & Lott, 2011; Gurun & Butler, 2012; Heston & Sinha, 2017). However, we expect the stock price to only respond to relevant BCB news – i.e., when investors can identify valuation relevant information from the 10-K report and news story and integrate it to stock price (Loughran & McDonald, 2014).

Finally, although BCB stocks could react to relevant news regarding bitcoin or blockchain technology, the news's content or sentiment may not directly predict the direction of the reaction. Unlike fiat currencies, bitcoin reacts positively irrespective of the news sentiment (Rognone et al., 2019). Consequently, BCB stocks could also react positively to both positive and negative BCB news as long as the bitcoin price is rising. Therefore, the stock performance of BCB stocks could depend on the interaction between the arrival of relevant news and bitcoin price movements or cryptocurrencies sentiment (Baig et al., 2019; Smuts, 2019). We thus predict the BCB stocks to react to relevant news and move in the direction of bitcoin returns. Accordingly, we formulate our main hypotheses as follows:

> H1: The BCB stocks will react more strongly to BCB-related news stories that are similar in content to the 10-K disclosure.
>
> H2: The BCB stocks will comove more strongly with bitcoin on days when a news story that is similar to the 10-K disclosure is released.

We argue that the price of movement of BCB stocks – in the presence of relevant news – depends strongly on bitcoin sentiment rather than the sentiment of the news story. However, we cannot rule out the potential impact of news sentiment, especially since prior studies have identified different stock market reactions to positive versus negative news about the firm (e.g., Heston & Sinha, 2017). To examine this, we consider the following research questions:

> RQ1: Do the BCB stocks react more strongly to negative or positive news stories?
>
> RQ2: Is the relationship between a stock's price and bitcoin affected by the positive or negative sentiment of news stories?

# 3. Data and Methodology

## 3.1. Sample Construction

We construct our sample to measure firms' exposure to blockchain and cryptocurrency risk and their stock returns. We start by searching for relevant keywords, "blockchain," "bitcoin," "cryptocurrency," and their variants, in the 10-K filings submitted to the Securities and Exchange Commission (SEC).[8] We identify 324 firms that have mentioned any of the keywords in their 10-K reports in the fiscal years of 2013-2018. We then drop any firms from our list with missing fundamentals data from the Standard and Poor's Compustat database in the same fiscal year as the 10-K filings. Similarly, we drop any firms with missing stock return data from the Center for Research in Security Prices (CRSP) in the same or following calendar year. Finally, we drop any firm whose name contains a BCB keyword. This strategy allows us to construct our main variables and control variables and leaves us with a sample of 110 unique stocks and 190 annual observations.

[8] We use SeekEdgar service to identify a list of companies that have mentioned any of the relevant keywords in their SEC filings, and to retrieve the address of the filings on the SEC EDGAR website.

We match the 10-K reports with news about blockchain, bitcoin, or cryptocurrencies in the WSJ and the NYTimes in the calendar year following each report (i.e., the calendar years of 2014-2019). We identify 855 relevant news articles over 574 days within our sample period. The final sample is constructed by combining the fiscal year-end 10-K and fundamentals data with the calendar year news and stock return data. It consists of 45,850 stock-day observations, with 16,783 observations on days with a related news story published in the WSJ or NYTimes.

### 3.2. Key Variables

We use a novel, text-based approach to investigate how the BCB stock prices comove with bitcoin price. In the past decade, the application of textual analysis and text-based measures has increased significantly in the finance and accounting literature.[9] For example, Hoberg & Phillips (2010, 2016) develop a text-based, time-varying industry classification based on the content of the 10-K reports of public U.S. firms. They find that their classification outperforms traditional measures in explaining product market synergies in mergers and acquisitions and product differentiation among peer firms. In our approach, we first extract snippets from each 10-K report that contain any of our keywords. The snippets are generated by extracting five sentences around any appearance of a keyword in the document. All graphics and exhibits are excluded, and any overlapping sentences are included only once. Then, we follow well-accepted textual analysis techniques and apply preprocessing procedures to the news articles and 10-K report snippets (Loughran & McDonald, 2011, 2016; Shapiro et al., 2020). These procedures include removing punctuations, numbers, stop words (such as “the,” “of,” and “and”), and any words with less than

[9] See Loughran & McDonald (2016) for a recent survey of textual analysis in the accounting and finance literature.

three characters. They also include lemmatization, which maps a word to its "lemma" or dictionary form.[10]

In the next step, we create a Bag of Words (BoW) of the 5,000 most frequently used words from the preprocessed corpus of the 855 news articles. This BoW represents our "terms space" and is used to generate fixed-length, binary document vectors for each news article and 10-K report snippet. Each vector element corresponds to a word or term in our "terms space" and takes the value of one if the associated word is used in the given document and zero otherwise. Finally, we calculate the cosine similarity between each 10-K report and news articles published in the following calendar year. The cosine similarity between binary document vectors $\boldsymbol{V_1}$ and $\boldsymbol{V_2}$ is calculated as follows[11]:

$$\text{Similarity}(\boldsymbol{V_1}, \boldsymbol{V_2}) = \frac{\sum_{i=1}^{n} V_{1,i} V_{2,i}}{\sqrt{\sum_{i=1}^{n} {V_{1,i}}^2} \sqrt{\sum_{i=1}^{n} {V_{2,i}}^2}}, \tag{1}$$

where $V_{1,i}$ and $V_{2,i}$ represent the $i$th element of vectors $\boldsymbol{V_1}$ and $\boldsymbol{V_2}$, respectively. Since the vector elements are non-negative, the similarity measure ranges from 0 to 1 and is invariant to document length. To create a daily measure of similarity, we take the average of cosine similarity between a report and all the news articles published on the same day. In other words, the cosine similarity identifies the semantic similarity between the 10-K reports and the relevant news stories published on a particular day.

We retrieve daily return data from CRSP and Fama-French Factors databases. Similar to Ince & Porter (2006) and Hou et al. (2011), we screen outliers in the return data. Specifically, we set any

[10] We conduct textual analysis using KNIME Analytics Platform (Berthold, et al., 2007). KNIME provides an extensive text processing toolset based on Stanford CoreNLP Natural Language Processing library.
[11] See Appendix A for examples of similarity scores, the excerpts from the 10-K and news story, and a daily plot of the similarity scores.

daily return above 13.64% (the equivalent of 300% monthly) to missing if it reverses the following day. Additionally, we trim the daily returns at the 0.1% and 99.9% of the sample distribution. Our primary dependent variable is the adjusted daily stock return. Adjusted returns are the error terms from the full-sample time-series regressions of excess daily stock returns on the Fama-French-Carhart four (FF4) factors (excess return on the market, small minus big, high minus low, and momentum), without the intercept (Fama & French, 1992; Carhart, 1997). Excess returns are the difference between the CRSP daily stock returns and the risk-free rate, or the one-month U.S. Treasury Bill rate. Market return is the value-weighted return of all CRSP firms incorporated in the U.S. and listed on one of the three major exchanges.

This study focuses on how exposure to blockchain and cryptocurrencies affect stock performance. If a firm is exposed to such risk, we expect its stock performance to depend on the market sentiment toward bitcoin. We use two different variables to measure this sentiment. First, we use bitcoin return, which is the daily percent change in bitcoin's price. Alternatively, we use the sentiment of the news stories. News sentiment is the number of positive words minus the number of negative words, divided by the total number of words in a news article.

We follow a procedure similar to Shapiro et al. (2020) and use two lexicons frequently used in sentiment analysis to identify positive and negative words in a document: 1) the 2014 updated version of the Loughran-McDonald financial dictionary (Loughran & McDonald, 2011); and 2) the Hu-Liu sentiment lexicon (Hu & Liu, 2004). Additionally, any positive word is counted as negative if preceded within two words by a negation term, such as "not." The list of negation words is retrieved from the VADER open-source sentiment analysis tool (Gilbert & Hutto, 2014). Shapiro et al. show that this sentiment analysis model outperforms models with only the financial lexicon or without the "negation rule" in predicting human sentiment rating.

Consistent with the extant literature, we control for factors that affect stock return in our panel regressions. We control for stock liquidity, firm size, market-to-book ratio, equity beta, and prior-year return. All the control variables are calculated annually in the same calendar or fiscal year as the 10-K report. Additionally, the variables are winsorized at the 1% and 99% levels of their sample distributions. Stock liquidity is the total annual trading volume scaled by the average shares outstanding. Size is the natural logarithm of market capitalization in millions of USD. Market capitalization (market equity) is the closing price multiplied by the number of shares outstanding (in millions) at the end of the fiscal year. Market-to-book is the ratio of market equity to book equity. Book equity is common equity plus deferred taxes and investment tax credits. Equity beta is the coefficient estimate from the daily Capital Asset Pricing Model (CAPM) regression in the corresponding calendar year. The annual return is the buy-and-hold return on the stock in the corresponding calendar year. Finally, we conduct additional tests to examine the variations in trading volume for the stocks in our sample around the relevant news. We use the daily trading volume scaled by the number of shares outstanding as dependent variable in those regressions.

### 3.3. Empirical Methodology

We start our analysis by examining the time-series variation of the return on the BCB stock portfolio. Consequently, we estimate the following time-series regression of the daily excess return on the equal-weighted portfolio of BCB stocks on several risk factors:

$$Excess\ BCB_t = \alpha + \beta_1 \times Excess\ Market_t + \beta_2 \times SMB_t + \beta_3 \times HML_t + \beta_4 \times UMD_t + \beta_5 \times Excess\ Bitcoin_t + \beta_6 \times HML\ Similarity_t + \varepsilon_t, \quad (2)$$

where $Excess\ Market_t$, $SMB_t$, $HML_t$, and $UMD_t$ are the FF4 factors described in the previous section. The excess bitcoin return is the difference between the return on bitcoin and the risk-free rate. $HML\ Similarity_t$ or the high-minus low similarity factor-mimicking portfolio return, is the difference between the daily return on the high-similarity and low-similarity BCB stocks. The high- and low-similarity BCB stock portfolios are constructed every year to include the BCB stocks with an average annual cosine similarity score above the 70$^{th}$ percentile and below the 30$^{th}$ percentile, respectively.

We continue by comparing the stock performance of the firms in our sample to the market and bitcoin return over the period of 2014 to 2019.[12] Next, we divide our sample across three dimensions: News sentiment, cosine similarity, and bitcoin return. Specifically, we compare the average stock return between the following subsamples: 1) days with negative versus days with positive news sentiments; 2) days with a below-median similarity versus days with above-median similarity (between the 10-K report and the news article); and 3) days with low (below the 30$^{th}$ percentile) bitcoin return versus days high (above the 70$^{th}$ percentile) bitcoin return. Moreover, we conduct average return comparisons across two-way and three-way split samples. This initial analysis enables us to examine what factors drive the performance of stocks in our sample.

In the next step, we estimate the linear panel regressions of stock returns. To minimize the influence of common risk factors on our results, we use the FF4-adjusted return as our primary dependent variable. We hypothesize that the stock performance of a firm exposed to bitcoin and blockchain is correlated with the market sentiment toward bitcoin or bitcoin return, but only in the presence of relevant news. We use bitcoin return, cosine similarity, and their interaction as our main explanatory variables to test this hypothesis. In particular, we estimate the following Ordinary Least Squares (OLS) model:

[12] In unreported results, we restrict the sample to 2017-2019 to be consistent with the relevant literature. However, since there are not many observations in the earlier years, the results remain qualitatively unchanged. These results are available upon request from the authors.

$$Adjusted\ Return_t^i = \alpha + \beta_1 \times Bitcoin\ Return_t + \beta_2 \times Similarity_t^i + \beta_3 \times Bitcoin\ Return_t \times Similarity_t^i + \sum_s Year_s + \boldsymbol{\Gamma} \times \boldsymbol{X_t^i} + \boldsymbol{\Phi} \times \boldsymbol{Z_{s-1}^i} + \varepsilon_t^i, \quad (3)$$

where $\boldsymbol{X_t^i}$ and $\boldsymbol{Z_{s-1}^i}$ are the sets of daily and annual (lagged) control variables, with all variables described in the previous subsection. In order to account for potential time and firm effects, which lead to bias in our standard errors, we include the year fixed effects in all our models and cluster the standard errors by firm (Petersen, 2009). A positive $\beta_3$ supports the notion that the stock price of firms exposed to cryptocurrencies and blockchain technology is driven by bitcoin return on days with a relevant, or similarly-worded, news story (H2). In alternative specifications, we also include firm and year fixed effects to address the concern that unobserved variables may impact our results.

Finally, we examine if trading volume is affected by bitcoin return, similarity, and stock performance. We argue that if investors take note of the content of 10-K reports and news stories around blockchain and cryptocurrencies, they will react to bitcoin price shocks by more heavily trading the corresponding stocks. Therefore, we expect to observe a similar pattern impacting the stock performance also to affect trading volume. We test this notion by first comparing the average daily trading volume across sub-samples formed based on news sentiment, similarity, and bitcoin return.

Next, we repeat our panel regressions using the daily trading volume as the dependent variable. Since we expect the change in trading volume to be mainly affected by the magnitude of the bitcoin price change and not its direction, we use the absolute value of bitcoin return in our specification. In particular, we estimate the following model:

$$Trading\ Volume_t^i = \alpha + \beta_1 \times |Bitcoin\ Return_t| + \beta_2 \times Similarity_t^i + \beta_3 \times |Bitcoin\ Return_t| \times Similarity_t^i + \sum_s Year_s + \boldsymbol{\Gamma} \times \boldsymbol{X_t^i} + \boldsymbol{\Phi} \times \boldsymbol{Z_{s-1}^i} + \varepsilon_t^i \quad (4)$$

# 4. Results

## 4.1. Summary Statistics

First, we present a basic overview of our data. In Table 1, we present the summary statistics of our daily and annual variables. The variable definitions are also provided in the table. Of note is the average buy-and-hold annual return of our sample of stocks, which is 0.7%, compared to the average daily return that is very close to zero. However, as we will demonstrate later, these stocks have extremely high returns on certain days. In Table 2, we provide the correlations of select variables. We find that the raw and risk-adjusted stock returns of the BCB stocks and the market return are positively and significantly (at a 5% level) related to bitcoin return. Bitcoin can be viewed as a haven or alternative investment, but in our sample, stock market returns are positively correlated with bitcoin returns, albeit at a low level.

[Table 1 goes here]

[Table 2 goes here]

To start, we examine how an equal-weighted portfolio of these BCB stocks loads on the FF4-factors, bitcoin return, and a long-short similarity score portfolio (high similarity minus low similarity). We provide the results of the regression shown in Eq. (2) in Table 3. The portfolio positively and significantly loads on all four traditional factors, as shown in Column (1). We also find that the excess bitcoin return factor has a positive and significant loading. Further, the similarity score factor carries a significantly positive coefficient, whether the bitcoin factor is included or not. For all specifications, the alphas are insignificant. Thus, these preliminary results suggest that the BCB stocks significantly react to both similar news stories and bitcoin return, lending support to H1 but not necessarily H2.

[Table 3 goes here]

### 4.2. Average Returns

We will now further investigate how these BCB stocks react to large bitcoin price changes and news related to blockchain and cryptocurrencies. We examine the average returns of our selected stocks on certain days based on the positive or negative sentiment of the news story, low or high similarity to the news story, and low or high bitcoin return. In Table 4, we provide the univariate average stock returns, market returns, and risk-adjusted returns (based on the FF4-factor model). We find in Panel A that the stocks have higher average returns on days that a positive news story is released compared to all other days, although the difference between positive and negative news story days is not statistically different (and adjusted returns are similar).[13] While news story days with a high similarity score have a negative return, the difference in raw returns for high and low similarity scores is not significantly different (see Panel B of Table 4).

[Table 4 goes here]

Finally, in Panel C of Table 4, we show the stocks' average returns on days of low bitcoin return (below the 30$^{th}$ percentile), high bitcoin return (above the 70$^{th}$ percentile), and medium bitcoin return (30$^{th}$-70$^{th}$ percentile). On the low bitcoin return days, the stocks have an average annualized return of -32%, compared to 17% on the high bitcoin return days. While the difference is noticeably large (and statistically significant) at 49 percentage points, the medium bitcoin return days result in an average annualized stock return of 19%, even higher than the high bitcoin return days. However, the risk-adjusted returns on medium bitcoin return days are -4.8% annualized, while the

[13] Although the differences in Panel A and B of Table 4 are large in magnitude and likely economically significant, they are not significantly different (due to large standard errors).

risk-adjusted returns on high bitcoin return days are 22.3% annualized. This is likely due to the market having a much higher return on the medium bitcoin return days. The risk-adjusted BCB stock returns on low and high bitcoin return days are significantly different as well. Also, although we reported a positive correlation between market returns and bitcoin returns in Table 2, the market has a low average return on high bitcoin return days (about ten annual percentage points lower than low bitcoin days). It appears that these stocks could make a good hedge to market risk in addition to cryptocurrency or blockchain risk.

The univariate sorts in Table 4 show that the BCB stocks have higher returns on days of high bitcoin return, which is similar to other findings in the literature. Also, the similarity score and news sentiment by themselves do not show significant differences in the average stock returns. However, it is the interaction between these that we are truly interested in: do they stocks still show high returns on high bitcoin return days if there is no relevant news on those days? Therefore, in Table 5, we perform bivariate sorts and report the average annualized returns. First, in Panel A, we sort based on bitcoin return and the similarity score. Surprisingly, we find that both the BCB stocks' average return and the average market return are higher on days when bitcoin return is low and a news story with a low similarity score is released, compared to those days when bitcoin return is high. Thus, on days with a low similarity score for the news story, the stocks do not positively comove with bitcoin. We do find that bitcoin and the BCB stocks positive comove when the similarity score is high, though. On days with highly similar news stories, the BCB stocks have an average annualized return of -53% when bitcoin return is below the 30$^{th}$ percentile, compared to an average annualized return of 46% when bitcoin return is above the 70$^{th}$ percentile. We report a similar and even stronger difference for the risk-adjusted BCB stock returns. Both differences are significant at a 1% level. This is the opposite of the market return, which is significantly lower on these days of high similarity scores and high bitcoin return (compared to days of high similarity scores and low bitcoin return).

In Panel B of Table 5, we see that the negatively worded news stories seem to matter more than the positively worded stories. The BCB stocks (and the market) have significantly higher raw and risk-adjusted returns on high bitcoin return and negative news sentiment days compared to low bitcoin return and negative news sentiment days. However, when the news sentiment is positive, this pattern is reversed for the raw stock returns. The risk-adjusted returns and market returns are still significantly higher on the high bitcoin return days, though. In Panel C, we report the results when sorting on both the similarity score and news sentiment. Here, we see that on negative news story days, returns on stocks with a low similarity score have a significantly higher return than those with a high similarity score. We again see that positive news story days result in a higher return compared to negative news story days, but the differences are not significantly different. To summarize, as in Table 4, we see in Table 5 that the BCB stocks positive comove with bitcoin, but now we see that this is only the case when the news is similar or negative. We also find that typically the overall stock market has the opposite pattern as the BCB stocks on those days.

[Table 5 goes here]

Finally, we perform sorts based on all three variables and report the average annualized returns in Table 6. In Panel A, we sort in the following order: first based on news sentiment, then similarity score, and finally bitcoin return, resulting in eight distinct subsamples. We report the average returns for each subsample, and we also report the difference between low and high bitcoin return days (the last sort). When there is a negatively worded news story with a low similarity score, there is no significant BCB stock return difference on low and high bitcoin return days (with high bitcoin return days performing slightly better). However, when there is a negatively worded news story with a *high* similarity score, there is a substantial (and statistically significant) difference between all three returns on low and high bitcoin days. Within the negatively worded stories and high similarity score sorts, on the low bitcoin return days the BCB stocks have an average annualized return of -89%, compared to +53% on the high bitcoin return days. We find a similar pattern for positively worded news stories as well, although only the adjusted return is significantly different in that case.

[Table 6 goes here]

In Panel B of Table 6, we change the sorting order to be first news sentiment, then bitcoin return, then similarity score. Here we find that on days with a negatively worded news story and low bitcoin return, stocks with a low similarity score have an average annualized return of almost 4%, while stocks with a high similarity score have an average annualized return of -87% (with the difference between the two being statistically significant at the 1% level). The same is true for their risk-adjusted returns. Thus, if bitcoin price has fallen and a negatively worded story is in the news, the BCB stock prices will only fall (on average) if their 10-K BCB disclosure content is similar to the news story. The opposite is true when bitcoin return is high (and news sentiment is negative): stocks with a high similarity score have an average annualized return of 38%, while those with a low similarity score have an average annualized return of -4% (although this difference is not statistically significant). This pattern also holds for positively worded news stories.

To summarize, stocks that mention bitcoin/cryptocurrency/blockchain in their previous year's 10-K have much higher average returns on days where both bitcoin return is high and a news story is released that is similar in content to the 10-K disclosure. The results in Tables 4-6 provide some support for H1 (BCB stocks reacting to similar news stories), but strong support for H2 (BCB stocks comoving more strongly with bitcoin when there is a similar news story). While the stocks may not necessarily react to a similar news story in isolation, they do react quite strongly to bitcoin price movements that coincide with a similar news story. And we also find the key result that the BCB stocks do not appear to comove with bitcoin if there is irrelevant (low similarity score) news.

As to our proposed research questions related to the effect of the sentiment of the news stories, the differences in average BCB stock returns are typically greater on days with negatively worded stories. Thus, it appears our answer to RQ1 is that the BCB stock prices react more to negative news stories. Similarly, the answer to RQ2 is that the BCB stock prices and bitcoin prices appear to comove more strongly when the news sentiment is negative. We argue that this is due to the negative news stories garnering more attention and possibly being more salient. It is not clear why the stocks would have such large, positive returns on days with a negative news story and high bitcoin return, though. We explore this more later in the paper when we examine the trading volume on these days.

### 4.3. Regression Analysis

We next perform several panel regressions to observe the impact of news sentiment, similarity score, and bitcoin return (and their interactions) on our sample of stocks' returns. We also add our control variables. We report the results of the regressions in Eq. (3), using for raw stock returns as the dependent variable, in Table 7. First, we see in our univariate regression in Column (1) that bitcoin return has a significantly positive coefficient. However, the sign is reversed when the similarity score and the interaction term between the two are added, again lending support to H2. The coefficient estimates of the similarity score are statistically insignificant. They are initially negative, but change sign when the controls variables are added. Thus, the results here do not support H1. The interaction between bitcoin return and similarity score has a significantly positive coefficient. Thus, bitcoin return only has a positive and significant relationship with our BCB stock returns when either 1) the similarity score is not included, or 2) when bitcoin return is interacted with the similarity score.

A dummy for positive news sentiment is statistically insignificant when added, which somewhat matches the earlier results: the news sentiment seems to amplify the relationship between bitcoin and the BCB stocks, but it does not matter much on its own. The results hold when the control variables are added as well. In Table 8, we report results that are qualitatively similar using the risk-adjusted stock returns as the dependent variable.

[Table 7 goes here]

[Table 8 goes here]

Other than the stock's return in the previous calendar year, the only control variable that is significant is liquidity. We also add a triple interaction term between bitcoin return, the similarity score, and liquidity in Column (5) of both Tables 7 and 8. Liquidity has a negative coefficient, while the triple interaction term has a positive and significant coefficient. Thus, the more liquid stocks tend to have lower returns, although the coefficient is only statistically significant at the 10% level in Table 8. The positive and significant coefficient on the triple interaction term means that a higher similarity score, higher bitcoin return, and higher liquidity results in a higher return. This could perhaps be interpreted as investors being able to trade based on the news more quickly and effectively when the stock is more liquid.

The results in Tables 7 and 8 confirm our earlier findings and lend further support to H2: the BCB stock prices appear to only positive comove with bitcoin price on days with a similar news story.

The panel regression results also show that the interaction between news events and bitcoin price is what seems to matter most in relation to BCB stock price movement.

### 4.4. Trading Volume

Thus far, we have described how these BCB stocks perform on average on various days. We now investigate the trading volume for these stocks as well. This is especially relevant for the negative news story days. Are investors reacting more to the negative news in their trading? Of course, if a company has invested in bitcoin or blockchain, it makes intuitive sense that their stock would react to shocks related to those, as the company's underlying assets may have changed in value. But are investors aware that the underlying assets may have changed, and do they react in the appropriate direction? We attempt to investigate if investors are reacting to these shocks and heavily trading the stock on those days. In other words, are enough investors paying attention to make the stock prices move in response to related news?

To attempt to answer this question, we start with the fact that liquidity is significant in the regressions in Tables 7 and 8. We then examine the trading volume on the days of high and low bitcoin return, high and low similarity scores, and positive and negative news stories. Using daily volume scaled by the number of shares outstanding, we report these results in Table 9. In Panel A of Table 9, we see that trading volume is higher on the days of news stories in general, with negatively worded stories resulting in significantly higher volume than positively worded stories. Also, trading volume is significantly higher when the news story is highly similar to the 10-K report content (compared to a low similarity score). Moreover, we find that trading volume is significantly higher on high bitcoin return days compared to low bitcoin return days.

[Table 9 goes here]

In Panel B of Table 9, we perform two-way sorts for the average daily trading volume. We find that within low bitcoin return days, high bitcoin return days, negative news story days, and positive news story days, high similarity scores result in significantly higher trading volume compared to low similarity scores. Also, the trading volume on negative news story days is significantly higher than on positive news story days when bitcoin return is high (but not when bitcoin return is low). In Panel C, we perform three-way sorts for the trading volume. We again find that high similarity scores result in significantly higher trading volume compared to low similarity scores, no matter the bitcoin return or news sentiment. We also find that the only time high bitcoin return days have significantly higher trading volume than low bitcoin return days is when there is a negative news story and the similarity score is high. High bitcoin return days have higher trading volume than low bitcoin return days for all other subsamples as well, but the differences are not significant in those cases.

Finally, in Table 10, we report the regression results of Eq. (4), where daily trading volume is the dependent variable. In Panel A, we use daily volume scaled by the total number of shares outstanding. We find the same general pattern as we did for our earlier tables: the absolute value of bitcoin return by itself has a significantly positive coefficient, but it turns negative and significant when the similarity score and the interaction term between bitcoin return and the similarity score are added. The similarity score coefficient is positive and significant (at least at a 10% level) for all regressions. The interaction term (between the absolute value of bitcoin return and the similarity score) is positive and significant for all regressions at the 1% level. Thus, when bitcoin return is of large magnitude in either direction *and* a similar (compared to the 10-K BCB disclosure content) news story is released, the volume is significantly higher.

We also find, for all specifications, a significantly negative coefficient for the dummy variable that equals one when the news story has a positive sentiment. Thus, there is significantly less trading on positively worded news story days, and significantly more trading on negatively worded news story days. We argue that this is evidence in favor of a stronger investor reaction due to the attention and saliency of a more negative story. However, when a negative and relevant news story is released but bitcoin return is high, investors react positively to this stock, as both return and volume are higher. Here, we should point out that the sentiment measure does not capture context or what part of the story the negative/positive tone is addressing. While it could be that the news is negative in relation to BCB, it is possible that the negative wording is referring to something else in the story. It could also be that the news content is negative in relation to bitcoin, but the company is invested only in blockchain. Using another example, the company could be investing in cryptocurrencies or holding an initial coin offering, and the news story is discussing (with a negative tone) the risks that cryptocurrencies represent to banks. This is where the similarity score should better capture what should be relevant for the stock. Nonetheless, the interaction between news sentiment and similarity both matter for these stocks, with our untested hypothesis being that investors react more strongly to the saliency of a negative story.

[Table 10 goes here]

The results in Tables 9 and 10 match our earlier results in that, for the subsamples in which the BCB stocks' returns are higher, their trading volume is also higher. Thus, we find some evidence that investors are reacting to only the relevant news/bitcoin shocks. While they do react to large movements in the price of bitcoin, it appears to be mostly when that is in conjunction with the release of a relevant news story. The effect is also amplified when the news story is negatively worded.

## 5. Conclusion

In this paper, we search firms' 10-K filings for mention of bitcoin, blockchain, cryptocurrency, (BCB), and other variants of those words. We end up with 110 firms that mention at least one of these words and have the data we require. We find that these firms' stock prices react to bitcoin movements, similar to findings in the existing literature. However, we hypothesize that these BCB stocks are unlikely to react to all movements in bitcoin price, only the relevant ones. Thus, we examine news stories in the Wall Street Journal and New York Times that mention BCB. Using textual analysis, we then measure the positivity/negativity of the news article and the similarity between the article and the firms' 10-K BCB disclosure. We find that the stock price reactions to large bitcoin movements are only significant when a news story is released that is similar in content to that firm's 10-K filing, with the effect amplified when the story is negative.

We find that investors, in general, seem to react more to negative news stories. Trading volume on these BCB stocks is on average higher on days with negative news stories, especially if the news story is similar in content to the 10-K. Additionally, on days where bitcoin return is low (and likely highly negative) and a similar but negative news story is released, the stocks have an average annualized return of -87% to -89%, depending on the sorting order. This strongly contrasts with the 38% to 53% annualized average return range if bitcoin return is high and a similar but negative news story is released. These high returns may be a sign that the negative wording of the news story lacks the appropriate context. Also, we do not control for what the negative words are referring to in the article. We acknowledge that our sentiment measure by itself should not be used to make wide-ranging conclusions. However, this could be an area for future textual analysis research to examine: do the negative stories have negative wording related to the appropriate BCB disclosure of the firm or is it unrelated? Our similarity score is independent of the sentiment measure, which means an unrelated negative wording is possible.

We control for several variables in a regression setting and use risk-adjusted returns for all our analysis and still find the same general pattern of results. We also find that trading volume is higher on days when bitcoin return is high, days when similar news stories are released, and days when both occur. Thus, investors seem to be aware of the relevant BCB news, and they incorporate this information into their stock valuation. Based on our results, news or shocks to BCB must be related to what the firm disclosed in their most recent 10-K report for there to be a stock price reaction. We, therefore, argue that firms should think carefully regarding the wording and content of their 10-K report, and they should think carefully regarding their investment in or exposure to cryptocurrencies and blockchain. To summarize, stock prices of firms invested in or exposed to BCB do not typically react to all news related to BCB. The stock prices do not typically react to all bitcoin price movements, either.

When there is a similar news story released, we find a large and significant difference in returns on days of low bitcoin return (which have an average return of -53% annualized) compared to days of high bitcoin return (which have an average return of 46% annualized). However, on days when the news story has a low similarity score, these average annualized returns are 25% for days of low bitcoin return and 10% for days of high bitcoin return. Thus, investors seem to be aware of the 10-K BCB disclosure content (or at least the implications within) and subsequent relevant news and events. A possible extension of this result is to investigate whether the content of the 10-K (or other financial filings) related to items other than cryptocurrencies and blockchain is important to investors. Of course, one would expect investors to be aware of disclosures that affect the assets of the firm, but is there a similarly large difference in returns when news is released about these items? Future research could explore this in more detail.

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**Table 1: Summary statistics**

This table reports the descriptive statistics for the main variables in the sample. The sample includes 110 unique firms that have mentioned bitcoin, blockchain, or cryptocurrency (i.e., the keywords) in their 10-K reports in the fiscal years of 2013-2018. The firms (10-K reports) are matched with news about blockchain or cryptocurrencies in the Wall Street Journal or the New York Times in the following calendar year. Panel A reports the daily variables. Raw returns are the CRSP daily stock returns. Market return is the Fama-French market return (the value-weighted return of all CRSP firms incorporated in the U.S. and listed on one of the three major exchanges). Adjusted returns are the error terms from the full-sample time-series regressions of excess daily stock returns on the Fama-French-Carhart four (FF4) factors (excess return on the market, small minus big, high minus low, and momentum) as in Fama & French (1992) and Carhart (1997). Bitcoin return is the daily percent change in bitcoin price. News story sentiment is the number of positive words minus the number of negative words, divided by the total number of words in a news story. Similarity is the cosine similarity between the content of each news story and the snippet containing a keyword in the 10-K report. The Snippets are generated by extracting the five sentences around any appearance of a keyword in the report. Any overlapping sentences are included only once. Panel B reports the annual variables. Stock liquidity is the total trading volume divided by the average number of shares outstanding throughout the prior calendar year. Size is the natural logarithm of market capitalization in millions of USD. Market capitalization (market equity) is the closing price multiplied by the number of shares outstanding (in millions) at the end of the fiscal year. Market-to-book is the ratio of market equity to book equity. Book equity is common equity plus deferred taxes and investment tax credits. Equity beta is the coefficient estimate from the daily Capital Asset Pricing Model (CAPM) regression in the previous calendar year. Annual return is the buy-and-hold return on the stock in the past calendar year. The sentiment of the 10-K report snippets is calculated similarly to the news sentiments.

| *Panel A: Daily Variables* | | | | | |
|---|---|---|---|---|---|
| Variable | N | Mean | Std. Dev | Min | Max |
| Raw Stock Return | 16,783 | -0.00002 | 0.02823 | -0.17581 | 0.27500 |
| Market Return | 16,783 | 0.00099 | 0.00835 | -0.04024 | 0.02339 |
| Adjusted Stock Return | 16,783 | -0.00065 | 0.02637 | -0.19115 | 0.28769 |
| Bitcoin Return | 16,783 | 0.00009 | 0.04790 | -0.18646 | 0.22948 |
| News Story Sentiment | 16,783 | -0.01023 | 0.03153 | -0.18274 | 0.07418 |
| Similarity | 16,783 | 0.13009 | 0.05001 | 0.00000 | 0.39135 |

| *Panel B: Annual Variables* | | | | | |
|---|---|---|---|---|---|
| Variable | N | Mean | Std. Dev | Min | Max |
| Stock Liquidity | 190 | 2.91313 | 4.23030 | 0.14763 | 32.22898 |
| Size | 190 | 7.78349 | 2.71207 | 1.75180 | 12.81121 |
| Market-to-Book Ratio | 190 | 4.76789 | 6.42075 | 0.45909 | 38.03821 |
| Equity Beta | 190 | 1.03099 | 0.69128 | -5.56572 | 2.54240 |
| Annual Return | 190 | 0.00702 | 0.44345 | -0.97911 | 1.79432 |

**Table 2: Full-sample pairwise correlations of selected variables**

This table reports the Pearson's correlation coefficients between selected variables in the sample. The variables are defined in Table 1. The stars denote the statistical significance of the coefficients at the 5% level.

| Variable | Sent_News | BTCRet | Return | MktRet | AR | StkLqd |
|---|---|---|---|---|---|---|
| News Story Sentiment (Sent_News) | 1 | | | | | |
| Bitcoin Return (BTCRet) | 0.0036 | 1 | | | | |
| Raw Stock Return (Return) | 0.0101 | 0.0613* | 1 | | | |
| Market Return (MktRet) | 0.0446* | 0.0355* | 0.2913* | 1 | | |
| Adjusted Stock Return (AR) | -0.0070 | 0.0605* | 0.9407* | 0.0167* | 1 | |
| Annual Stock Liquidity (StkLqd) | -0.0009 | -0.0092 | -0.0514* | -0.0047 | -0.0567* | 1 |

**Table 3: Factor regressions of the BCB stock portfolio return**

This table reports the results from the time-series factor model regressions. The dependent variable is the excess return on the equal-weighted portfolio of stocks that disclose BCB activity (the BCB stocks). The explanatory variables are the returns on the factor-mimicking portfolios (FMPs) and market and bitcoin excess returns. The first four explanatory variables are the Fama-French-Carhart four (FF4) factors described in Table 1. The excess bitcoin return is the difference between the return on bitcoin and the risk-free rate. The high- and low-similarity portfolios are constructed every year to include the BCB stocks with an average annual cosine similarity score above the 70th percentile and below the 30th percentile, respectively. The high-minus low similarity FMP return is the difference between the daily return on the high-similarity and low-similarity BCB stocks. Portfolio alpha is the intercept of the time-series regressions. The coefficient estimates and robust t-statistics (appearing below in parentheses) are reported. *, **, and *** denote the statistical significance of the coefficients at the 10%, 5%, and 1% levels, respectively.

| Variable | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Excess Return on the Market | 1.0350*** | 1.0160*** | 1.0377*** | 1.0136*** |
| | (53.02) | (49.13) | (53.79) | (49.96) |
| Small-Minus-Big Return (SMB) | 0.5113*** | 0.5251*** | 0.4837*** | 0.4890*** |
| | (15.38) | (15.08) | (14.59) | (14.17) |
| High-Minus-Low Return (HML) | 0.2011*** | 0.2013*** | 0.2027*** | 0.2047*** |
| | (5.66) | (5.30) | (5.77) | (5.49) |
| Momentum (UMD) | 0.0907*** | 0.1220*** | 0.0889*** | 0.1205*** |
| | (3.62) | (4.56) | (3.59) | (4.59) |
| Excess Return on Bitcoin | | 0.0204*** | | 0.0197*** |
| | | (5.20) | | (5.13) |
| High-Minus-Low Similarity BCB stock Return | | | 0.0771*** | 0.0981*** |
| | | | (6.18) | (7.36) |
| Portfolio Alpha | -0.0001 | -0.0002 | -0.0001 | -0.0002 |
| | (-0.88) | (-1.10) | (-0.78) | (-1.03) |
| Observations | 1,510 | 1,362 | 1,510 | 1,362 |
| $R^2$ | 69.18% | 68.40% | 69.95% | 69.62% |

**Table 4: One-way average return comparisons within sub-samples**

This table presents the mean daily return comparisons between subsamples formed based on news sentiment, similarity, and bitcoin return values. The initial sample is expanded to contain additional trading days on which there is no news related to bitcoin, blockchain, or cryptocurrency. The combined sample consists of 45,977 firm-day observations (16,839 firm-days with a news story). All return values are in annualized percentage (i.e., the return values are multiplied by 252 × 100). In Panel A, the sample is divided into three subsamples based on the value of News Sentiment (no news, negative news sentiment, and positive news sentiment). In Panel B, the sample is divided into three sub-samples based on the value of Similarity (no news, below the median, and above the median similarity). In Panel C, the sample is divided into three sub-samples based on the value of bitcoin return (low or below the 30$^{th}$ percentile, medium, and high or above the 70$^{th}$ percentile). The last row of each panel reports the difference in average values between the positive and negative (in Panel A) or high and low (in Panels B and C) portfolios. *, **, and *** denote the statistical significance of the mean difference tests at the 10%, 5%, and 1% levels, respectively.

| *Panel A: News Sentiment* | | | | |
|---|---|---|---|---|
| | N | Stock Return | Market Return | Adjusted Return |
| No news | 29,067 | 5.235 | 10.365 | -2.655 |
| Negative News Sentiment | 10,828 | -4.583 | 21.141 | -16.096 |
| Positive News Sentiment | 5,955 | 6.941 | 32.058 | -17.172 |
| Difference | | 11.524 | 10.918*** | -1.076 |

| *Panel B: Similarity Between the News and 10-K Reports* | | | | |
|---|---|---|---|---|
| | N | Stock Return | Market Return | Adjusted Return |
| No news | 29,067 | 5.235 | 10.365 | -2.655 |
| Low Similarity (below the median) | 8,392 | 6.446 | 26.639 | -6.398 |
| High Similarity (above the median) | 8,391 | -7.435 | 23.390 | -26.559 |
| Difference | | -13.881 | -3.249 | -20.161** |

| *Panel C: Bitcoin Return* | | | | |
|---|---|---|---|---|
| | N | Stock Return | Market Return | Adjusted Return |
| Medium Bitcoin Return | 18,321 | 18.909 | 28.288 | -4.848 |
| Low Bitcoin Return (below the 30$^{th}$ percentile) | 13,769 | -31.636 | 12.479 | -41.536 |
| High Bitcoin Return (above the 70$^{th}$ percentile) | 13,760 | 16.935 | 2.254 | 22.310 |
| Difference | | 48.571*** | -10.226*** | 63.846*** |

**Table 5: Two-way average return comparisons within sub-samples**

This table presents the mean daily returns for two-by-two sorts based on different news sentiment, similarity, and bitcoin return values. The extended sample and sorting are similar to Table 3. All return values are reported in annualized percentages. In Panel A, firm-days are sorted based on the similarity score and bitcoin return. In Panel B, firm-days are grouped into four portfolios based on the news sentiment and bitcoin return. In Panel C, firm-days are sorted based on the similarity score and the news sentiment. The difference in average return values between the mean return on these days and the mean returns for all other firm-days (no news or medium bitcoin return) are also reported. *, **, and *** denote the statistical significance of the mean difference tests at the 10%, 5%, and 1% levels, respectively.

*Panel A: Similarity (10-K and News) and Bitcoin Return*

| | | Low Bitcoin Return | High Bitcoin Return | Difference | All Other Days |
|---|---|---|---|---|---|
| Low Similarity | N | 2,883 | 2,828 | | 34,939 |
| | Stock Return | 25.209 | 9.652 | -15.557 | 1.944 |
| | Market Return | 50.107 | 29.529 | -20.578*** | 9.747 |
| | Adjusted Return | -11.405 | 3.073 | 14.478 | -5.583 |
| High Similarity | N | 2,669 | 2,531 | | |
| | Stock Return | -53.001 | 46.395 | 99.396*** | |
| | Market Return | 37.534 | 20.706 | -16.828*** | |
| | Adjusted Return | -90.605 | 42.407 | 133.012*** | |
| Difference | Adjusted Return | -79.200*** | 39.334** | | |

*Panel B: News Sentiment and Bitcoin Return*

| | | Low Bitcoin Return | High Bitcoin Return | Difference | All Other Days |
|---|---|---|---|---|---|
| Negative News Sentiment | N | 3,286 | 3,619 | | 34,939 |
| | Stock Return | -41.341 | 27.702 | 69.043*** | 1.944 |
| | Market Return | 12.426 | 22.561 | 10.134** | 9.747 |
| | Adjusted Return | -48.561 | 24.688 | 73.249*** | -5.583 |
| Positive News Sentiment | N | 2,266 | 1,740 | | |
| | Stock Return | 29.596 | 25.558 | -4.038 | |
| | Market Return | 89.939 | 31.188 | -58.751*** | |
| | Adjusted Return | -50.810 | 15.331 | 66.141*** | |
| Difference | Adjusted Return | -2.249 | -9.357 | | |

**Table 5 – *continued***

| *Panel C: Similarity and News Sentiment* | | | | | |
|---|---|---|---|---|---|
| | | Negative News Sentiment | Positive News Sentiment | Difference | All Other Days |
| Low Similarity | N | 5,707 | 2,685 | | 29,067 |
| | Stock Return | 0.405 | 19.287 | 18.881 | 5.235 |
| | Market Return | 19.163 | 42.529 | 23.366*** | 10.365 |
| | Adjusted Return | -2.879 | -13.878 | -11.000 | -2.655 |
| High Similarity | N | 5,121 | 3,270 | | |
| | Stock Return | -10.141 | -3.196 | 6.945 | |
| | Market Return | 23.345 | 23.461 | 0.116 | |
| | Adjusted Return | -30.826 | -19.876 | 10.950 | |
| Difference | Adjusted Return | -27.948** | -5.997 | | |

**Table 6: Three-way (triple-sorted) average return comparisons within sub-samples**

This table presents the mean daily returns for triple-sorted averages based on different news sentiment, similarity, and bitcoin return values. All return values are reported in annualized percentages. In Panel A, the extended sample is first split into Negative News Sentiment and Positive News Sentiment. Then, each subsample is further split into Low Similarity (below-median) and High Similarity (above-median. Finally, each of the four subsamples is further split into Low Bitcoin Return (below the 30th percentile) and High Bitcoin Return (above the 70th percentile) subsamples. All other trading days are excluded. Panel B provides an alternative sorting order. The differences in average return values between portfolios are also reported. *, **, and *** denote the statistical significance of the mean difference tests at the 10%, 5%, and 1% levels, respectively.

*Panel A: Main Results*

| | | Low Similarity | | | High Similarity | | |
|---|---|---|---|---|---|---|---|
| | | Low Bitcoin Return | High Bitcoin Return | Difference | Low Bitcoin Return | High Bitcoin Return | Difference |
| Negative News Sentiment | N | 1,637 | 1,622 | | 1,643 | 1,624 | |
| | Stock Return | -0.635 | 8.279 | 8.914 | -88.974 | 52.867 | 141.841*** |
| | Market Return | 17.630 | 14.962 | -2.669 | 0.188 | 27.814 | 27.626*** |
| | Adjusted Return | -5.850 | 8.338 | 14.188 | -91.489 | 42.020 | 133.509*** |
| Positive News Sentiment | N | 895 | 868 | | 899 | 891 | |
| | Stock Return | 22.691 | -7.242 | -29.933 | -22.950 | 30.956 | 53.906 |
| | Market Return | 60.433 | 17.167 | -43.266*** | 77.590 | 6.824 | -70.766*** |
| | Adjusted Return | -16.035 | -7.715 | 8.321 | -97.239 | 42.450 | 139.689*** |

*Panel B: Alternative Sorting Order*

| | | Low Bitcoin Return | | | High Bitcoin Return | | |
|---|---|---|---|---|---|---|---|
| | | Low Similarity | High Similarity | Difference | Low Similarity | High Similarity | Difference |
| Negative News Sentiment | N | 1,632 | 1,632 | | 1,623 | 1,622 | |
| | Stock Return | 3.741 | -87.083 | -90.824*** | -4.322 | 38.006 | 42.327 |
| | Market Return | 17.013 | 6.909 | -10.103 | 7.916 | 11.684 | 3.767 |
| | Adjusted Return | -0.045 | -96.213 | -96.168*** | 7.718 | 40.877 | 33.159 |
| Positive News Sentiment | N | 915 | 915 | | 872 | 872 | |
| | Stock Return | 25.378 | -36.788 | -62.166** | 17.487 | 31.943 | 14.455 |
| | Market Return | 55.570 | 65.117 | 9.547 | 54.726 | 6.790 | -47.936*** |
| | Adjusted Return | -11.593 | -98.163 | -86.570*** | -12.241 | 42.629 | 54.871* |

**Table 7: The OLS regressions of raw daily stock returns**

This table reports the results from the Ordinary Least Squares (OLS) panel regressions of daily stock returns on bitcoin return, similarity, and their interaction, and a set of control variables. The variables are explained in Table 1. The coefficient estimates and robust *t*-statistics (appearing below in parentheses) are reported. The standard errors are clustered by firm, and all specifications include year dummies. *, **, and *** denote the statistical significance of the coefficients at the 10%, 5%, and 1% levels, respectively.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Bitcoin Return | 0.0353*** | -0.1086*** | -0.1082*** | -0.1078*** | -0.0551*** |
| | (3.28) | (-2.94) | (-2.93) | (-2.93) | (-2.66) |
| Similarity | | -0.0093 | -0.0095 | 0.0043 | 0.0038 |
| | | (-1.07) | (-1.09) | (0.75) | (0.68) |
| Bitcoin Return × Similarity | | 1.1410*** | 1.1386*** | 1.1341*** | 0.4738** |
| | | (3.33) | (3.32) | (3.32) | (2.34) |
| Positive News Sentiment | | | 0.0002 | 0.0001 | 0.0003 |
| | | | (0.59) | (0.31) | (0.65) |
| Stock Liquidity | | | | -0.0003 | -0.0002 |
| | | | | (-1.61) | (-1.55) |
| Bitcoin Return × Similarity × Stock Liquidity | | | | | 0.0690*** |
| | | | | | (3.13) |
| Size | | | | 0.0004*** | 0.0004*** |
| | | | | (3.88) | (3.89) |
| Market-to-Book Ratio | | | | 0.0001 | 0.0001 |
| | | | | (1.40) | (1.39) |
| Equity Beta | | | | 0.0008* | 0.0008* |
| | | | | (1.68) | (1.77) |
| Annual Return | | | | 0.0010 | 0.0010 |
| | | | | (1.43) | (1.44) |
| *Firm Clustering* | Yes | Yes | Yes | Yes | Yes |
| *Year Fixed Effects* | Yes | Yes | Yes | Yes | Yes |
| *Observations* | 16,783 | 16,783 | 16,783 | 16,783 | 16,783 |
| $R^2$ | 0.61% | 1.52% | 1.52% | 1.97% | 2.79% |

**Table 8: The OLS regressions of adjusted daily stock returns**

This table reports the results from the OLS panel regressions of FF4-adjusted daily stock returns on bitcoin return, similarity, and their interaction, and a set of control variables. The variables are explained in Table 1. The coefficient estimates and robust *t*-statistics (appearing below in parentheses) are reported. The standard errors are clustered by firm, and all specifications include year dummies. *, **, and *** denote the statistical significance of the coefficients at the 10%, 5%, and 1% levels, respectively.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Bitcoin Return | 0.0327*** | -0.1135*** | -0.1138*** | -0.1135*** | -0.0608*** |
| | (3.00) | (-3.11) | (-3.12) | (-3.12) | (-3.02) |
| Similarity | | -0.0129 | -0.0127 | 0.0006 | 0.0001 |
| | | (-1.60) | (-1.58) | (0.10) | (0.02) |
| Bitcoin Return × Similarity | | 1.1592*** | 1.1617*** | 1.1579*** | 0.4973** |
| | | (3.40) | (3.41) | (3.41) | (2.50) |
| Positive News Sentiment | | | -0.0002 | -0.0003 | -0.0002 |
| | | | (-0.64) | (-0.92) | (-0.55) |
| Stock Liquidity | | | | -0.0003* | -0.0003* |
| | | | | (-1.75) | (-1.69) |
| Bitcoin Return × Similarity × Stock Liquidity | | | | | 0.0690*** |
| | | | | | (3.18) |
| Size | | | | 0.0003*** | 0.0003*** |
| | | | | (2.85) | (2.85) |
| Market-to-Book Ratio | | | | 0.0000 | 0.0000 |
| | | | | (0.85) | (0.83) |
| Equity Beta | | | | 0.0005 | 0.0005 |
| | | | | (1.15) | (1.22) |
| Annual Return | | | | 0.0009 | 0.0009 |
| | | | | (1.38) | (1.38) |
| *Firm Clustering* | Yes | Yes | Yes | Yes | Yes |
| *Year Fixed Effects* | Yes | Yes | Yes | Yes | Yes |
| *Observations* | 16,783 | 16,783 | 16,783 | 16,783 | 16,783 |
| $R^2$ | 0.45% | 1.54% | 1.55% | 1.93% | 2.87% |

**Table 9: Daily trading volume comparisons within sub-samples**

This table presents the mean trading volume comparisons between subsamples formed based on news sentiment, similarity, and bitcoin return values. The main variable is the daily trading volume scaled by the number of shares outstanding. Panels A, B, and C report the one-way, two-way, and three-way comparisons, respectively. The subsample formations are similar to Tables 3-5. The differences in average trading volume between subsamples are also reported. *, **, and *** denote the statistical significance of the mean difference tests at the 10%, 5%, and 1% levels, respectively.

*Panel A: One-way Comparisons*

| | News Sentiment | | Similarity | | Bitcoin Return | |
|---|---|---|---|---|---|---|
| | N | Volume | N | Volume | N | Volume |
| Other | 29,067 | 0.0110 | 29,067 | 0.0110 | 18,321 | 0.0113 |
| Negative/Low | 10,828 | 0.0146 | 8,392 | 0.0078 | 13,769 | 0.0120 |
| Positive/High | 5,955 | 0.0125 | 8,391 | 0.0200 | 13,760 | 0.0131 |
| Difference | | -0.0021** | | 0.0122*** | | 0.0011* |

*Panel B: Two-way Comparisons*

| | | Low Bitcoin Return | High Bitcoin Return | Difference | All Other Days |
|---|---|---|---|---|---|
| Low Similarity | N | 2,883 | 2,828 | | 34,939 |
| | Volume | 0.0077 | 0.0079 | 0.0002 | 0.0114 |
| High Similarity | N | 2,669 | 2,531 | | |
| | Volume | 0.0198 | 0.0224 | 0.0025 | |
| Difference | Volume | 0.0121*** | 0.0145*** | | |
| | | Low Bitcoin Return | High Bitcoin Return | Difference | All Other Days |
| Negative News Sentiment | N | 3,286 | 3,619 | | 34,939 |
| | Volume | 0.0143 | 0.0159 | 0.0016 | 0.0114 |
| Positive News Sentiment | N | 2,266 | 1,740 | | |
| | Volume | 0.0125 | 0.0123 | -0.0001 | |
| Difference | Volume | -0.0018 | -0.0036** | | |
| | | Negative News Sentiment | Positive News Sentiment | Difference | All Other Days |
| Low Similarity | N | 5,707 | 2,685 | | 29,067 |
| | Volume | 0.0079 | 0.0075 | -0.0003 | 0.0110 |
| High Similarity | N | 5,121 | 3,270 | | |
| | Volume | 0.0222 | 0.0165 | -0.0056*** | |
| Difference | Volume | 0.0143*** | 0.0090*** | | |

**Table 9 – *continued***

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| *Panel C: Three-way Comparisons* | | | | | | | |
| | | Low Similarity | | | High Similarity | | |
| | | Low Bitcoin Return | High Bitcoin Return | Difference | Low Bitcoin Return | High Bitcoin Return | Difference |
| Negative News Sentiment | N | 1,637 | 1,622 | | 1,643 | 1,624 | |
| | Volume | 0.0077 | 0.0082 | 0.0005 | 0.0206 | 0.0253 | 0.0047 |
| Positive News Sentiment | N | 895 | 868 | | 899 | 891 | |
| | Volume | 0.0077 | 0.0072 | -0.0006 | 0.0193 | 0.0175 | -0.0019 |
| | | Low Bitcoin Return | | | High Bitcoin Return | | |
| | | Low Similarity | High Similarity | Difference | Low Similarity | High Similarity | Difference |
| Negative News Sentiment | N | 1,632 | 1,632 | | 1,623 | 1,622 | |
| | Volume | 0.0080 | 0.0206 | 0.0126*** | 0.0077 | 0.0246 | 0.0169*** |
| Positive News Sentiment | N | 915 | 915 | | 872 | 872 | |
| | Volume | 0.0074 | 0.0187 | 0.0113*** | 0.0073 | 0.0173 | 0.0100*** |

**Table 10: The OLS regressions of daily trading volume**

This table reports the results from the OLS panel regressions of the natural daily trading volume on the absolute value of bitcoin return, similarity, and their interaction, and a set of control variables. The dependent variable is the daily trading volume scaled by the number of shares outstanding. The explanatory and control variables are explained in Table 1. The coefficient estimates and robust t-statistics (appearing below in parentheses) are reported. The standard errors are clustered by firm, and all specifications include year dummies. *, **, and *** denote the statistical significance of the coefficients at the 10%, 5%, and 1% levels, respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| \|Bitcoin Return\| | 0.0488** | -0.1541** | -0.1618** | -0.1762** |
| | (2.44) | (-2.10) | (-2.15) | (-2.29) |
| Similarity | | 0.1576*** | 0.1586*** | 0.1166** |
| | | (3.12) | (3.13) | (2.52) |
| \|Bitcoin Return\| × Similarity | | 1.7123** | 1.7676** | 1.8397** |
| | | (2.34) | (2.37) | (2.47) |
| Positive News Sentiment | | | -0.0037*** | -0.0035*** |
| | | | (-2.72) | (-2.68) |
| Daily Stock Return | | | | 0.2427*** |
| | | | | (4.32) |
| Size | | | | -0.0023*** |
| | | | | (-3.90) |
| Market-to-Book Ratio | | | | 0.0006** |
| | | | | (2.01) |
| Equity Beta | | | | 0.0074** |
| | | | | (2.52) |
| Annual Return | | | | -0.0047 |
| | | | | (-0.78) |
| *Firm Clustering* | Yes | Yes | Yes | Yes |
| *Year Fixed Effects* | Yes | Yes | Yes | Yes |
| *Observations* | 16,783 | 16,783 | 16,783 | 16,783 |
| $R^2$ | 0.50% | 4.44% | 4.55% | 8.00% |

# 7. Appendix A

Similarity example 1 (score of 0.3696):

- *Wall Street Journal*, October 22, 2018, **Wealth Management (A Special Report) --- Can Bitcoin Become a Dominant Currency?**
    - "Bearish views on bitcoin rarely argue with these design characteristics, however. They typically focus on current limitations, arguing that bitcoin will never achieve the requisite level of stability, transaction capacity, security, ubiquity of merchant acceptance, governmental blessing, and trust to function as an alternative currency and payment system."
- OVERSTOCK.COM, INC., FORM 10-K for the fiscal year ended December 31, 2017; "SPECIAL CAUTIONARY NOTE REGARDING FORWARD-LOOKING STATEMENTS"
    - "any losses or issues we may encounter as a consequence of accepting or holding bitcoin or other cryptocurrencies, whether as a result of regulatory, tax or other legal issues, technological issues, value fluctuations, lack of widespread adoption of bitcoin or other cryptocurrencies as an acceptable medium of exchange or otherwise;"

Similarity example 2 (score of 0.3220):

- *Wall Street Journal*, September 18, 2019, by Geron, Tomio, **Cybersecurity (A Special Report) --- Companies Compete to Be Cryptocurrency Custodians: The battle pits some of the biggest financial-services companies against startups.**
    - "There has long been uncertainty about regulatory requirements and the logistics of holding digital assets. After some well-known digital-token thefts, cryptocurrencies face a perception that they aren't safe, since a hacker attack or security misstep could mean losing your coins forever."
- SQUARE, INC., FORM 10-K for the fiscal year ended December 31, 2018;
  "Item 1A. RISK FACTORS"
    - "Any loss of private keys relating to, or hack or other compromise of, digital wallets used to store our customers' bitcoins could adversely affect our customers' ability to access or sell their bitcoins and could harm customer trust in us and our products."

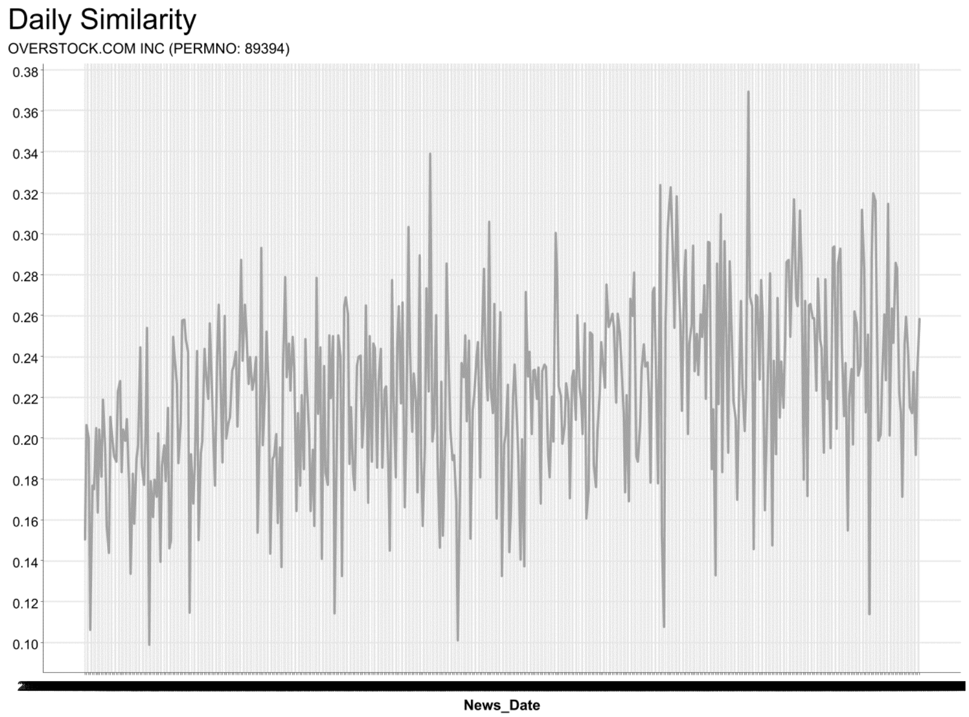


**Figure A-1: Daily Similarity Score Example (High Average Similarity)**

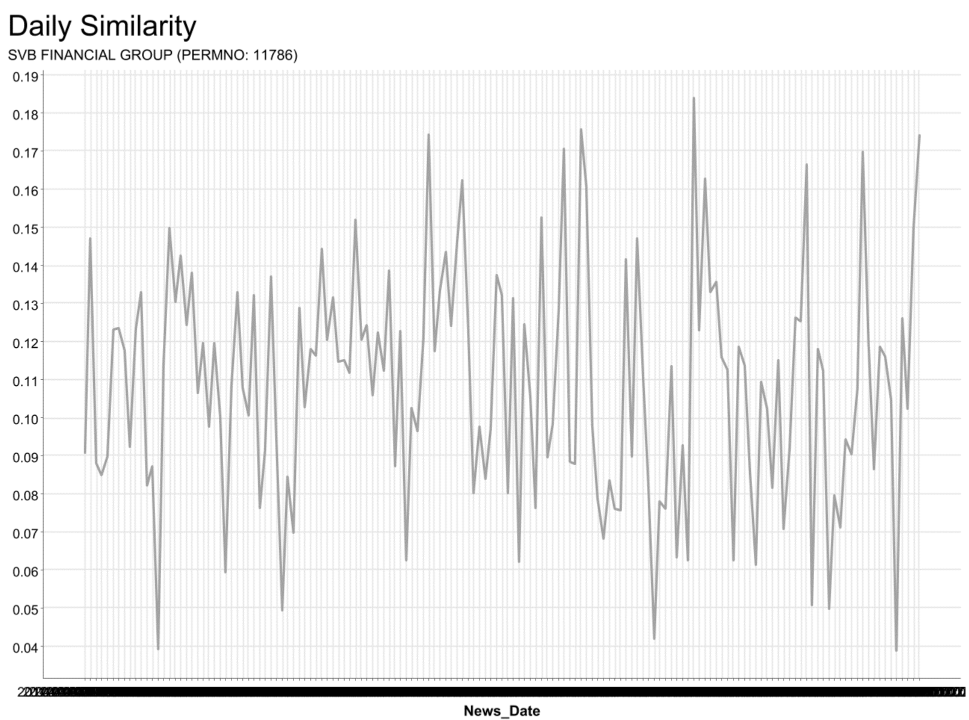


**Figure A-2: Daily Similarity Score Example (Medium Average Similarity)**

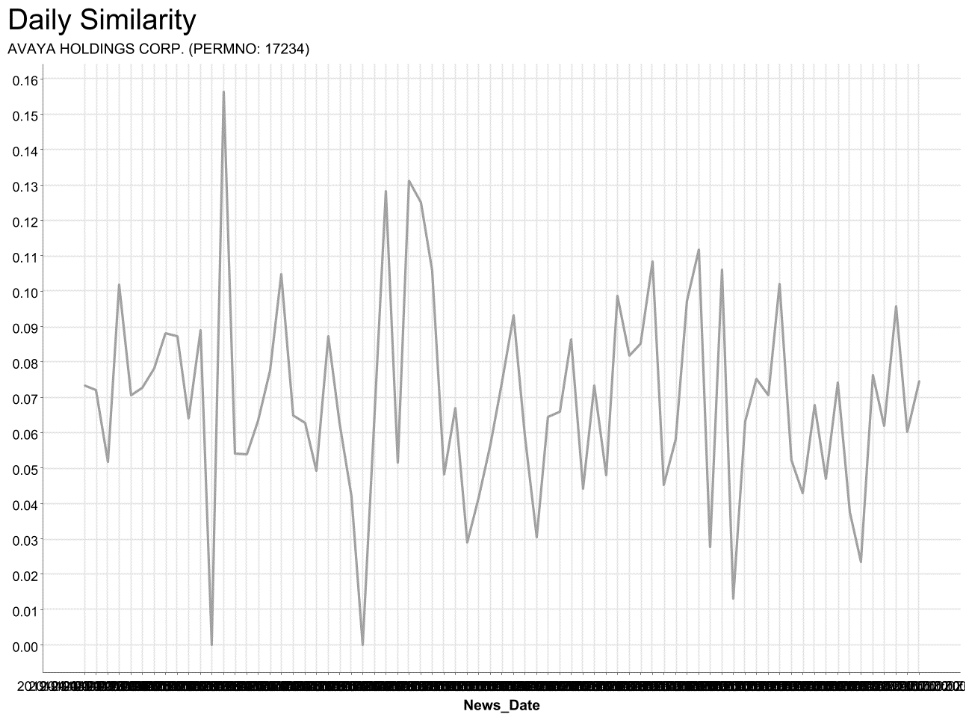


**Figure A-3: Daily Similarity Score Example (Low Average Similarity)**