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论文题目: Beyond the Blockchain Announcement: Signaling Credibility and Market Reaction

Beyond the Blockchain Announcement: Signaling Credibility and Market Reaction

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Abstract

With the blockchain announcements as the research object, we document the important interactions between signaling credibility of corporate announcements and market reactions. The announcements have led to a significantly positive increase in the value of listed firms since blockchain technology was valued in China in 2016. High-tech firms with more technological attributes and reserves could be seen as more credible and trigger more significant stock returns than non-high-tech firms. In addition, stateowned high-tech firms with normal financial status and voluntary disclosure would augment such signaling credibility. In general, the results support that signaling credibility of corporate announcements are of vital importance for market reaction.

Keywords: Blockchain Announcement; Signaling Credibility; Event Study; Market Reaction

JEL Codes: G12, G14

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1 Introduction

Accurate information disclosure represents one of the important channels to improve capital market efficiency (Goldstein and Yang, 2019). A large number of researchers, such as Barber et al. (2013), Levi and Zhang (2015), Savor and Wilson (2016), have been devoted to revealing the effectiveness of information disclosure in responding to a firm's value and how investors react to such information. Specifically, a series of literatures have identified the heterogeneous impact of some structural factors on market reaction, such as earnings quality, financial reporting frequency, and investors' expectations (Francis et al., 2008; Hwang et al., 2008; Fu et al., 2012). However, one essential issue that has yet to be discussed in the literature on information disclosure is whether the signaling credibility of disclosed information triggers the different reactions of investors to the same kind of information.

We select the blockchain announcements to study the underlying relationship between signaling credibility of disclosed information and market reaction. As blockchain technology is an emerging technology first formally proposed by Nakamoto (2008) and its application scenarios are constantly improving, the information about blockchain disclosed by the listed firms is basically strategic arrangement, talent introduction and technology research, and the firms' underlying cash flow and overall risk have not changed significantly. The information contained in the blockchain announcements is purer than that in earnings statement and M&A announcements, providing a cleaner environment to test the market reaction triggered by the announcements with different signaling credibility.

There have been relatively few published studies of the announcement credibility and heterogeneous market reactions. Previous literature only concludes that investors are more likely to recognize earnings announcements issued by firms audited by the high-quality accounting firms, stimulating a more intense market reaction (Teoh and Wong, 1993; Balsam et al., 2003). In addition, Pevzner et al. (2015) advocated that in countries with higher social trust, accounting information could be more rapidly incorporated into market price. In this paper, we study whether the market response caused by blockchain announcements is related to the technology density of listed companies, which indirectly measures the credibility of the firm's successful integration of blockchain technology into its own development.

A blockchain is a virtual chain of ordered blocks that allows transaction records to be stored and shared without the need for a third or central party (Chiu and Koeppl, 2019; Saleh, 2021). Based on these above advantages, blockchain technology has been applied to many scenarios, such as the Internet industry and finance. However, since blockchain technology involves comprehensive, cutting-edge technologies of multiple disciplines, firms' integration of blockchain technology requires a higher foundation for technological development and faces technical challenges (Hassani et al., 2018; Demirkan et al., 2020). In doing so, high-tech firms have higher scientific and technological attributes and technical reserves, and when they announce their blockchain planning, relevant statements would be credible. Consequently, investors will buy the story, and we predict that market reaction will be more positive.

For the purpose of verifying the impact of signaling credibility, we construct a sample where all firms have made substantive plans for blockchain technology during the sample period. Apart from the previous research on blockchain announcements (Cheng et al., 2019; Autore et al., 2020; Cahill et al., 2020), we select China's public firms as the research sample rather than those in developed economies such as the United States due to the imperfect information channels in emerging markets and prominent differences in investors' market response. By collecting the announcements of all listed firms in Shanghai and Shenzhen A shares and conducting textual analysis, 302 sample firms are finally selected.

We find significant evidence that investors faced with blockchain announcements released by high-tech firms respond more strongly, which is consistent with the hypothesis that investors perceive blockchain announcements issued by firms with more technological property as more credible. In detail, the difference in cumulative abnormal returns (CARs) between blockchain announcements of high-tech firms and non-high-tech firms is approximately 7.29% over a long window of 41 trading days [-20, 20] and 2.45% over a short window of 11 trading days [-5, 5]. Using OLS regression, the conclusion still holds, and our findings are robust when incorporating an alternative proxy for the firms' technological attributes, excluding extreme CARs and altering the model of calculating CARs.

We further enhance our results on the positive relationship between signaling credibility and market reaction from three aspects. First, we examine the impact of operating status on high-tech firms' announcement credibility, and find that the special treatment to a listed firm, which demonstrates an abnormal financial status, would erode the credibility and thus reduce CARs. Second, our main results do not distinguish between voluntary and involuntary disclosure. Voluntary disclosure is always thought to be the mechanism that managers could use to elicit market feedback (Jayaraman and Shuang, 2020). To identify the effect of voluntary disclosure, we classify the blockchain announcements into two categories, and find that the voluntariness does add to the signaling credibility. Third, previous research has found that the governance of state-owned enterprises (SOEs) is obviously different from that of non-state-owned enterprises, giving more consideration to social benefits (Jiang and Kim, 2020). At the same time, the main driving force of SOEs' managers is to be promoted to senior government positions (Jiang and Kim, 2015). Therefore, SOEs are more cautious and conservative in strategic planning and must have been demonstrated many times. As mentioned earlier, the results show that blockchain announcements of SOEs are more convincing to investors.

In our further analysis, we extend our principal analysis in three interesting directions, focusing on the impact of investors' positive sentiment on the perception of signaling credibility. We first conduct a textual analysis on the full text of the blockchain announcement to analyze the sentiment polarity that investors can obtain from it. The empirical results show that positive textual sentiment can improve credibility perception. Then, it is widely accepted in the literature that the investors' attention and mania to Bitcoin have spurred their positive perspective of the blockchain. Introducing the cumulative return of Bitcoin as the proxy of investors' positive attitude induced by Bitcoin, our findings are not in line with those of Cahill et al. (2020), clearly indicating that the Bitcoin return could not disturb the investors' expectation towards blockchain technology in China. Lastly, despite years of economic reform, the Chinese government's dominant position in resource allocation has not changed, and the impact of national policies on specific industries is enormous. We introduce the 18th collective learning of the Political Bureau of the 19th CPC Central Committee as the cut-off point. At the meeting, President Xi led the national leaders to learn about blockchain technology, which can be seen as the most powerful support. The results indicate the national support can stimulate investors' perception of the signaling credibility of blockchain announcements.

Some related researches have focused on the general classification of blockchain announcements and their heterogeneous impact. Cheng et al. (2019) identified 79 U.S. firms with their Form 8-K disclosures associated with blockchain and found the different market reactions across speculative firms and existing firms. Cahill et al. (2020) further deepened this strand of literature by exploring the ongoing relationship between Bitcoin and market reaction. Autore et al. (2020) mainly identified the credibility information based on the context rather than firms' fundamentals, and found that the firms which were currently using or would imminently use the blockchain for a commercial purpose would be more convincing to investors. Our paper differentiates from these studies in several crucial ways. First, by analyzing the blockchain announcements of listed firms in an emerging capital market, i.e., China, we obtain a significantly different sample and insight into the topic due to the differentiation of information perception caused by imperfect capital market. Second, we mainly consider the heterogeneous impact of blockchain announcements caused by the signaling credibility, which is induced by the firms' technological reserves and attributes. The properties of the announcement text are not the basis for measuring the credibility in our paper, since the announcements may send false signals due to the firm's announcement strategy. Therefore, we go beyond the blockchain announcements to extract the signaling credibility based on the firms' fundamentals. Third, our research design facilitates a study on the perception of signaling credibility by incorporating several dimensions that may affect the credibility of blockchain announcements, including investors' sentiment.

Our study makes contributions in two aspects. First, we formally identify the signaling credibility as a new factor that can provide a more reliable perspective for explaining the heterogenous market reactions caused by the same type of announcements. Our results indicate that the capital market reaction to the listed firms' disclosure is not only affected by the country-level social trust (Guiso et al., 2008; Pevzner et al., 2015), but also by the firm-level signaling credibility. By analyzing the impact of the credibility on the firms' announcement acceptance, we add to the existing literature about the factors affecting the communication efficiency of information disclosure among investors.

Second, our findings highlight that the signaling credibility significantly affects the investors' trading behavior faced with the homogenous information disclosure among different firms. The positive impact of signaling credibility on the market reaction to the blockchain announcements implies that information contained in more credible announcements is digested more quickly. This suggests the firms' managers take specific measures to improve the credibility of their information disclosure so as to enhance the information transmission, potentially resulting in a more efficient capital market. Meanwhile, driven by the announcement context, relevant Bitcoin mania and national support policy, investors with positive sentiment are more likely to perceive the announcements as credible and respond more strongly. This result has implications for the growing literature that focuses on the relationship between sentiment and stock returns (Tetlock et al., 2008; Loughran and Mc-Donald, 2011; Garcia, 2013).

The remainder of the paper proceeds as follows: In Section 2, we review the related literature and present our hypothesis development. In Section 3, we explain our sample construction with collecting announcements information and methodology used to measure the market reaction. Section 4 presents our empirical results about the relationship between signaling credibility and market reaction to blockchain announcements. Section 5 further analyzes the perception of signaling credibility, and Section 6 draws a conclusion.

2 Literature review and hypotheses

One of the most widely accepted theories related to financial markets championed by most economists like Shiller (2015) argues that investors' enthusiasm drives asset prices higher than the fundamentals, and vice versa. In this context, the content to which investors pay attention further affects their expectations, beliefs and ultimate decisions (Bosman et al., 2017). In a world rich in information and diverse in choice, investors tend to pay more attention to hot issues in the market and react more sharply, since they have limited attention and processing power (Hirshleifer and Teoh, 2003; Peng and Xiong, 2006; Barber and Odean, 2008). Far and away, blockchain technology is one of the hottest topics at the moment.

With the Fintech innovation, investors believe that young start-ups and large mature technology companies are trying to disrupt the existing market landscape, using blockchain technology to launch new products and business models that provide important new competition (Cong and He, 2019; Goldstein et al., 2019). According to Chen et al. (2019), blockchain technology could bring enormous economic value to innovators, industries, and incumbent firms. Therefore, investors would respond more vigorously to the information contained in the firms' blockchain announcements.

The literature extensively suggests that investors' expectations play a decisive role in the formation of stock price (Keran, 1971; Franker, 2008; Hurd et al., 2011). Hwang et al. (2008) pointed out that the market reacts far more to a surprise stock split than to one that was anticipated. On this basis, a strand of literature focuses on the impact of a firm's reputation on how the stock market views the credibility of its subsequent announcements (Bonaimé, 2012; Ota et al., 2019; Hutton and Stocken, 2021). Nevertheless, the actual impact of signaling credibility on investors' utilization of firms' announcements remains unexplored. As stated above, listed firms need to have sufficient technical reserves to overcome the challenges

in the process of introducing blockchain technology. Therefore, investors are likely to follow a firm's blockchain announcements more closely and react to the information therein more intensely when they find that the firm issuing the blockchain announcements is a high-tech enterprise.

Hypothesis 1. The blockchain announcements trigger positive market reactions, and signaling credibility induced by high-tech firms augments the positive effect.

A large and fruitful literature indicates that the signaling credibility could vary with firmlevel characteristics. First, the literature related to the firm's financial status mainly argues that the firms with financial distress would incur the negative market response (Clark and Weinstein, 1983; Chen and Church, 1996; Whitaker, 1999; Baranchuk and Rebello, 2018). In our context, we predict that the abnormal financial status would decay the signaling credibility brought by high-tech attributes, since investors spontaneously doubt firms' ability to continuously fund their blockchain technology plans. Second, state ownership is an unavoidable issue in the study of China's economic problems, and SOEs are still a critical pillar enterprise in China (Jiang and Kim, 2020). Bai et al. (2006) argue that SOEs assist the government in achieving the goal of maintaining social stability, which is also proved by Gan et al. (2018). The main motivation of their managers is to obtain a political promotion, and the power structure of state-owned enterprises is more bureaucratic (Jiang and Kim, 2015; Bradshaw et al., 2018). Therefore, state-owned enterprises will not issue blockchain announcements to stimulate stock prices out of short-term incentives. Instead, the plans listed must have been repeatedly discussed, and managers should bear the political responsibility of market feedback. From this perspective, the blockchain announcement issued by SOEs will be more convincing to investors. Third, voluntary disclosure is often regarded as a signal of corporate value because of its reduction in the degree of information asymmetry (Hughes, 1986; Diamond and Verrecchia, 1991; Francis et al., 2008). Through modeling, Stocken (2000) finds that managers generally make truthful disclosure in a voluntary disclosure to ensure the credibility of the announcement. Hence, we conclude these three directions to phrase our second hypothesis:

Hypothesis 2. The positive relation between the signaling credibility induced by high-tech firms and market reactions of blockchain announcements is more significant in state-owned high-tech firms with normal financial status and voluntary disclosure.

Investors' sentiment will affect their perception of signaling credibility, and we extract three most important aspects that may affect investor sentiment from the literature. In the first place, public corporate disclosures are a natural source of textual sentiment insofar as they are official releases that come from insiders who have better knowledge of the firm than outsiders (Li, 2010; Price et al., 2012; Kearney and Liu, 2014). This suggests that more positive blockchain announcements are more persuasive for investors and enhance the positive effect of signaling credibility. In the next place, as shown by Cheng et al. (2019) and Cahill et al. (2020), the performance of Bitcoin could stimulate investors' interest in the underlying blockchain technology, indicating that investors would pay more attention to the blockchain announcements when Bitcoin prices soar. However, the Chinese regulatory authorities issued a notice to prevent Bitcoin risk in 2013 and Bitcoin mining and trading have been hit by the Chinese administration 1 , indicating that there may be no significant effect as shown by Cahill et al. (2020). In the end, strong policy guidance and support could also increase the perception of signaling credibility, since the cultivation and development of China's industry or technology are still policy-oriented to a great extent. As stated by Chen and Kung (2019), China is ruled by a single political party comprising tight-knit political elites. The Politburo of the Communist Party of China (CPC) is at the top with national rank, the members of which wield disproportionate power in setting economic and other policies (Chen and Kung, 2019; Gao et al., 2021). Thus, after Politburo's collective learning of blockchain technology, the signal of national support for the application of blockchain technology is quite straightforward for investors. Hereby, we propose the third hypothesis

¹The 51st meeting of the Financial Stability and Development Committee of The State Council clearly proposed to crack down on bitcoin mining and trading. Please refer to http://www.gov.cn/xinwen/2021-05/21/content_5610192.htm for details.

regarding the perception of signaling credibility.

Hypothesis 3. The investors' positive sentiment driven by the textual sentiment of blockchain announcements and national policy supply could enhance the investors' perception of signaling credibility, but Bitcoin return could not have such effect in China.

[PLEASE INSERT FIGURE 1 HERE]

Overall, we illustrate these three hypotheses and their relationships in Figure 1 to enhance the hypothesis development, which shows the Hypothesis 1 in the trunk, Hypothesis 2 and Hypothesis 3 in the branch.

3 Data and methodology

3.1 Data

Since December 2015, China's blockchain application has become a hot topic. The Ministry of Industry and Information Technology released the first white paper on blockchain in 2016. In the same year, blockchain was included in the 13th five-year national information plan issued by the State Council. Under this background, our research sample spans a 5-year period from 2016 to 2020. We have collected all announcements of A-share listed firms from Eastmoney website ², including firm's code, abbreviation, announcement date, title and full text. To construct the research sample, we traverse and retrieve all announcements to get all blockchain announcements using the keyword *blockchain*, which are then further processed in the following steps: (i) eliminate the announcements that only describe the current technological development status; (ii) exclude general announcements about the concept of blockchain technology; (iii) eliminate announcements not related to the company's blockchain application or strategy; (iv) following Cahill et al. (2020), we only select the initial

²Eastmoney website is a large financial information website and utilized by many studies, for instance Hong et al. (2014). It provides us with a convenient and clean environment to crawl announcements information, see details for http://data.eastmoney.com/notices/.

blockchain announcements to avoid any bias in selecting event dates. Hence, we obtain a total of 443 announcements related to the company's application of blockchain technology.

We extract state ownership, industry information, annual financial information, daily share prices and market-index data from Wind database. The identification information and valid patent information of high-tech firms are sourced from CSMAR database. To estimate the cumulative abnormal returns, we require each company to have at least 255 trading-day data prior to the blockchain announcement. We then compare the announcement dates with the initial public offering (IPO) dates and further drop announcements made less than 255 trading days after the IPO. This further removes 141 announcements, giving a final sample of 302 blockchain announcements, one for each company.

3.2 Variable definitions

3.2.1 Market reaction measures

We measure the investors' reaction to blockchain announcements by the cumulative abnormal returns for the event days. Following Campbell et al. (1998), we first calculate abnormal returns with the market model as:

$$AR_{i,t} = R_{i,t} - \left[\hat{\alpha}_i + \hat{\beta}_i R_{m,t}\right] \tag{1}$$

where $AR_{i,t}$ and $R_{i,t}$ are the abnormal return and actual return for the stock *i* on event day *t*, and $R_{m,t}$ is the Chinese market return (Shanghai Composite Index). The parameters $\hat{\alpha}_i$ and $\hat{\beta}_i$ are estimated by adopting an estimation window from 255 trading-day to 46 trading-day prior to the event day (Child et al., 2021) from the following equation:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t} \tag{2}$$

We further calculate the cumulative abnormal returns (CARs) for the event windows [-20, 20], [-10, 10], [-5, 5] and [-1, 1]. For each firm i, the CAR for the interval $[t_1, t_2]$ is calculated as:

$$CAR[t_1, t_2]_i = \sum_{t=t_1}^{t_2} AR_{i,t}$$
 (3)

3.2.2 Signaling credibility measures

Under the background of China's transition economic system, the firms' RD investment intensity is relatively low and the innovation ability is generally insufficient. By the end of 2007, RD expenditure accounted for only 0.56% of the sales revenue among the enterprises above designated size in China, which aroused the government's concern. In order to encourage enterprises to increase RD investment, *Administrative Measures for the Recognition of High-Tech Enterprises* came into being as a matter of course in 2008. For the identification of high-tech firms, the administrative measures have detailed requirements for the proportion of RD expenses, RD personnel and the income of high-tech products, which provides a reliable proxy variable for us to identify the blockchain announcements credibility of listed firms. We divide firms into two categories according to whether they pass the identification, namely high-tech firms and non-high-tech firms, and set a dummy variable *High-Tech* in the OLS regression that is valued as one if a firm passes the identification.

To verify the second hypothesis, we incorporate three variables to further measure the signaling credibility of blockchain announcements, i.e., financial status, state ownership and voluntary disclosure. ST is an indicator variable that equals one if the firm-year observation is within a special treatment period, indicating abnormal financial status. SOE is also an indicator variable equal to one if the firm is state-owned. To identify whether the blockchain announcements are voluntary or involuntary disclosure, we classify unconventional reports as involuntary disclosure, including investors' communication minutes and replies to regulatory letters, and mark the variable Type as one.

3.2.3 Control variables

The firm-level covariates are included to control other basic firm characteristics that could have an impact on the relationship between blockchain announcements and market reactions. Following Pevzner et al. (2015), Acemoglu et al. (2016) and Cahill et al. (2020), we introduce the following variables as our control variables. *Size* is the natural logarithm of the total assets at the last fiscal year before the announcement. *ROE* is the profitability measured by the return on assets. *Lev* is the total liabilities divided by total assets. The details of all variables are presented in Table 1.

[PLEASE INSERT TABLE 1 HERE]

3.3 Methodology

To test Hypothesis 1, we estimate the baseline regression model specified as:

$$CAR [t_1, t_2]_i = a_0 + a_1 High - Tech_i + X'\delta + \epsilon_i$$
(4)

where the dependent variable $CAR[t_1, t_2]_i$ denotes the cumulative abnormal return of firm *i* for the interval $[t_1, t_2]$. *High-Tech_i* captures the signaling credibility of blockchain announcements derived by whether firm *i* has passed the identification of high-tech firms. X is the vector of control variables, including *Size*, *ROE* and *Lev*. Hypothesis 1 predicts a_1 to be positive as the high-tech firms with more technological attributes would add up to the credibility of blockchain announcements, inducing a more positive market reaction.

To test Hypothesis 2, we estimate the regression model specified below.

$$CAR [t_1, t_2]_i = a_0 + a_1 High - Tech_i + a_2 Group_i + a_3 Group_i \times High - Tech_i + X'\delta + \epsilon_i$$
(5)

where $Group_i$ equal to $\{ST_i, SOE_i, Type_i\}$ represents the three indicator variables that play a decisive role in the signaling credibility of blockchain announcements, i.e., special treatment, state ownership and voluntary disclosure respectively. We mainly focus on the coefficient a_3 , which we expect to be positive with $Group_i = \{SOE_i, Type_i\}$ and negative with $Group_i = \{ST_i\}$.

We also examine Hypothesis 3 by estimating the following regression model.

$$CAR [t_1, t_2]_i = a_0 + a_1 High-Tech_i + a_2 Perception_i + a_3 Perception_i \times High-Tech_i + X'\delta + \epsilon_i$$
(6)

In this model, $Perception_i$ is equal to $\{Text_i, CRB_i, CLP_i\}$, and represents the three variables that affect the investors' perception of signaling credibility, that is the textual sentiment of the announcements (Text), cumulative return of Bitcoin (CRB), pre- or post-18th collective learning of Politburo of CPC (CLP). We predict that the core coefficient a_3 could be positive when the three factors stimulate the positive sentiment of investors and increase the perception of signaling credibility.

Following the previous studies (Pevzner et al., 2015; Cahill et al., 2020), we incorporate the industry fixed effects and year fixed effects into all the models, and adjust the standard errors for heteroskedasticity and industry level clustering.

4 Empirical results

4.1 Descriptive statistics

We report the descriptive statistics of the regression variables in Table 1. The mean values of the dependent variables utilized in our model, including CAR[-1,1], CAR[-5,5], CAR[-10,10], CAR[-20,20], range from 0.95% (CAR[-1,1]) to 3.08% (CAR[-20,20]). With respect to the core independent variable (*High-Tech*), 60.40% of firms in our research sample passed the

recognition of high-tech firms. Regarding the other three variables about signaling credibility, on average, only 0.99% of firms are in abnormal financial status (ST), but 26.40% of firms are state-owned and 84.16% of blockchain announcements are voluntarily disclosed. Furthermore, 28.38% of announcements are issued after the 18th collective learning of Politburo of CPC, with an average textual sentiment score of 0.83. The cumulative return of Bitcoin involved is 8.14%. When checking robustness, we incorporate the number of valid patents, which is 52.52 ($e^{3.98} - 1$) on average.

[PLEASE INSERT TABLE 2 HERE]

Figure 2 presents the quarterly frequency of blockchain announcements in our research sample with two categories, that is high-tech and non-high-tech firms. Over the full sample and different categories, we observe a peak in the number of blockchain announcements in the second quarter of 2018. We also find that high-tech firms always issue more announcements than non-high-tech firms.

[PLEASE INSERT FIGURE 2 HERE]

4.2 Univariate tests

Figure 3 plots CARs for high-tech and non-high-tech firms over a [-20,20] trading day window surrounding the blockchain announcements. Visually, firms in the full sample experience a significant CAR around the event window, and the two groups of firms show evident divergence, which preliminarily indicates high-tech firms would trigger more positive market reaction due to the signaling credibility.

[PLEASE INSERT FIGURE 3 HERE]

Table 3 further conducts the univariate analysis, and reports the CARs for the full sample, high-tech sample and non-high-tech sample from Panel A to Panel C. In panel A, the mean value of CARs is significantly positive at the level of 1%, implying that the blockchain announcements could stimulate the positive market reaction. For a short three trading-day window [-1,1] around the announcement, firms gain 0.95% averagely, and for a long 41 trading-day window [-20,20], firms gain 3.08% averagely. Panel B and Panel C jointly show that high-tech subsamples have a more significant and positive market impact than non-high-tech subsamples. We further conduct the difference-in-means tests to compare the market reaction between the blockchain announcements issued by the two subsamples with different levels of signaling credibility. During the event windows [-20,20], [-10,10] and [-5,5], CARs of high-tech subsamples are significantly higher than those of non-high-tech subsamples (7.29%, 4.44% and 2.45%, respectively). With the event window [-1,1], the difference remains to be positive but insignificant and the magnitude decreases to 0.41%, which indicates that investors need a short period to respond to the credibility of blockchain announcements. The above results provide preliminary evidence for Hypothesis 1.

[PLEASE INSERT TABLE 3 HERE]

4.3 Baseline regression results

We further test Hypothesis 1 by estimating the regression model specified in Eq. (4). The results are shown in Table 4. In Panel A, we only incorporate the explanatory variable *High-Tech* other than year and industry fixed effects. In Panel B, we include three characteristics, namely *Size*, *ROE* and *Lev* as the control variables. We find that the magnitude and significance of all main coefficient estimates remain unchanged, implying the robustness of our results to some extent. Hence, we mainly focus on the regression results in Panel B.

[PLEASE INSERT TABLE 4 HERE]

Consistent with the findings in Section 4.2, when incorporating CAR[-20,20], CAR[-10,10] and CAR[-5,5] as the dependent variables, the coefficient estimates on *High-Tech* are positive and significant at a level of at least 10%, varying from 2.02% to 6.42%. These results have directly proved our Hypothesis 1, that is, high-tech firms have stronger scientific

and technological attributes and technical reserves, so they have higher credibility in the application of blockchain technology, and market investors will respond more strongly to their blockchain announcements. The coefficient in column (1) is negative but insignificant, probably because investors need time to digest the announcement information and respond to the credibility of the information.

4.4 Cross-firm variations in signaling credibility

In this subsection, we examine our Hypothesis 2 by estimating Eq. (5) to test three plausible firm characteristics that may affect the signaling credibility of blockchain announcements issued by high-tech firms.

First, we test whether the financial status of high-tech firms augments the signaling credibility of blockchain announcements, and Table 5 reports the results from this aspect. We incorporate the interaction term $High-Tech \times ST$ as the main explanatory variable and in all columns, the coefficient estimates are significant and negative at the level of 5%. For instance, the coefficient of $High-Tech \times ST$ on CAR[-20,20] is -0.1158 with a robust t-statistic of -9.49. These findings determine that the abnormal financial status would decay the signaling credibility of high-tech firms' blockchain announcements, as there is little reason to believe high-tech firms with financial distress have enough cash flow to invest in blockchain technology.

[PLEASE INSERT TABLE 5 HERE]

Second, we introduce the state ownership of high-tech firms as a factor affecting signaling credibility. As evidenced by the coefficient estimates in columns (3) and (4) of Table 6, the positive and significant coefficients on the interaction term, 4.73% and 8.19% respectively, imply that state-owned high-tech firms could add to the signaling credibility of the announcements, since the credit endorsement of SOEs avoids the possibility of pursuing short-term interests in non-SOEs. Comparing the results in columns (1) and (2) with those in columns

(3) and (4), we further conclude that investors would recognize the signaling credibility with a long event window rather than a short one.

[PLEASE INSERT TABLE 6 HERE]

Third, we estimate the regression model specified in Eq. (2) by incorporating the variable Type indicating that the blockchain announcements are voluntary or involuntary. As shown in Table 7, the interaction term between *High-Tech* and *Type* has significant positive coefficients at the level of 1% with CAR[-20,20] and CAR[-10,10] as the dependent variables, suggesting that the positive effect of high-tech attributes on market reaction to blockchain announcements is more pronounced when high-tech firms voluntarily disclose the information. And results in columns (1) and (2) show again that investors' judgment of information will lag behind.

[PLEASE INSERT TABLE 7 HERE]

The three results stated above are consistent with our Hypothesis 2 that state-owned hightech firms with normal financial status and voluntary disclosure will augment the signaling credibility of the blockchain announcements and trigger more positive market reaction.

4.5 Robustness tests

Our results are robust to a battery of alternative settings. We first adjust the model for CARs calculation, i.e., Eq. (1) and Eq. (2). Following Fama and French (2015), we collect the data of five factors in China from the CSMAR database, and again calculate the predicted returns using the following equation:

$$R_{i,t} - R_{F,t} = a_i + b_i \left(R_{M,t} - R_{F,t} \right) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{i,t}$$
(7)

where $R_{M,t}$ and $R_{F,t}$ are the market return and the risk-free rate at time t respectively, SMB is the return spread of small minus large stocks, HML is the return spread of cheap minus expensive stocks, RMW is the return spread of the most profitable firms minus the least profitable, and *CMA* is the return spread of firms that invest conservatively minus aggressively. After obtaining the CARs with Fama-French five-factor model, we rerun the regression model in Eq. (4) and the results are shown in Table 8. We find that all the coefficient estimates in all columns are similar to those in Table 4, including the positive effect and significance level. Therefore, our results are not driven by the estimation model of CARs.

[PLEASE INSERT TABLE 8 HERE]

Second, we check the robustness of our results to the alternative measures of signaling credibility, which we utilize the recognition of high-tech firms in Section 4.3. Specifically, we reestimate Eq. (4) by introducing the valid patents up to the announcement date as a proxy for the signaling credibility of blockchain announcements. Results presented in Table 9 indicate that the alternative proxy of signaling credibility remains positive and significant at the level of 5%, regardless of whether we measure investors' reactions with a short or long event window.

[PLEASE INSERT TABLE 9 HERE]

Given that the results would be driven by the extreme values in the research sample, following Acemoglu et al. (2016), we mitigate this concern by excluding firms with extreme CARs, defined as those larger than the 99th percentile or smaller than the 1st percentile. As reported in Table 10, the results in all columns are quite close to those in Table 4, especially the significance level, indicating that the positive relation between signaling credibility and market reactions surrounding the blockchain announcements is fairly robust in OLS specifications.

[PLEASE INSERT TABLE 10 HERE]

Finally, we address the question of whether firms perform better after blockchain announcements because of other revolutionary technologies issued in the same announcement rather than the signaling credibility endorsed by the high-tech firms, especially the artificial technology (AI). We additionally control a dummy variable equal to one if the blockchain announcement contain the term artificial technology. As can be clearly seen from Table 11, after controlling the potential influence induced by artificial technology, the results present a similar pattern with those in Table 4. Thus, we can alleviate the concern that the positive market reaction with other revolutionary technology is more pronounced, instead of signaling credibility.

[PLEASE INSERT TABLE 11 HERE]

5 Further analysis

In this section, we examine our Hypothesis 3 and investigate whether the effect of signaling credibility on market reaction to blockchain announcements displays any variations along investors' perception of signaling credibility. We assume that the perception of signaling credibility is augmented when investors' sentiment is more positive. We introduce three proxies that may affect investors' sentiment, that is the textual sentiment of blockchain announcements, the cumulative return of Bitcoin recently and the national support policy.

Regarding the perception of signaling credibility, the textual sentiment of the announcement is the first concern. We analyze sentiment using HowNet Sentiment Lexicon, the most widely used Chinese lexical knowledge base (Dong and Dong, 2003; Zhu et al., 2006). The sentiment polarity of each announcement is determined by calculating the proportion of positive words, which constructs the variable *Text*. We examine this hypothesis by incorporating the interaction term *High-Tech* with *Text*, and rerunning the Eq. (6). The OLS results in Table 12 show that all the coefficients on the interaction term are positive, but only the result in column (4) is significant at the level of 5%, which indicates that the textual sentiment in the announcement context needs a longer period to be captured by investors, and that the market has no obvious response in the short term.

[PLEASE INSERT TABLE 12 HERE]

Furthermore, Cahill et al. (2020) argue that blockchain-related announcements are related to Bitcoin price and returns, since investors would be influenced by the nominal prices (Birru and Wang, 2016). We also incorporate the 30-day cumulative return of Bitcoin (*CRB*) prior to the blockchain announcements, and reestimate the coefficients in Eq. (6). The results are presented in Table 13, from which we can tell that the variables of interest, i.e., the interaction term, are positive but almost insignificant. In one case that the coefficient estimate is significant at the level of 10%, that is in a short 3-day event window, which implies that the findings are not in line with those obtained by Cahill et al. (2020). Interestingly, this result is closely related to the strict regulatory policy of Bitcoin in China. For example, in December 2013, the regulatory authorities issued a notice to prevent Bitcoin risk, and in 2018, the financing of token issuance was determined to be illegal. Therefore, Chinese investors are cautious about Bitcoin, and Bitcoin returns will not affect their perception of signaling credibility associated with blockchain announcements.

[PLEASE INSERT TABLE 13 HERE]

In the analysis thus far, we focus on the signaling credibility and investors' perception mainly induced by the firm characteristics or the relevant capital performance. However, inspired by Pevzner et al. (2015) who pointed out the positive effect of societal trust on investors' reactions to earnings announcements, we switch our attention to the impact of national support policy on the investors' perception of signaling credibility. As is known to all, the Politburo of the CPC is the most decisive group that rules the country, and thus we select the 18th collective learning of Politburo (CLP) of the 19th CPC central committee as the research event. In this collective learning, President Xi led the Politburo members to learn about the development status and trend of blockchain technology, which actually has provided endorsement and support to the blockchain industry. Thus, we incorporate a dummy variable with the value of one if a blockchain announcement was issued after the collective learning. The results are displayed in Table 14. We mainly concentrate on the coefficients of interest. The findings suggest that with relatively long event windows, national support policy would significantly increase investors' perception of signaling credibility.

[PLEASE INSERT TABLE 14 HERE]

Overall, the regression results reported in this section have proved our Hypothesis 3 to a great extent. In other words, despite the signaling credibility provided by technological attributes and reserves of high-tech firms, investors' perception of signaling credibility would also affect market reaction.

6 Conclusions

In this paper, we examine whether signaling credibility of firms' announcements affects market reaction. Specifically, with 302 blockchain announcements of Chinese A-share listed firms over the period 2016-2020 as the research sample, our research results indicate that blockchain announcements do have a positive impact on the market reaction. We further partition our sample into high-tech firms and non-high-tech firms according to national identification results. According to our estimates, high-tech firms with more technological attributes and reserves would convey the signaling credibility of blockchain announcements to the investors, incurring more cumulative abnormal returns. Our findings are robust using Fama-French five-factor model to estimate CARs, with an alternative measure of signaling credibility, and also excluding extreme CARs.

To further demonstrate what firm characteristics would influence the signaling credibility of high-tech firms, we incorporate the financial status, state ownership and disclosure type into our model. Then, it is evidenced that the signaling credibility of blockchain announcements is augmented in state-owned high-tech firms with normal financial status and voluntary information disclosure. Additionally, we analyze the factors that may affect the investors' perception of signaling credibility. Our findings show the textual sentiment and national support policy increase the investors' perception in the relatively long event windows.

On the whole, our investigation partly fills the gap in how the signaling credibility of listed firms' announcements, especially strategic announcements, affects the market reaction. Therefore, our findings indicate that investors' reactions are influenced not only by the signaling credibility following the firms' fundamentals but also the investors' perception of signaling credibility induced by the textual sentiment or relevant policies. These results have implications for listed firms about the importance of conveying credible information, and for regulators about how to improve capital market efficiency.

References

Autore D M, Clarke N, Jiang D. Blockchain speculation or value creation? Evidence from corporate investments[J]. Financial Management, 2020, forthcoming.

- Bai C E, Lu J, Tao Z. The multitask theory of state enterprise reform: Empirical evidence from China[J]. American Economic Review, 2006, 96(2): 353-357.
- Baranchuk N, Rebello M J. Spillovers from good-news and other bankruptcies: Real effects and price responses[J]. Journal of Financial Economics, 2018, 129(2): 228-249.
- Barber B M, Odean T. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors[J]. The Review of Financial Studies, 2008, 21(2): 785-818.
- Barber B M, De George E T, Lehavy R, et al. The earnings announcement premium around the globe[J]. Journal of Financial Economics, 2013, 108(1): 118-138.
- Balsam S, Krishnan J, Yang J S. Auditor industry specialization and earnings quality[J]. Auditing: A Journal of Practice & Theory, 2003, 22(2): 71-97.
- Birru J, Wang B. Nominal price illusion[J]. Journal of Financial Economics, 2016, 119(3): 578-598.
- Bonaimé A A. Repurchases, reputation, and returns[J]. Journal of Financial and Quantitative Analysis, 2012, 47(2): 469-491.
- Bosman R, Kräussl R, Mirgorodskaya E. Modifier words in the financial press and investor expectations[J]. Journal of Economic Behavior Organization, 2017, 138: 85-98.
- Bradshaw M, Liao G, Ma M S. Agency costs and tax planning when the government is a major shareholder[J]. Journal of Accounting and Economics, 2019, 67(2-3): 255-277.
- Campbell J Y, Lo A W, MacKinlay A C, et al. The econometrics of financial markets[J]. Macroeconomic Dynamics, 1998, 2(4): 559-562.
- Cahill D, Baur D G, Liu Z F, et al. I am a blockchain too: How does the market respond to companies' interest in blockchain? [J]. Journal of Banking & Finance, 2020, 113: 105740.
- Child T B, Massoud N, Schabus M, et al. Surprise election for Trump connections[J]. Journal of Financial Economics, 2021, 140(2): 676-697.
- Chen T, Kung J K. Busting the Princelings: The campaign against corruption in China's primary land market[J]. The Quarterly Journal of Economics, 2019, 134(1): 185-226.
- Chen K C W, Church B K. Going concern opinions and the market's reaction to bankruptcy filings[J]. Accounting Review, 1996: 117-128.
- Chen M A, Wu Q, Yang B. How valuable is FinTech innovation?[J]. The Review of Financial Studies, 2019, 32(5): 2062-2106.

- Cheng S F, De Franco G, Jiang H, et al. Riding the blockchain mania: public firms' speculative 8-K disclosures[J]. Management Science, 2019, 65(12): 5901-5913.
- Chiu J, Koeppl T V. Blockchain-based settlement for asset trading[J]. The Review of Financial Studies, 2019, 32(5): 1716-1753.
- Clark T A, Weinstein M I. The behavior of the common stock of bankrupt firms[J]. The Journal of Finance, 1983, 38(2): 489-504.
- Cong L W, He Z. Blockchain disruption and smart contracts[J]. The Review of Financial Studies, 2019, 32(5): 1754-1797.
- Demirkan S, Demirkan I, McKee A. Blockchain technology in the future of business cyber security and accounting[J]. Journal of Management Analytics, 2020, 7(2): 189-208.
- Diamond D W, Verrecchia R E. Disclosure, liquidity, and the cost of capital[J]. The Journal of Finance, 1991, 46(4): 1325-1359.
- Dong Z, Dong Q. HowNet-a hybrid language and knowledge resource[C]//International Conference on Natural Language Processing and Knowledge Engineering, 2003. Proceedings. 2003. IEEE, 2003: 820-824.
- Fama E F, French K R. A five-factor asset pricing model[J]. Journal of Financial Economics, 2015, 116(1): 1-22.
- Francis J, Nanda D, Olsson P. Voluntary disclosure, earnings quality, and cost of capital[J]. Journal of Accounting Research, 2008, 46(1): 53-99.
- Frankel D M. Adaptive expectations and stock market crashes[J]. International Economic Review, 2008, 49(2): 595-619.
- Francis J, Nanda D, Olsson P. Voluntary disclosure, earnings quality, and cost of capital[J]. Journal of Accounting Research, 2008, 46(1): 53-99.
- Fu R, Kraft A, Zhang H. Financial reporting frequency, information asymmetry, and the cost of equity[J]. Journal of Accounting and Economics, 2012, 54(2-3): 132-149.
- Gao H, Ru H, Tang D Y. Subnational debt of China: The politics-finance nexus[J]. Journal of Financial Economics, 2021.
- Gan J, Guo Y, Xu C. Decentralized privatization and change of control rights in China[J]. The Review of Financial Studies, 2018, 31(10): 3854-3894.
- Garcia D. Sentiment during recessions[J]. The Journal of Finance, 2013, 68(3): 1267-1300.
- Goldstein I, Jiang W, Karolyi G A. To FinTech and beyond[J]. The Review of Financial Studies, 2019, 32(5): 1647-1661.
- Goldstein I, Yang L. Good disclosure, bad disclosure[J]. Journal of Financial Economics, 2019, 131(1): 118-138.
- Guiso L, Sapienza P, Zingales L. Trusting the stock market[J]. The Journal of Finance, 2008, 63(6): 2557-2600.

- Hassani H, Huang X, Silva E. Banking with blockchain-ed big data[J]. Journal of Management Analytics, 2018, 5(4): 256-275.
- Hirshleifer D, Teoh S H. Limited attention, financial reporting and disclosure[J]. Journal of Accounting and Economics, 2003, 36(1-3): 337-386.
- Hong H, Jiang W, Wang N, et al. Trading for status[J]. The Review of Financial Studies, 2014, 27(11): 3171-3212.
- Hughes P J. Signaling by direct disclosure under asymmetric information[J]. Journal of Accounting and Economics, 1986, 8(2): 119-142.
- Hutton A P, Stocken P C. Prior Forecasting Accuracy and Investor Reaction to Management Earnings Forecasts[J]. Journal of Financial Reporting, 2021, 6(1): 87-107.
- Hurd M, Van Rooij M, Winter J. Stock market expectations of Dutch households[J]. Journal of Applied Econometrics, 2011, 26(3): 416-436.
- Hwang S, Keswani A, Shackleton M B. Surprise vs anticipated information announcements: Are prices affected differently? An investigation in the context of stock splits[J]. Journal of Banking & Finance, 2008, 32(5): 643-653.
- Jayaraman S, Shuang Wu J. Should I stay or should I grow? Using voluntary disclosure to elicit market feedback[J]. The Review of Financial Studies, 2020, 33(8): 3854-3888.
- Jiang F, Kim K A. Corporate governance in China: A modern perspective[J]. Journal of Corporate Finance, 2015, 32: 190-216.
- Jiang F, Kim K A. Corporate governance in China: A survey[J]. Review of Finance, 2020, 24(4): 733-772.
- Kearney C, Liu S. Textual sentiment in finance: A survey of methods and models[J]. International Review of Financial Analysis, 2014, 33: 171-185.
- Keran M W. Expectations, money, and the stock market[M]. Research Department [of the] Federal Reserve Bank, 1971.
- Levi S, Zhang X J. Asymmetric decrease in liquidity trading before earnings announcements and the announcement return premium[J]. Journal of Financial Economics, 2015, 118(2): 383-398.
- Li F. The information content of forward_looking statements in corporate filings—A naive Bayesian machine learning approach[J]. Journal of Accounting Research, 2010, 48(5): 1049-1102.
- Loughran T, McDonald B. When is a liability not a liability? Textual analysis, dictionaries, and 10_Ks[J]. The Journal of Finance, 2011, 66(1): 35-65.
- Nakamoto S. Bitcoin: A peer-to-peer electronic cash system[J]. Decentralized Business Review, 2008: 21260.
- Ota K, Kawase H, Lau D. Does reputation matter? Evidence from share repurchases[J].

Journal of Corporate Finance, 2019, 58: 287-306.

- Peng L, Xiong W. Investor attention, overconfidence and category learning[J]. Journal of Financial Economics, 2006, 80(3): 563-602.
- Pevzner M, Xie F, Xin X. When firms talk, do investors listen? The role of trust in stock market reactions to corporate earnings announcements[J]. Journal of Financial Economics, 2015, 117(1): 190-223.
- Price S M K, Doran J S, Peterson D R, et al. Earnings conference calls and stock returns: The incremental informativeness of textual tone[J]. Journal of Banking & Finance, 2012, 36(4): 992-1011.
- Saleh F. Blockchain without waste: Proof-of-stake[J]. The Review of Financial Studies, 2021, 34(3): 1156-1190.
- Savor P, Wilson M. Earnings announcements and systematic risk[J]. The Journal of Finance, 2016, 71(1): 83-138.
- Shiller R J. Irrational exuberance[M]. Princeton university press, 2015.
- Stocken P C. Credibility of voluntary disclosure[J]. The RAND Journal of Economics, 2000: 359-374.
- Tetlock P C, Saar_Tsechansky M, Macskassy S. More than words: Quantifying language to measure firms' fundamentals[J]. The Journal of Finance, 2008, 63(3): 1437-1467.
- Teoh S H, Wong T J. Perceived auditor quality and the earnings response coefficient[J]. Accounting Review, 1993: 346-366.
- Whitaker R B. The early stages of financial distress[J]. Journal of Economics and Finance, 1999, 23(2): 123-132.
- Zhu Y L, Min J, Zhou Y, et al. Semantic orientation computing based on HowNet[J]. Journal of Chinese Information Processing, 2006, 20(1): 14-20.

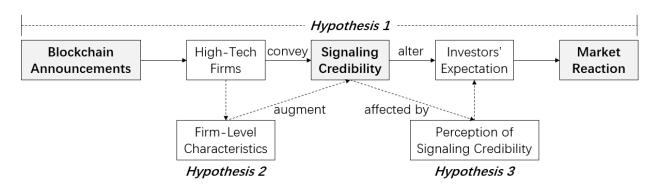
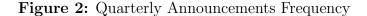
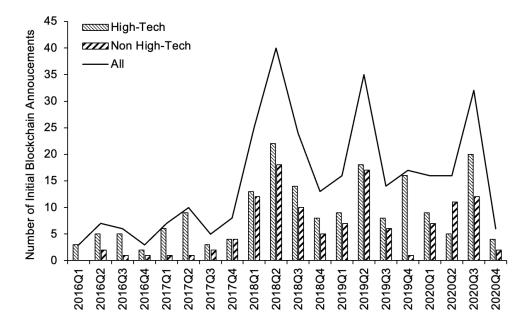


Figure 1: Illustrating the Hypotheses Development

Notes: This figure illustrates the hypotheses development, including three hypotheses we presented.





Notes: This figure presents the quarterly frequency of blockchain announcements in our research sample and also shows it with two categories, that is high-tech and non-high-tech firms. High-tech firms are defined as firms have been recognized as high-tech firms according to Administrative Measures for the Recognition of High-Tech Enterprises.

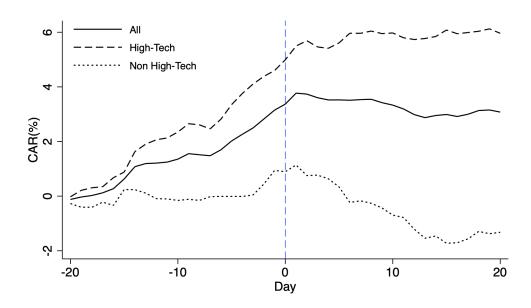


Figure 3: Cumulative Abnormal Returns around the Blockchain Announcements

Notes: This figure plots CARs for high-tech and non-high-tech firms over a [-20,20] tradingday window surrounding the blockchain announcements. CARs are calculated using the market model with adopting an estimation window from 255 trading-day to 46 trading-day prior to the event day.

Variable	Definition
$\operatorname{CAR}[t_1, t_2]$	Cumulative abnormal return from time t_1 to time t_2 .
High-Tech	An indicator variable that takes the value of 1 if the firm is recognized
	as a high-tech enterprise according to the Administrative Measures for the
	Recognition of High-Tech Enterprises, and 0 otherwise.
ST	An indicator variable that takes the value of 1 if the firm is in the ST period
	on the blockchain announcement day, i.e., the stock exchange determines
	that it is a listed company with abnormal financial status, and 0 otherwise
Type	An indicator variable that takes the value of 1 if the blockchain announce
	ment issued by the firm belongs to the active disclosure, including regular
	financial reports and information disclosure, instead of the passive disclo
	sure, including investor activity information or response to the supervision
	letter, and 0 otherwise.
SOE	An indicator variable that takes the value of 1 if the firm is state-owned
	and 0 otherwise.
CLP	An indicator variable that takes the value of 1 if the firm's blockchain an
	nouncement date is before the 18th collective learning of the Political Bu
	reau of the 19th CPC Central Committee, and 0 otherwise.
Text	The number of positive words divided by the sum of the number of positive
	words and negative words, and the judgment of emotional polarity come
	from HowNet Sentiment Lexicon.
CRB	Cumulative return of the Bitcoin 30 days before the firm's blockchain and nouncement date.
Pat	The natural logarithm of the number of firm's valid patents plus 1 by the
	end of the last fiscal year on the announcement date.
Size	The natural logarithm of the total assets by the end of the last fiscal year
	on the announcement date.
ROE	Return on equity by the end of the last fiscal year on the announcement
	date.
Lev	The ratio of total liabilities divided by total assets by the end of the last
	fiscal year on the announcement date.

 Table 1: Variable Definitions

Variable	Mean	Min	25th pctile	50th pctile	75th pctile	Max	St. dev	N
CAR[-1,1]	0.01	-0.19	-0.02	0.00	0.03	0.25	0.06	302
CAR[-5,5]	0.02	-0.31	-0.03	0.01	0.06	0.43	0.10	302
CAR[-10, 10]	0.02	-0.37	-0.05	0.01	0.08	0.53	0.12	302
CAR[-20,20]	0.03	-0.52	-0.08	0.01	0.12	0.85	0.18	302
ST	0.01	0.00	0.00	0.00	0.00	1.00	0.10	302
Type	0.84	0.00	1.00	1.00	1.00	1.00	0.37	302
SOE	0.26	0.00	0.00	0.00	1.00	1.00	0.44	302
CLP	0.28	0.00	0.00	0.00	1.00	1.00	0.45	302
Text	0.83	0.59	0.79	0.83	0.87	0.97	0.06	302
CRB	8.14	-52.23	-11.36	4.37	25.16	145.20	30.19	302
Pat	3.98	0.69	3.00	4.08	5.02	7.12	1.50	272
Size	22.60	19.69	21.45	22.27	23.32	30.89	1.80	302
ROE	0.07	-0.62	0.04	0.08	0.12	0.39	0.10	302
Lev	0.43	0.01	0.26	0.41	0.58	1.75	0.23	302

 Table 2: Descriptive Statistics

Notes: This table summarizes the summary statistics and our research sample spans a 5year period from 2016 to 2020. After the essential data processing, we have a final sample of 302 blockchain announcements, one for each company. All variables are defined in Table 1.

CAR[-20,20]	CAR[-10,10]	CAR[-5,5]	CAR[-1,1]
Panel A: Full Sam	nple		
0.0308***	0.0209***	0.0183***	0.0095^{***}
(2.9582)	(3.0097)	(3.2972)	(2.8687)
Panel B: High-Tee	ch Sample		
0.0596^{***}	0.0384***	0.0280***	0.0111**
(4.0839)	(3.8852)	(3.4868)	(2.4367)
Panel C: Non-Hig	h-Tech Sample		
-0.0132	-0.0059	0.0035	0.0070
(-1.0164)	(-0.7113)	(0.5279)	(1.5116)
Panel D: Differen	ce		
0.0729***	0.0444^{***}	0.0245**	0.0041
(3.4878)	(3.1775)	(2.1732)	(0.6122)

 Table 3: Univariate Tests for Cumulative Abnormal Returns

Notes: This table shows the cumulative abnormal returns for four different event windows, i.e., [-20,20], [-10,10], [-5,5], [-1,1]. Results within full sample, high-tech sample and non-high-tech sample are reported in Panel A to Panel C. Panel D presents the univariate tests between the two categories. t-statistics are shown in parentheses. *, ** and *** denotes the significance at the 10%, 5% and 1% level, respectively. All variables are defined in Table 1.

	(1)	(2)	(3)	(4)
	CAR[-1,1]	CAR[-5,5]	CAR[-10, 10]	CAR[-20,20]
Panel A: Excl	uding control	variables		
High-Tech	-0.0028	0.0239*	0.0484***	0.0791***
	(-0.54)	(2.16)	(5.59)	(7.13)
Constant	0.0109***	0.0033	-0.0091***	-0.0178**
	(3.44)	(0.49)	(-1.73)	(-2.65)
Year FEs	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
Observations	302	302	302	302
R-squared	0.0409	0.0548	0.0643	0.1350
Panel B: Inclu	ding control v	ariables		
High-Tech	-0.0056	0.0202*	0.0432***	0.0642***
	(-1.00)	(1.92)	(4.40)	(5.92)
Size	-0.0020	0.0011	-0.0030	-0.0190**
	(-0.64)	(0.24)	(-0.56)	(-2.44)
ROE	0.0509	0.0063	-0.0260	-0.0240
	(1.29)	(0.11)	(-0.57)	(-0.35)
Lev	-0.0176	-0.0595	-0.0368	-0.0032
	(-0.81)	(-1.74)	(-1.39)	(-0.05)
Constant	0.0615	0.0071	0.0792	0.4239**
	(0.96)	(0.08)	(0.68)	(2.65)
Year FEs	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
Observations	302	302	302	302
R-squared	0.0524	0.0657	0.0696	0.1521

Table 4: Signaling Credibility and Market Reactions to the Blockchain Announcement

Notes: This table summarizes the estimation of Eq.(4) using CARs with different event windows as the dependent variable, and year fixed effects and industry fixed effects are controlled in all columns. Robust t-statistics are shown in parentheses. *, ** and *** denotes the significance at the 10%, 5% and 1% level, respectively, similarly hereinafter. All variables are defined in Table 1.

	(1)	(2)	(3)	(4)
	CAR[-1,1]	CAR[-5,5]	CAR[-10, 10]	CAR[-20,20]
$\mathrm{High}\text{-}\mathrm{Tech}\times\mathrm{ST}$	-0.0199**	-0.0659***	-0.1466***	-0.1158***
	(-2.81)	(-6.00)	(-16.75)	(-9.49)
High-Tech	-0.0052	0.0231*	0.0467^{***}	0.0679^{***}
	(-0.89)	(2.06)	(5.09)	(6.59)
ST	0.0216	0.1767^{***}	0.1723***	0.1937**
	(0.40)	(3.62)	(3.21)	(2.37)
Size	-0.0017	0.0032	-0.0011	-0.0168**
	(-0.48)	(0.61)	(-0.20)	(-2.35)
ROE	0.0503	0.0035	-0.0370	-0.0337
	(1.24)	(0.06)	(-0.72)	(-0.47)
Lev	-0.0212	-0.0893***	-0.0656**	-0.0356
	(-0.74)	(-3.14)	(-2.29)	(-0.64)
Constant	0.0572	-0.0297	0.0485	0.3878**
	(0.79)	(-0.28)	(0.42)	(2.64)
Year FEs	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
Observations	302	302	302	302
R-squared	0.0531	0.0788	0.0901	0.1610

Table 5: The Impact of Financial Status on the Signaling Credibility

Notes: This table summarizes the estimation of Eq.(5) incorporating the indicator variable ST for firms' financial status, and year fixed effects and industry fixed effects are controlled in all columns.

	(1)	(2)	(3)	(4)
	CAR[-1,1]	CAR[-5,5]	CAR[-10, 10]	CAR[-20,20]
$\text{High-Tech}\times\text{SOE}$	-0.0020	0.0214	0.0473*	0.0819***
	(-0.15)	(1.24)	(1.85)	(4.75)
High-Tech	-0.0084	0.0193	0.0490***	0.0694^{***}
	(-1.31)	(1.26)	(6.01)	(4.44)
SOE	-0.0050	-0.0016	0.0171	0.0237^{*}
	(-0.69)	(-0.20)	(1.57)	(1.79)
Size	-0.0017	0.0012	-0.0041	-0.0206**
	(-0.56)	(0.26)	(-0.78)	(-2.79)
ROE	0.0517	0.0065	-0.0254	-0.0208
	(1.35)	(0.11)	(-0.55)	(-0.30)
Lev	-0.0184	-0.0598	-0.0371	-0.0057
	(-0.83)	(-1.59)	(-1.28)	(-0.10)
Constant	0.0568	0.0056	0.0984	0.4528^{**}
	(0.91)	(0.06)	(0.88)	(2.97)
Year FEs	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
Observations	302	302	302	302
R-squared	0.0539	0.0657	0.0712	0.1538

Table 6: The Impact of State Ownership on the Signaling Credibility

Notes: This table summarizes the estimation of Eq.(5) incorporating the indicator variable SOE for firms' state ownership, and year fixed effects and industry fixed effects are controlled in all columns.

	(1)	(2)	(3)	(4)
	CAR[-1,1]	CAR[-5,5]	CAR[-10, 10]	CAR[-20,20]
$\text{High-Tech} \times \text{Type}$	-0.0034	0.0008	0.0370***	0.0789***
	(-0.45)	(0.04)	(6.49)	(4.29)
High-Tech	0.0028	0.0014	0.0216^{**}	0.0617^{**}
	(0.26)	(0.13)	(2.74)	(2.57)
Type	0.0040	-0.0238	-0.0106	0.0147
	(0.55)	(-1.62)	(-0.95)	(0.86)
Size	-0.0021	0.0014	-0.0026	-0.0190**
	(-0.68)	(0.33)	(-0.49)	(-2.45)
ROE	0.0530	0.0076	-0.0311	-0.0308
	(1.36)	(0.12)	(-0.63)	(-0.43)
Lev	-0.0160	-0.0617*	-0.0407	-0.0049
	(-0.78)	(-1.95)	(-1.43)	(-0.08)
Constant	0.0606	0.0198	0.0817	0.4127**
	(0.97)	(0.23)	(0.74)	(2.54)
Year FEs	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
Observations	302	302	302	302
R-squared	0.0535	0.0683	0.0712	0.1531

 Table 7: The Impact of Voluntary Disclosure on the Signaling Credibility

Notes: This table summarizes the estimation of Eq.(5) incorporating the indicator variable Type for firms' voluntary disclosure, and year fixed effects and industry fixed effects are controlled in all columns.

	(1)	(2)	(3)	(4)
	CAR[-1,1]	CAR[-5,5]	CAR[-10, 10]	CAR[-20, 20]
High-Tech	-0.0022	0.0167^{*}	0.0425***	0.0763***
	(-0.38)	(2.11)	(5.93)	(8.76)
Size	-0.0005	0.0031	0.0028	-0.0017
	(-0.16)	(0.90)	(0.92)	(-0.44)
ROE	0.0336	0.0002	-0.0248	-0.0492
	(0.85)	(0.00)	(-0.30)	(-0.44)
Lev	-0.0218	-0.0644**	-0.0563***	-0.0687*
	(-1.25)	(-2.56)	(-3.34)	(-1.84)
Constant	0.0277	-0.0370	-0.0508	0.0375
	(0.48)	(-0.52)	(-0.81)	(0.48)
Year FEs	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
Observations	302	302	302	302
R-squared	0.0484	0.0567	0.0740	0.1307

 Table 8: Robustness Test of Utilizing Fama-French Five Factor Model for CARs

Notes: This table presents the reestimation results of Eq.(4) utilizing Fama-French five-factor model to calculate CARs, and year fixed effects and industry fixed effects are controlled in all columns.

	(1)	(2)	(3)	(4)
	CAR[-1,1]	CAR[-5,5]	CAR[-10,10]	CAR[-20,20]
Pat	0.0079**	0.0090**	0.0181***	0.0265***
	(3.02)	(2.98)	(4.08)	(3.57)
Size	-0.0057	-0.0008	-0.0094	-0.0315**
	(-1.24)	(-0.16)	(-1.66)	(-2.62)
ROE	0.0614	0.0141	-0.0230	-0.0372
	(1.58)	(0.32)	(-0.91)	(-0.76)
Lev	-0.0215	-0.1176***	-0.1075***	-0.0886*
	(-0.78)	(-4.53)	(-5.15)	(-1.92)
Constant	0.1119	0.0515	0.2100*	0.6777^{**}
	(1.30)	(0.47)	(1.87)	(2.87)
Year FEs	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
Observations	272	272	272	272
R-squared	0.0779	0.0823	0.0965	0.1849

Table 9: Robustness Test of Alternative Measure for the Signaling Credibility

Notes: This table presents the reestimation results of Eq.(4) incorporating the valid patents as the measure of signaling credibility, and year fixed effects and industry fixed effects are controlled in all columns.

	(1)	(2)	(3)	(4)
	CAR[-1,1]	CAR[-5,5]	CAR[-10, 10]	CAR[-20,20]
High-Tech	-0.0063	0.0194*	0.0343**	0.0530***
	(-1.05)	(1.86)	(2.35)	(4.52)
Size	-0.0033	-0.0027	-0.0042	-0.0134
	(-1.44)	(-0.72)	(-1.13)	(-1.63)
ROE	0.0572	-0.0152	-0.0578	0.0145
	(1.37)	(-0.26)	(-1.08)	(0.20)
Lev	0.0007	-0.0231**	-0.0222	-0.0409
	(0.04)	(-2.30)	(-1.42)	(-0.83)
Constant	0.0835	0.0767	0.1078	0.3165^{*}
	(1.73)	(0.94)	(1.23)	(1.86)
Year FEs	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
Observations	296	296	296	295
R-squared	0.0611	0.0771	0.0619	0.0755

Table 10: Robustness Test of Excluding Extreme CARs (1%/99%)

Notes: This table presents the reestimation results of Eq.(4) excluding firms with extreme CARs, defined as those larger than the 99th percentile or smaller than the 1st percentile, and year fixed effects and industry fixed effects are controlled in all columns.

	(1)	(2)	(3)	(4)
	CAR[-1,1]	CAR[-5,5]	CAR[-10, 10]	CAR[-20,20]
High-Tech	-0.0058	0.0201*	0.0426***	0.0632***
	(-1.04)	(1.88)	(4.46)	(5.81)
AI	0.0039	0.0037	0.0151	0.0281^{*}
	(0.97)	(0.43)	(1.23)	(1.96)
Size	-0.0021	0.0010	-0.0034	-0.0198**
	(-0.65)	(0.21)	(-0.63)	(-2.47)
ROE	0.0501	0.0055	-0.0291	-0.0298
	(1.26)	(0.10)	(-0.62)	(-0.44)
Lev	-0.0171	-0.0591	-0.0351	0.0000
	(-0.78)	(-1.75)	(-1.35)	(0.00)
Constant	0.0618	0.0073	0.0802	0.4259^{**}
	(0.95)	(0.08)	(0.65)	(2.54)
Year FEs	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
Observations	302	302	302	302
R-squared	0.0533	0.0660	0.0729	0.1571

Table 11: Robustness Test of Controlling for AI impact

Notes: This table presents the reestimation results of Eq.(4) introducing a dummy variable AI that indicates whether there is artificial technology information in the blockchain announcements, and year fixed effects and industry fixed effects are controlled in all columns.

	(1)	(2)	(3)	(4)
	CAR[-1,1]	CAR[-5,5]	CAR[-10, 10]	CAR[-20,20]
$\text{High-Tech} \times \text{Text}$	0.0527	0.3218	0.3190	0.6161**
	(0.69)	(1.61)	(1.09)	(2.44)
High-Tech	-0.0480	-0.2424	-0.2174	-0.4392**
	(-0.82)	(-1.43)	(-0.95)	(-2.22)
Text	-0.1338**	-0.3873**	-0.3574**	-0.6513***
	(-2.41)	(-3.03)	(-2.26)	(-3.69)
Size	-0.0015	0.0026	-0.0016	-0.0164*
	(-0.51)	(0.51)	(-0.25)	(-1.97)
ROE	0.0591	0.0242	-0.0102	0.0036
	(1.37)	(0.38)	(-0.18)	(0.04)
Lev	-0.0193	-0.0661**	-0.0431	-0.0149
	(-1.02)	(-2.29)	(-1.78)	(-0.31)
Constant	0.1603^{*}	0.2913***	0.3412***	0.9010***
	(1.87)	(3.45)	(6.24)	(7.19)
Year FEs	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
Observations	302	302	302	302
R-squared	0.0630	0.0823	0.0783	0.1646

Table 12: The Perception of Signaling Credibility affected by Textual Sentiment

Notes: This table summarizes the estimation of Eq.(6) incorporating the variable *Text* measuring the textual sentiment of blockchain announcements, and year fixed effects and industry fixed effects are controlled in all columns.

	(1)	(2)	(3)	(4)
	CAR[-1,1]	CAR[-5,5]	CAR[-10,10]	CAR[-20,20]
$\text{High-Tech} \times \text{CRB}$	0.0004*	0.0002	0.0003	0.0006
	(1.90)	(0.57)	(1.16)	(1.36)
High-Tech	-0.0088	0.0187	0.0406^{***}	0.0589^{***}
	(-1.27)	(1.63)	(4.17)	(4.78)
CRB	-0.0003*	-0.0003	-0.0003	-0.0005
	(-2.08)	(-1.34)	(-1.20)	(-1.22)
Size	-0.0020	0.0012	-0.0030	-0.0191**
	(-0.60)	(0.27)	(-0.57)	(-2.57)
ROE	0.0509	0.0045	-0.0258	-0.0230
	(1.29)	(0.08)	(-0.57)	(-0.34)
Lev	-0.0169	-0.0577	-0.0364	-0.0029
	(-0.79)	(-1.72)	(-1.35)	(-0.05)
Constant	0.0636	0.0052	0.0813	0.4292**
	(0.93)	(0.06)	(0.71)	(2.78)
Year FEs	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
Observations	302	302	302	302
R-squared	0.0609	0.0689	0.0707	0.1541

Table 13: The Perception of Signaling Credibility affected by the Bitcoin Return

Notes: This table summarizes the estimation of Eq.(6) incorporating the variable CRB measuring the 30-day cumulative return of Bitcoin prior to the blockchain announcements, and year fixed effects and industry fixed effects are controlled in all columns.

	(1)	(2)	(3)	(4)
	CAR[-1,1]	CAR[-5,5]	CAR[-10, 10]	CAR[-20,20]
$\mathrm{High}\text{-}\mathrm{Tech}\times\mathrm{CLP}$	-0.0097	0.0090	0.0344*	0.0621***
	(-1.41)	(0.64)	(2.07)	(3.10)
High-Tech	-0.0088	0.0272**	0.0534^{***}	0.0771^{***}
	(-1.37)	(2.71)	(4.39)	(7.11)
CLP	-0.0138	0.0059	0.0179	0.0335
	(-1.13)	(0.28)	(0.83)	(0.97)
Size	-0.0020	0.0009	-0.0031	-0.0191**
	(-0.62)	(0.22)	(-0.62)	(-2.56)
ROE	0.0514	0.0033	-0.0297	-0.0278
	(1.35)	(0.06)	(-0.63)	(-0.37)
Lev	-0.0173	-0.0609*	-0.0385	-0.0050
	(-0.75)	(-1.85)	(-1.55)	(-0.09)
Constant	0.0646	0.0091	0.0787	0.4194^{**}
	(0.99)	(0.10)	(0.69)	(2.79)
Year FEs	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
Observations	302	302	302	302
R-squared	0.0546	0.0692	0.0740	0.1552

Table 14: The Perception of Signaling Credibility affected by National Support Policy

Notes: This table summarizes the estimation of Eq.(6) incorporating a dummy variable CLP that takes the value of one if a blockchain announcement is issued after the 18th collective learning of 19th CPC central committee, and year fixed effects and industry fixed effects are controlled in all columns.

Appendix. Code

```
1 # -*- coding:utf-8 -*-
2 import requests
3 import re
4 import json
5 import datetime
6 import math
7 import time
8 import pandas as pd
9 import threading, queue
10 import os
11 from eprogress import LineProgress, CircleProgress, MultiProgressManager
12
13 def Bar(date,total, all):
14
       percent = round(1.0 * total / all * 100, 2)
       print("{} | process:{} [{}/{}]". format(date,
15
           str(percent) + '%', total, all))
16
17
18
   def Get_DateQueue(start_date, end_date):
19
       offset = datetime.timedelta(days=1)
20
       interval_days = (end_date - start_date).days
21
       DateQueue = queue.Queue(maxsize=interval_days + 1)
22
23
       for i in range(interval_days + 1):
           DateQueue.put((start_date + offset * i).strftime("%Y-%m-%d"))
24
25
       return DateQueue
26
27
   class EM_Notice(threading.Thread):
28
       def __init__(self,DateQueue):
29
30
            super(EM_Notice, self).__init__()
31
           self.cop = re. compile("[^u4e00-u9fa5^a-z^A-Z^0-9]")
           self.headers = {
32
               'Accept': '*/*',
33
```

34	'Accept-Encoding': 'gzip, deflate',
35	'Accept-Language': 'zh-CN,zh;q=0.9',
36	'Connection': 'keep-alive',
37	'Cookie': 'qgqp_b_id=fc0d4332a20a65cbeea276a2bcd30009; _qddaz=QD
	.yckwlq.rqbkg9.kq6i6bf4; cowCookie=true; st_si
	=37975780934967; intellpositionL=541px; cowminicookie=true;
	st_asi=delete;
	=2021-06-21%2012%3A02%3A10;
	<pre>eastmoney.com%2Fzlsj%2F2015-03-31-1-2.html; st_sn=13; st_psi</pre>
	=20210714161425558-113300301472-0662840520; intellpositionT
	=455px',
38	'Host': 'np-anotice-stock.eastmoney.com',
39	'Referer': 'http://data.eastmoney.com/',
40	'User-Agent': 'Mozilla/5.0 (Windows NT 10.0; Win64; x64)
	AppleWebKit/537.36 (KHTML, like Gecko) Chrome/91.0.4472.124
	Safari/537.36'
41	}
42	<pre>self.columns = ['code', 'name', 'announcement date', 'title', 'text'</pre>
]
43	<pre>self.params = {</pre>
43 44	<pre>self.params = { 'cb': 'jQuery1123032592532175909694_1626249781039',</pre>
	<pre>self.params = {</pre>
44	<pre>self.params = { 'cb': 'jQuery1123032592532175909694_1626249781039',</pre>
44 45	<pre>self.params = { 'cb': 'jQuery1123032592532175909694_1626249781039', 'sr': '-1',</pre>
44 45 46	<pre>self.params = { 'cb': 'jQuery1123032592532175909694_1626249781039', 'sr': '-1', 'page_size': '100',</pre>
44 45 46 47	<pre>self.params = { 'cb': 'jQuery1123032592532175909694_1626249781039', 'sr': '-1', 'page_size': '100', 'page_index': '1', 'ann_type': 'A', 'client_source': 'web',</pre>
44 45 46 47 48	<pre>self.params = { 'cb': 'jQuery1123032592532175909694_1626249781039', 'sr': '-1', 'page_size': '100', 'page_index': '1', 'ann_type': 'A',</pre>
44 45 46 47 48 49	<pre>self.params = { 'cb': 'jQuery1123032592532175909694_1626249781039', 'sr': '-1', 'page_size': '100', 'page_index': '1', 'ann_type': 'A', 'client_source': 'web',</pre>
44 45 46 47 48 49 50	<pre>self.params = { 'cb': 'jQuery1123032592532175909694_1626249781039', 'sr': '-1', 'page_size': '100', 'page_index': '1', 'ann_type': 'A', 'client_source': 'web', 'f_node': '0',</pre>
44 45 46 47 48 49 50 51	<pre>self.params = { 'cb': 'jQuery1123032592532175909694_1626249781039', 'sr': '-1', 'page_size': '100', 'page_index': '1', 'ann_type': 'A', 'client_source': 'web', 'f_node': '0', 's_node': '0',</pre>
44 45 46 47 48 49 50 51 52 53 54	<pre>self.params = { 'cb': 'jQuery1123032592532175909694_1626249781039', 'sr': '-1', 'page_size': '100', 'page_index': '1', 'ann_type': 'A', 'client_source': 'web', 'f_node': '0', 's_node': '0', 'begin_time': '2016-07-14', 'end_time': '2021-07-12', }</pre>
44 45 46 47 48 49 50 51 52 53 54 55	<pre>self.params = { 'cb': 'jQuery1123032592532175909694_1626249781039', 'sr': '-1', 'page_size': '100', 'page_index': '1', 'ann_type': 'A', 'client_source': 'web', 'f_node': '0', 's_node': '0', 'begin_time': '2016-07-14', 'end_time': '2021-07-12', } self.pdf_params = {</pre>
44 45 46 47 48 49 50 51 52 53 54 55 56	<pre>self.params = { 'cb': 'jQuery1123032592532175909694_1626249781039', 'sr': '-1', 'page_size': '100', 'page_index': '1', 'ann_type': 'A', 'client_source': 'web', 'f_node': '0', 's_node': '0', 'begin_time': '2016-07-14', 'end_time': '2021-07-12', } self.pdf_params = { 'cb': 'jQuery1123024374455058233568_1626272109929', </pre>
44 45 46 47 48 49 50 51 52 53 54 55 56 57	<pre>self.params = { 'cb': 'jQuery1123032592532175909694_1626249781039', 'sr': '-1', 'page_size': '100', 'page_index': '1', 'ann_type': 'A', 'client_source': 'web', 'f_node': '0', 's_node': '0', 'begin_time': '2016-07-14', 'end_time': '2021-07-12', } self.pdf_params = { 'cb': 'jQuery1123024374455058233568_1626272109929', 'art_code': '', </pre>
44 45 46 47 48 49 50 51 52 53 54 55 56	<pre>self.params = { 'cb': 'jQuery1123032592532175909694_1626249781039', 'sr': '-1', 'page_size': '100', 'page_index': '1', 'ann_type': 'A', 'client_source': 'web', 'f_node': '0', 's_node': '0', 'begin_time': '2016-07-14', 'end_time': '2021-07-12', } self.pdf_params = { 'cb': 'jQuery1123024374455058233568_1626272109929', </pre>

```
60
                '_': '1626254607613'
61
           }
62
           self.url = 'http://np-anotice-stock.eastmoney.com/api/security/ann'
63
           self.notice_url = 'http://np-cnotice-stock.eastmoney.com/api/content
               /ann'
64
           self.DateQueue=DateQueue
65
           self.datas=[]
66
           self.max 1=32759
67
68
69
       def Get_Content(self, page_size, notice_content):
70
           for i in range(2, page_size + 1):
71
                self.pdf_params['page_index'] = i
72
                resource = requests.get(self.notice_url, params=self.pdf_params)
                   .text
73
                result = re.findall('.?\((.+)\)', resource)[0]
74
                result = json.loads(result)
75
                try:
                    notice_content += result['data']['notice_content']
76
77
                except:
78
                    # print(i, result)
79
                    pass
80
           return notice_content
81
82
       def Get_info(self, art_code='', date=''):
           self.pdf_params['art_code'] = art_code
83
           self.pdf_params['page_index'] = 1
84
           resource = requests.get(self.notice_url, params=self.pdf_params).
85
               text
86
           result = re.findall('.?\((.+)\)', resource)[0]
87
           result = json.loads(result)
           stock, country, notice_title, notice_content = None, None, None,
88
               None
           stock = result['data']['security'][0]['stock']
89
90
           country = result['data']['security'][0]['short_name']
           notice_title = result['data']['notice_title']
91
```

```
page_size = result['data']['page_size']
 92
 93
            try:
 94
                 notice_content = result['data']['notice_content']
 95
                 if page_size > 1:
                     notice_content += self.Get_Content(page_size, notice_content
 96
                        )
 97
                 notice_content = self.cop.sub('', notice_content)
 98
                 l_content = len(notice_content)
                 n = math.ceil(l_content / self.max_l)
 99
                 for i in range(1, n + 1):
100
101
                     self.datas.append(
102
                         (stock, country, date, notice_title, notice_content[(i -
                             1) * self.max_l:i * self.max_l]))
103
            except:
104
                 # print(result)
105
                 pass
106
107
        def Get_Ann_ByDay(self, date):
108
            self.datas=[]
109
            self.params['begin_time'] = date
110
            self.params['end_time'] = date
111
            try:
112
                 resource = requests.get(self.url, params=self.params, headers=
                    self.headers).text
                 result = re.findall('.?\((.+)\)', resource)[0]
113
114
                 total_hits = json.loads(result)['data']['total_hits']
                 sum_of_pageNum = math.ceil(total_hits / 100)
115
                 total = 0
116
117
                 for i in range(1, sum_of_pageNum + 1):
118
                     self.params['page_index'] = i
119
                     resource = requests.get(self.url, params=self.params,
                        headers=self.headers).text
120
                     result = re.findall('.?\((.+)\)', resource)[0]
121
                     datas = json.loads(result)['data']['list']
122
                     for data in datas:
123
                         art_code = data['art_code']
```

```
124
                         self.Get_info(art_code=art_code, date=date)
125
                         Bar(date, total, total_hits)
126
                         total+=1
127
                         time.sleep(0.1)
128
                 return True
129
             except:
130
                 return False
131
132
133
         def Download_Day_Notices(self, date):
134
             if self.Get_Ann_ByDay(date):
135
                 pd.DataFrame(self.datas, columns=self.columns).to_csv('data/{}.
                    csv'.
                    format(date), index=None, encoding='gbk')
136
                 return True
137
             else:
138
                 return False
139
140
         def Download_All_By_nThread(self, thread_num):
141
             pass
142
143
         def run(self):
144
             while True:
145
                 if self.DateQueue.empty():
146
                     break
147
                 date= self.DateQueue.get()
148
                 if os.path.exists('data/{}.csv'. format(date)):
149
                     print('data/{}.csv already exists'. format(date))
150
                 else:
151
                     if not self.Download_Day_Notices(date):
152
                         self.DateQueue.put(date)
153
154
    def Download_by_nThread(ThreadNum,DateQueue):
155
         n=DateQueue.qsize()
156
         if ThreadNum>n:
             ThreadNum=n
157
```

```
158
            print('No:{} datasize:{}'. format(ThreadNum,n))
159
        for thread in range(ThreadNum):
160
            thread=EM_Notice(DateQueue=DateQueue)
161
            thread.start()
162
163
164 if __name__ == '__main__':
165
        start_date = '2021-04-03'
        start_date = datetime.datetime.strptime(start_date, "%Y-%m-%d")
166
167
        end_date = '2021-05-05'
168
        end_date = datetime.datetime.strptime(end_date, "%Y-%m-%d")
169
        DateQueue = Get_DateQueue(start_date, end_date)
170
171
        # notice=EM_Notice(DateQueue=None)
172
        # notice.Download_Day_Notices('2021-01-04')
173
174
        ThreadNum=50
175
        Download_by_nThread(ThreadNum, DateQueue)
        # notice.Download_Day_Notices('2021-07-13')
176
```

Acknowledgements

1. Topic Origin

With blockchain looking to be a prevalent piece of technology in the future, I was drawn to the idea of how firms would try to implement that technology to their own good and how those announcements of using this technology would affect the market as a whole. With the impact that this technology could potentially have on the market, I was deeply interested in how new technology such as this appeals to investors and how that affects the signaling credibility and reaction from the overall market.

2. Background

The impact of signaling credibility has been a problem that many researchers have as tempted to identify. With the emerging blockchain technology, it provides a brand-new perspective to analyze signaling credibility and market reaction due to how much this technology is valued in China. With many firms appearing to use this technology in China as well, it looked to be an interesting topic to look at in the lens of signaling credibility and resulting market reaction.

3. Process

We started the process deciding on using the event study method to look at the effects of those blockchain announcements, specifically analyzing the cumulative abnormal returns of said firms to reach a conclusion based on textual sentiment as well as national support policies. To find this data, we developed a data mining program to look for data on the East Money website, then manually analyzing each firm's announcements to come to the conclusion whether the firms listed in Shenzhen and Shanghai stock exchanges are actually implementing blockchain technology or not. While being instructed by Professor Liu, I fulfilled the tasks of data mining, data processing, model constructions, as well as empirical research. I was assisted in these processes by Professor Liu's expert knowledge in financial modeling theories, inviting me to communicate with his research team and helping me deepen my understanding of using python to execute my data mining program as well as using Stata to conduct empirical research on the unstructured data coming from the data mining program.