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The differential impact of corporate blockchain-development as conditioned by sentiment and financial desperation

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Abstract

This paper investigates whether companies that initiated blockchain-development as a primary short-term corporate strategy, exhibited abnormal corporate performance as conditioned by financial performance, leverage, social media sentiment and previous experience of technologicaldevelopment. Results indicate that investors were subjected to a very sophisticated form of asymmetric information designed to propel sentiment and market euphoria. Technological-development firms are found to financially behave in a profoundly different fashion to speculative firms with no background in ICT technology, who experience an estimated, increased one-year probability of default of 170bps. Information shrouding is found to be of particular regulatory concern. Rating agencies are found to have under-priced the risk on-boarded by these speculative firms as they announced their entry into the blockchain sector, failing to identify that such firms should be placed under an increased degree of scrutiny. Sophisticated digital platforms, regulatory unpreparedness and mis-pricing by trusted market observers has resulted in a situation where investors and lenders have been placed in a compromised position with direct exposure to a financial asset class becoming known for criminal activity, financial losses and frequent reputational damage.

Keywords: Investor Sentiment; Blockchain; Leverage; Idiosyncratic Volatility; Behavioural Finance.

Highlights

- We test for corporate effects instigated by blockchain-related technological development
- Strategic blockchain firms behave in a profoundly different fashion to speculative firms
- Speculative block chain announcements generated abnormal premia in excess of 40%
- Rating agencies under-priced the risk on-boarded by these speculative firms
- Blockchain-based information shrouding significantly increases contagion risk
- Speculative projects by non-technological firms are of particular regulatory concern

1. Introduction

This paper investigates the hypothesis that a number of corporate entities utilised blockchain development in a manner that generated short-term profits and abnormal returns, directly creating a euphoric environment through which the corporate entity and shareholders could thrive. Such behaviour could be best described as ethically questionable. After the consideration of one hundred and fifty-six individual cases between January 2017 and July 2019, there remains no evidence provided of the physical delivery of these stated blockchain-development projects. In fact, from a regulatory perspective, some of these corporations found themselves under investigation by national regulatory authorities for a range of alleged charges including misleading investors, the release of false information and price manipulation, with a particular focus on those firms that changed their names to incorporate terms such as 'blockchain' and 'cryptocurrency' (Jain and Jain [2019]; Sharma et al. [2020]). The underlying motivations for these tactics are not singular. Some publicly traded companies that have found their industries in natural decline due to the challenges of international competitiveness, responsiveness to technological advances and changing consumer demand. This appears to motivate some companies to venture into blockchain. Successful projects incorporating blockchain development are found to provide an opportunity to return to former glory, and for others, an avenue to achieve rapid growth and to rapidly appear attractive for potential takeovers and prospective investors. Considering these motivations, it would not be unwarranted that regulatory bodies consider such announcements of blockchain and cryptocurrency projects to be 'unusual' and suspect, especially when considering corporations with no previous historical experience of ICT research and development.

Questions surrounding business ethics would be correctly asserted when sceptics observe a single, quite obvious example of this type of behaviour, particularly as a last stand by a corporation that was unfortunate to be in a sector experiencing natural decline. One such example was brought to the fore by (Corbet et al. [2020]). The Eastman Kodak Company, a firm founded by George Eastman in 1888, is a technology firm that was primarily associated with analogue photography and had developed a suite of products and patents related digital sensors, optics, chemicals and printing technologies. Kodak went bankrupt in 2012 and sold off a large portfolio of patents. The traditional analogue photographic business became known as Kodak Alaris and was sold off in 2013 to the Kodak UK Pension Plan. Eastman Chemical, a thriving research and development led subsidiary company of Kodak ceased to be part of the Kodak group in 1994. The remaining post-bankruptcy Eastman Kodak focuses on business printing, advanced materials, synthetic chemicals, products for the motion picture industry and brand licensing. Broadly considering that the company has been in long-term sectoral decline, investors and other market participants became particularly excited when rumours circulated in late 2017 that Kodak had observed an opportunity through which the company could thrive into the future. What followed in early 2018 was the announcement of KODAKOne, described as a revolutionary new image rights management and protection platform

secured in the blockchain. Simultaneously to the announcement, at 5.00pm (GMT) on 9 January, Kodak shares were worth \$3.10, while at 2.40pm (GMT) on 10 January, shares were trading at \$12.75.

In this research, we contribute to research surrounding corporate contagion, the behavioural aspects of corporate news release and the avenues through which the risks of new technological structures disseminate through investors and credit rating agencies. while developing upon a number of methodological structures and data relating to sentiment and both internal corporate structure and stock market performance, we set out to investigate a number of issues that are within the scope of current regulatory and policy-making concern. Primarily, we attempt to establish the scale of value addition through both rumours and official announcements relating to blockchain-development plans as denoted to be either strategic or speculative. Second, we analyse as to whether social media was used as a propellant to both generate and propagate hysteria related to the potential usage of blockchain within the corporate structure. Third, a variety of methodological techniques, we attempt to quantify the key characteristics of corporate entities that have entered administration, bankruptcy, or are found to be under the current scope of international regulatory authorities for the potential misuse of blockchain and cryptocurrency announcements to artificially boost their share price. Within this context, we specifically observe the use of leverage and other types of debt by these companies and as to how such capital adjustments can influence the corporate credit ratings. Finally, we compare our additional estimated credit risk to that provided by well-known credit rating agencies to observe as to whether the true risks of such investments were observed in such warnings to investors. We pay particular attention to companies initiating blockchain-development projects with no prior technological development experience.

Corporate insiders, such as directors and high-level executives, are most likely to possess information about the true estimates of firm value that would be considered superior to that possessed by those attempting to value the corporation from outside. Such directors and managers are central to the decision-making processes that influences the value of the corporation. This is a classic representation of asymmetric information and consequent moral hazard which has been the source of much debate. Lee et al. [2014] examined whether corporate restriction policies on insider trading are effective to find that they are successful in preventing negative information exploitation but insiders profit from inside information in a way that minimises their legal risk. Hillier et al. [2015] found that personal attributes such as an insider's year of birth, education and gender are a key driver of insider trading performance, and matter more in companies with greater information asymmetry and when outsiders are inattentive to public information. Cziraki et al. [2014] identified that insider transactions are more profitable at firms where shareholder rights are not restricted by anti-shareholder mechanisms. There has been much evidence to suggest the existence of significant abnormal returns from trading arising from these conditions of asymmetric information and moral hazard (Jeng et al. [2003]; Fidrmuc et al. [2006]). Blockchain technology, and speculative use of such, have created a very simplistic mechanism through which insiders can very simply generate

substantial marketability and public interest. The unprecedented and sustained price appreciation of Bitcoin afforded a new channel of asymmetric information, namely that corporate directors could partake in the development of blockchain and cryptocurrency projects to take advantage of the market exuberance that would follow thereafter. Our selected methodological approach generalises the literature based on corporate events and allows us to investigate the specific abnormal returns that existed across these trades, inclusive of derivatives markets where they existed.

We establish two individual release dates for blockchain news, the first being the 'rumour' as established through the first indication on social media such as Twitter, the second being the 'official announcement' made by the corporate entity through official channels. We quantify the changing behaviour of stock prices for both releases through abnormal returns and the implied volatility presented in options market. In addition, we investigate internal financial behaviour as measured by financial leverage and how this changes the probability of default for the firm. Such an approach results in the firm taking on a high risk strategy that could result in rapid rise in equity prices but also the potential to cause firm failure if such action is funded by leverage. Further evidence of high-risk strategies have been sourced in the use of junk bonds by companies seeking substantial rewards in rapid, with evidence provided of an increasing probability of default over a substantial period of time (Moeller and Molina [2003]; Basile et al. [2017]), and substantial exposure to time-varying liquidity risk (Acharya et al. [2013]).

We further break the sample into experience categories, some companies had previous technological development experience, some did not. A classic 'experience' example here is Facebook, a company with large cash holdings and extensive experience in ICT research and development and a strategic actor digital technologies. Kodak is a classic example of a 'no experience' firm, having come from an environment of technology but from the analogue economy of the 20th century. It is important to note that some companies were far less concerned with the views of sceptical regulatory authorities, and went as far as to change their entire corporate identity to take advantage of cryptocurrency hysteria. The company Long Island Ice Tea Corporation, a beverage company from Long Island, NY, that changed it's name in 2017 to Long Blockchain Corporation to take advantage of the price bubble associated with Bitcoin. The stock price then sharply increased almost 300% stating that it was 'shifting its primary corporate focus' from tea to distributed-ledger technology. The company was subsequently de-listed from NASDAQ in April 2018 and as the subsequent FBI search warrant application outlines, seeing evidence for insider trading following the arrest of Oliver Lindsay and Gannon Giguiere for securities fraud in relation to a separate company¹. There have

¹There have also been broad accusations about the presence of a 'pump-and-dump' scheme, where promoters buy a stock, start hyping it to investors with eye-catching claims, then sell their own holdings during the resulting mania, hopefully securing a profit before the stock comes crashing down. Based on a number of text messages that the FBI have since uncovered, they are interested in a person known as 'Eric W' in a series of messages, where the accused person owned approximately 15% of the shares in Long Island Iced Tea at the time that the company's name was changed. There is further investigation into the use of an investor relations program to develop hype around the company during this time.

also been two companies who have actually changed their name twice, in both cases from a noncrypto-exuberant name to a crypto-exuberant name and then back again, a strategy that would be considered to be extremely speculative. In August 2018, Focused Capital II Corp announced its intention on the TSX Venture Exchange to change its name to Fortress Blockchain Corp. issuing 71.2 million common shares and signalled its intention to begin trading on the TSXV under the ticker 'FORT'. In a largely unanticipated move, in April 2019, Fortress Blockchain then applied to the TSX Venture Exchange to change its name to Fortress Technologies Inc while continuing to use the same ticker. Riot Blockchain has also been investigated throughout 2018 and 2019 by the SEC. It had previously changed its name from Bioptix, where its previous business practices was based on the development of veterinary products patent and developing new ways to test for disease. Under Section 8e of the Securities Act of 1933, if the SEC thinks that the registration statement contained 'any untrue statement' or omitted any 'material facts,' it may issue a stop order suspending the effectiveness of the registration statement. The company did make an investment in a cryptocurrency exchange in September and two months later did purchase a company that has cryptocurrency mining equipment, but paying more than \$11 million for equipment reportedly valued at approximately \$2 million as stated within SEC filings. The filings also consider a number of very significant factors of interest including: 1) annual meetings that are postponed at the last minute; 2) insider selling soon after the name change; and 3) dilutive issuances on favourable terms to large investors. Further investigation identified one specific person of interest, who filed two 13Ds, including one in January 2017 that shows he/she owned 11.19% of the company, but his/her ownership dropped to less than 2% of outstanding common stock along with a small number of warrants in the time period immediately after the corporate name change. His/her purchase price ranged from \$2.77 to \$5.32 per share, according to the list of trades he provided to the SEC in 2017, until the total investment dropped below the 5% threshold for SEC filing when the stock had already climbed above \$20. While not explicitly identified to be under current investigation, some other companies with no other apparent technological investment have also participated in such crypto-exuberant behaviour. Vapetek Inc who previously made batteries and liquid for electronic cigarettes shifted its business practices to mine virtual currencies, while Croe, who previously sold women's fitness clothing before changing its name to The Crypto Company.

Cryptocurrencies have been largely under regulatory suspicion of facilitating pump-and-dump schemes that are found to operate when traders manipulate prices by purchasing assets in groups. One particular example of an infamous cryptocurrency pump-and-dump was based on the price of CloakCoin traded on the Binance exchange. While anticipated through the usage of messaging networks, the price proceeded to increase by over 50% to US\$5.77 before dropping substantially within two minutes to almost US\$1 with a total of 6,700 trades worth around US\$1.7 million. In the hour preceding the pump-and-dump, CloakCoin had zero volume traded.² Another example of potential

 $^{^{2}}$ In July 2018, the Wall Street Journal analysed trading data and online communications among traders between

misuse of cryptocurrencies has been identified in Venezuela and the announcement of the Petro. While we focus on the use of ICOs from a corporate perspective, the Petro presents an example of the misuse of an ICO in a sovereign setting. In mid-December 2018, the Venezuelan economy is estimated by the IMF to have exceeded 1.000,000% price inflation combined with a premium of approximately 2,500% between its official currency, the bolivar, and a black-market exchange rate. Throughout 2018, the Venezuelan government established a number of routes through which they could reduce the burden of economic collapse. One of the proposed mechanisms for the struggling population was to switch from the bolivar to a new cryptocurrency called the Petro which is defined³ as a cryptocurrency that would be supported 'by oil assets and issued by the Venezuelan State as a spearhead for the development of an independent, transparent and open digital economy open to direct participation of citizens'. White et al. [2020] identified that as a currency, Bitcoin as a representation of broad cryptocurrencies, fails as a unit of account despite its transactional value and diffuses like a technology-based product rather than like a currency. Moreover, one major concern identified in this new cryptocurrency's ability was to circumvent US sanctions that had been implemented on the Venezuelan economy and their ability to access international financing. While considering such specific issues, it is also important to observe the broader suspicious trading activities and structural problems within the cryptocurrency markets. Griffins and Shams [2018] examined whether Tether influenced Bitcoin and other cryptocurrency prices to find that purchases with Tether were timed following market downturns and resulted in significant increases in the price of Bitcoin. Further, less than 1% of the hours in which Tether experienced significant transactions were found to be associated with 50% of the increase of Bitcoin prices and 64% of other top cryptocurrencies, drawing the damning conclusion that Tether was used to provide price support and manipulate cryptocurrency prices. Furthermore, Gandal et al. [2018] identified the impact of suspicious trading activity on the Mt.Gox Bitcoin exchange theft when approximately 600,000 Bitcoins were attained. The authors demonstrated that the suspicious trading likely caused the spike in price in late 2013 from \$150 to \$1,000, most likely driven by one single actor. These two significant pieces of research have fine-tuned the focus of regulators, policy-makers and academics alike, as the future growth of cryptocurrencies cannot be sustained at pace with such significant questions of abnormality remaining unanswered. Corbet et al. [2019] provide a concise review of a broad number mechanisms through which cryptocurrencies can influence corporate entities and markets,

January and the end of July 2018 to identify 175 'pump and dump' schemes involving 121 different digital coins. It is estimated that these schemes resulted in approximately US\$825 million in trading activity and hundreds of losses by legitimate investors. The pump-groups are online chat-rooms, similar to boiler rooms, where the Big Pump Signal was denoted as the largest of these with more than 74,000 followers on the messaging app Telegram. There was evidence of a large number of private pump groups, accessible only by invitation.

³The base price of the Petro was denoted at one barrel of oil and the Venezuelan government stated that US\$3.3 billion was raised through the sale. However, a year after its announcement it has yet to present any physical evidence of commodity-support. Instead, it is simply backed by a government's guarantee that it is backed by oil. The very creation, advertisement and distribution of such a currency during a period of exceptional economic strife generated substantial concern about the credibility of this ground-breaking sovereign asset.

however, the point to a number of pathways through which the contagion risks of cryptocurrency markets can flow.

The contagion risks sourced within negative shocks sourced in cryptocurrency and blockchain fraud can manifest in substantial losses to uninformed investors should their inability to adequately quantify a true level of associated risk. Further, the inherent moral hazards contained within this new avenue of product development are quite exceptional die to the widespread evidence of substantial growth in the share price selected speculating companies. When analysing innovation within the context of retail financial products, Henderson and Pearson [2011] offering prices of 64 issues of a popular retail structured equity product were, on average, almost 8% greater than estimates of the products' fair market values obtained using option pricing methods. The results of this research are found to be consistent with the recent hypothesis that issuing firms might shroud some aspects of innovative securities or introduce complexity to exploit uninformed investors. A recent theoretical literature explores the equilibria in which firms shroud some aspects of the terms on which their products are offered in order to exploit uninformed consumers, and strategically create complexity to reduce the proportion of investors who are informed (Gabaix and Laibson [2006]; Carlin [2009]). In these equilibria, prices are found to be higher than they would be if consumers or investors were fully informed. In the context of structured equity products, these arguments imply that premiums are higher than they otherwise would be. When focusing on investor sentiment Danbolt et al. [2015] argued that sentiment subconsciously influences investor perception of potential merger synergies and risks, which is analysed with Facebook used as a proxy for sentiment, which is found to be positively related to bidder announcement returns. Huson and MacKinnon [2003] analysed the effect of corporate spin-offs on the trading environment, noting the substantial changes in the information environment of the firm, to find that increased transparency following spin-offs can obviate informed traders' information or make it more valuable. Further, transaction costs and the price impact of trades are also higher following spin-offs. Van Bommel [2002] found that an IPO's initial return contains new information about the true value of the firm, therefore providing vital feedback for the investment decision. Information production by market participants is found to increase the precision of the market feedback captured in the first competitively determined stock price. Easley and O'Hara [2004] investigate the role of information in affecting a firm's cost of capital to find that differences in the composition of information between public and private information affect the cost of capital, with investors demanding a higher return to hold stocks with greater private information. The authors identify that this higher return arises because informed investors are better able to shift their portfolio to incorporate new information, and uninformed investors are thus disadvantaged. Bloomfield et al. [2009] found that a dominated information set is sufficient to account for the contrarian behaviour observed that when informed traders also observe prices, uninformed traders generate reversals by engaging in contrarian trading, and that uninformed traders may in fact be responsible for long-term price reversals but play little role in driving short-term momentum. While, Albuquerque et al. [2008] identified that private information obtained from equity market data forecasts industry stock returns, and also currency returns Bruguier et al. [2010] hypothesise that Theory of Mind (ToM) that has enabled even fully uninformed traders, to infer information from the trading process, where perceived skill in predicting price changes in markets with insiders correlates with scores on two ToM tests, presenting support that investors present increased ability to read markets when there are insiders present. Further, Aitken et al. [2015] utilised a number of indices designed to test for market manipulation, insider trading, and broker-agency conflict based on the specific provisions of the trading rules of each stock exchange, along with surveillance to detect non-compliance with such rules, to find a significant reduction in the number of cases, however, increased profits per suspected case. Marin and Olivier [2008] identified that at the individual stock level, insiders' sales peak many months before a large drop in the stock price, while insiders' purchases peak only the month before a large jump. With regards to financial market misconduct, Cumming et al. [2015] reviewed recent research on the causes and consequence of different forms of financial market misconduct and potential agency conflicts and the impact of regulation, highlighting the presence of reciprocity in financial market misconduct regulation and enforcement.

While some previous works consider market reactions to specific corporate blockchain behaviour, to the best of our knowledge, this is the first study to analyse this behaviour in the context of social media sentiment, options trading and internal financial position. We argue that both companies in natural decline and those of smaller magnitude (such as small cap and penny stocks) were most likely to utilise channels incorporating the use of blockchain and cryptocurrency projects to generate both abnormal returns and profits. We find social media rumours to be central to the news dissemination process in the period before the official announcement. Investor responses can manifest across multiple forms, including abnormal returns and option to stock trading levels. We test each of these information channels while considering the scale and timing of the social media hysteria surrounding both the rumour and the official announcement of each blockchain project. The combination of these analyses presents a concise overview and signal of illicit behaviour.

Consistent with our hypotheses, the empirical analysis presented in this paper concludes that investors were subjected to a very sophisticated form of asymmetric information. This asymmetric information is decidedly modern since it connects to the ability of new forms of media to drive sentiment and market euphoria but for that media also to be open to digital manipulation that is nearly impossible to discern on the part of the untrained market participant that lacks access to sophisticated digital tools. This manipulation takes the form of 'bots', 'socialbots' and algorithmic programmed trades that 'read' sentiment. Blockchain technology and its most celebrated invention, Bitcoin, resulted in a classic movement of market euphoria associated with a new technology with investors generating a period of price exuberance. Firms sought to build upon this in a classic 'bandwagon effect' fashion and announcements were made of firms, some technology focused, others not, entering the blockchain product space. We find that sentiment drives equity prices for all firms, this sentiment is determined by social media communication via Twitter. We find that strategic firms, with a background in technology, behave in a profoundly different fashion to speculative firms with no background in ICT technology. The result is a desire to engage in 'shrouding' behaviour on the part of strategic firms, where rumours of activity in the blockchain space are the most important. By availing of digital support that is available at low cost and the lack of investor knowledge of the complexities of blockchain, speculative firms were able to use a lax regulatory environment during 2017 and early and the abnormal returns associated with Bitcoin to build interest and sentiment that drove abnormal returns. Further, our analysis of the internal financials of these speculative firms indicated that they used these bandwagon effects to increase their leverage, which dramatic rose their probability of default by 170bps. Astute market observers, such as rating agencies, under-priced the risk on-boarded by these speculative firms as they announced their entry into the blockchain sector. The final conclusion is that our investigations find that firms engaged in blockchain developments must be understood to be high risk and placed under a higher level of scrutiny than they currently are as sophisticated digital tools, regulatory unpreparedness and mispricing by trusted market observers has resulted in a situation where investors and lenders have been placed in a compromised position with exposure to association with criminal activity, financial losses and reputational damage.

These outcomes present evidence of the particular difficulties that regulatory authorities and policy-makers are confronted when considering the incorporation of a rapidly developing financial and technological product in the form of blockchain, and as to how it could be used to generate substantial information asymmetry and profits for companies in desperate times with little or no alternative choices other than bankruptcy and failure. However, the release of such anticipated blockchain project information with little or no intention of delivery is quite a worrying development. But it is overshadowed by some incredibly startling behaviour when considering the entire re-branding of an organisation to profit from social media hysteria surrounding blockchain, even though the entity had no prior connection to this developing sector. This not only creates substantial issues protecting uninformed investors from adverse selection that insiders can impose, but also substantial issues fostering price efficiency, particular when such corporate entities rely on substantial leverage to take such significant risks. Regulatory efforts reasonably need to go further to disincentivise insiders from exploiting short-term release of blockchain projects to take advantage of market hysteria. Should regulators anticipate that the prevention of the exploitation of such information asymmetries is necessary, stricter rules with respect to the timing of insider trades may be needed. Lock-out periods and the requirance of directors and other insiders to commit to extended stock and option holding periods beyond twenty-four month after the date of a blockchain announcement could be a potential approach.

The paper is structured as follows: The development process of the hypotheses tested are summarised in Section 2. Section 3 presents a thorough explanation of the wide variety of data used in this analyses, while Section 4 presents a concise overview of the methodologies utilised to analyse the presented hypotheses. Section 5 investigates the role that social media played as a driving force of abnormal returns and corporate mispricing of risk. Section 6 presents a concise overview of the results and their relevance for policy-makers and regulatory authorities, while Section 7 concludes.

2. Hypotheses Development

In this paper we investigate the behaviour of equities in response to announcements related to the development of blockchain technologies using social media. The social medium chosen is Twitter. Given the interest and attention given to blockchain technologies in the media and the wider public, we hypothesise that some firms will venture into the development or adoption of blockchain technology or the language of blockchain in order to improve equity performance. Other firms, which are connected to the technology sector will make these announcements as an enhancement of their current product suite or to improve the integrity of their existing products and will garner normal equity returns in line with an improvement in the fundamentals of the corporate entity. Our investigation therefore breaks down into four primary hypotheses, applying four different analytical techniques and checked for robustness against four different evaluation frameworks for social media impact. This paper uses three separate techniques in conjunction with three specific datasets to investigate the role of social media information on the behaviour of equities which indicate an association with blockchain technology. The following primary hypotheses are tested:

• Hypothesis H_1 : Blockchain announcements generate observable and significant changes in the perception of the firm to which the declaration or news is related: there exist significant differentials in both timing and market response as measured by social media sentiment to both the 'rumour' and the 'official announcement' of corporate blockchain-development

Hypothesis H1 is an investigation of the behaviour of social media with respect to a publicly traded firm that announces a new association or development or implementation of a blockchain or blockchain-related technology. The aim of this exercise is to at first determine the veracity of the claim that there exists an underlying blockchain response generated by social media communication.

• Hypothesis H_2 : Blockchain Twitter announcements influence market sentiment and financial valuation: cumulative abnormal returns evidence surrounding unofficial versus official announcements differ significantly

Hypothesis H2 is an investigation of the behaviour of equities with respect to the announcements, official or otherwise, made via Twitter of a firm developing or implementing blockchain or blockchain-related technology. The technique applied uses cumulative abnormal returns to illustrate how equities respond positively to announcements, "rumours" or "official announcements" to a move into blockchain. The underlying hypothesis is that a firm's equity valuation increases from an association with blockchain and the information content of social media is rapidly incorporated into prices. These first two hypotheses are then each tested against the following social media (Twitter) information sub-groupings where Hypothesis H_x equals the described Hypotheses H_1 through H_2 :

- Hypothesis H_{xA} : Twitter watershed: announcement of unofficial 'rumour' versus 'official' firm announcement of blockchain project.
- Hypothesis H_{xB} : High or Low risk blockchain projects as defined as for 'speculative' purposes versus security or operational purposes.
- Hypothesis H_{xC} : High or Low dissemination presented in low/medium low/medium high/high groupings.
- Hypothesis H_{xD} : Positive or Negative market sentiment as developed through a predetermined lexicon⁴.

Hypothesis H3 builds on the pricing relationship investigated in hypothesis H2, which is that the equity performance of a firm will improve as a result of being associated with the development or implementation of blockchain or a blockchain-related technology.

• Hypothesis H_3 : Corporate desperation⁵, as evidenced by a weak firm cash reserve and/or high leverage position, instigates the decision to incorporate blockchain technology.

Here firm fundamentals are evaluated against the increased probability of introducing or announcing such technological developments to improve the market position of a firm in distress due to poor cash-flows or excessive leverage. Hypothesis H3 takes as its prior that distressed firms will pursue "bandwagon effects" in order to buttress or strengthen their equity performance and appear to be a more attractive for investors. Using evidence from H1 and H2, the strength of the blockchain association can be set against firm-level behaviour.

• Hypothesis H_4 : Companies who instigate blockchain development projects present evidence of increased probability of default should they have no prior technological development experience

Hypothesis H4 is a development upon the investigations in H1, H2 and H3. Using a probit technique, this hypothesis investigates the behaviour of the selected companies as again separated by

 $^{^{4}}$ See Section 3 for the explanation of the functioning of this lexicon and Table A1 in the Appendices for a description of the individual data obtained.

 $^{{}^{5}}$ Corporate desperation is understood as the default probability using a discrete hazard model in the form of a multi-period logit relating to blockchain and investigate the cost-benefit trade-off of debt from the viewpoint of shareholders by estimating the net value that equity holders place on an incremental dollar of debt by using the Faulkender and Wang [2006] model of a firm's excess stock return regressed on changes in several investment and financial policy factors and the coefficient on the independent variables reflects the net cost (negative coefficient) or benefit (positive coefficient) to equity holders of expansion into blockchain.

strategic and speculative use, but further considering as to whether such companies can be identified as possessing previous experience of technological development. Specifically, this hypothesis focuses on speculative corporations with no previous technological experience, and presents evidence of the common characteristics inherent in such scenarios. While technological and corporate development is a welcome and necessary ambition for progress, we have observed a worrying trend in recent times where corporations with no previous experience in any element of technological development have announced their intentions to develop cryptocurrency, or indeed, change their name to incorporate a corporate identity that would present a case that blockchain and cryptocurrency development is central to the corporate raison d'être, which has been proven in a small number of cases to have been misleading to investors. Here the underlying prior is that internal actors within firms will underpin these decisions in an attempt to profit from the "bandwagon effects" associated with blockchain news as disseminated via Twitter hype and subsequent developing investor sentiment.

• Hypothesis H_5 : Credit ratings have adapted and segregated their consideration of the additional corporate risk associated with speculative and strategic blockchain development

Building on hypotheses H_3 and H_4 , our final hypothesis focuses on the theoretical impact of any potential differential in the associated probability of default stemming from the internal financial characteristics of blockchain-developing corporations, and as to whether this is reflected in credit rating agency announcements relating to each company. While considering a number of reputable measures of market risk, we specifically estimate the effects of internal financial factors and then represent the estimated credit rating in comparison to the actual credit rating provided during the period surrounding the announcement of plans to develop blockchain. Specifically, hypothesis H_5 considers the risk differential and potential under-pricing of the true risks inherent in such projects and blockchain-based decisions. This analysis would be very much of interest to both regulators and investors who continue to develop their understanding as to whether such projects represent 'true' financial innovation, or in fact, are simply an attempt to take advantage of a premium through association. These hypotheses are based upon the existing corporate finance literature as found for Hypothesis H_1 and H_2 in Corbet et al. [2020], Hypothesis H_3 and Hypothesis H_4 in Cathcart et al. [2020] and Hypothesis H_5 in Metz and Cantor [2006].

3. Data Description

We collect data from multiple sources to specifically analyse the established hypotheses. We primarily develop a concise list of corporate announcement that specifically constitute a news release relating to cryptocurrency development. To complete such a task, we develop a number of strict rules in an attempt to standardise the process across major international financial markets. The first implemented rule is that the specified company must be a publicly traded company with an available stock ticker between the period 1 January 2012 and 30 June 2019. However, the corporate announcement period covers from 1 January 2017 to 30 March 2019 due to the fact that we need to perform pre-and post-announcement analysis (announcement data for traded companies was not present in a robust manner prior to January 2017). We develop on a combined search of LexisNexis, Bloomberg and Thomson Reuters Eikon, search for the keywords⁶ under traditional corporate announcements. To obtain a viable observation, a single data observation must be present across the three search engines and the source was denoted as an international news agency, a mainstream domestic news agency or the company making the announcement itself. Forums, social media and bespoke news websites were omitted from the search. Finally, the selected observation is based solely on the confirmed news announcements being made on the same day across all of the selected sources. If a confirmed article or news release had a varying date of release, it was omitted due to this associated ambiguity. All observations found to be made on either a Saturday or Sunday (nine announcements in total) are denoted as active on the following Monday morning. The dataset incorporates 156 total announcements made during the selected time period. All times are adjusted to GMT, with the official end of day closing price treated as the listed observation for each comparable company when analysing associated contagion effects. The corporate announcements are then sub-categorised by perceived level of risk, denoted to be speculative in nature or structural-development. Within this context, and building on the work of Akyildirim et al. [2020], speculative announcements are found to be those relating to the change of corporate identity to include words such as 'blockchain' and 'cryptocurrency', and the development of corporate cryptocurrencies. Alternatively, structural-development includes announcements relating to internal security, and internal process, system and technological development. The following analysis will be sub-categorised within these sub-groups throughout.

The next stage of data collection surrounded the identification of investor sentiment. To complete this task, Twitter data was collected for a period between 1 January 2017 and 31 March 2019 for each of the identified companies. All tweets mentioning the name of the company plus either of the terms 'crypto', 'cryptocurrency' or 'blockchain' were computationally collected through the Search Twitter function on https://twitter.com/explore using the Python 'twitterscraper' package, observing platform rate limiting policies. A total number of 954,765 unique tweets were collected⁷. The data was then aggregated by company and by day, taking sums of the quantitative variables and aggregating the text. In a provisional methodology, we determine the very first tweet as identified on Twitter that was correctly based (identified as the 'rumour' hereafter) on the forthcoming corporate blockchain announcement (identified as the 'official announcement' hereafter). The associated statistics based on this Twitter activity as divided by time, reach and size is presented in Table 1. Both of these dates are used to identify the establishment of dummy variables through which the following analyses are built. Further to speculative and structural-development sub-divisions

⁶The selected keywords used in this search include that of: "cryptocurrency", "digital currency", "blockchain", "distributed ledger", "cryptography", "cryptographic ledger", "digital ledger", "altcoin" and "cryptocurrency exchange".

⁷For brevity, additional summary statistics based on these tweets are available from the authors upon request.

outlined above, results are further separated based on whether they were 'rumour' or 'official'. Such division of analysis provides the existence of a unique observation period in which stock market behaviour, internal financial behaviour and the stock and derivative trading behaviour of directors and senior management can be analysed. Further sub-division of tweets relating to corporate blockchain development and further separated based on the natural logarithm of the number of tweets relating to each company based on quartiles, but also based on high and low sentiment. The sentiment variables were computed using the Python package 'pysentiment' and are based on the Harvard General Inquirer IV-4 dictionary and the Loughran and McDonald Financial Sentiment dictionary⁸. Each includes the following measures to determine sentiment: 1) counts of positive terms; 2) counts of negative terms; 3) a measure of polarity calculated as the number of positive terms minus the number of negative terms divided by the sum of positive and negative terms; and 4) a measure of subjectivity (affect) calculated as the proportion of negative and positive terms relative to the total number of terms in the tweet.

Insert Table 1 about here

Considering the data presented in Table 1, we observe the key statistics as presented from the scale of interest and sentiment of the associated Twitter activity. Interest is sub-divided by quintile of the number of identified tweets, which are further separated as per type of blockchainannouncement, the year in which the announcement was made, and by company size. Further, we have included a final column that specifically investigates the average time difference, as measured in days, of the time between the first identified tweet, denoting the establishment of the 'rumour' and the 'official' announcement. This preliminary analysis of firms exhibits a very clear linkage between blockchain announcements and firm equity price performance. It would appear that the smaller the firm, the stronger the effect. The interest of social media is associated with the size of the company, while the effects of sentiment in relation to market capitalisation do not appear to present a clear relationship. There are clear differences in behaviour of rumour duration over the years between 2017-19, reflecting a changing regulatory environment. Most importantly, there is a strong bifurcation of the speculative and the strategic blockchain investment motivations. This split is important to note throughout the rest of the analyses, as there is consistent evidence that firms experience strong 'bandwagon effects' as a result of being associated with blockchain and that this effect is persistent. There is also evidence to suggest that 'rumours' enter social media almost a week earlier than the official announcement, in comparison to corporate entities who have signalled their intentions to begin strategic blockchain-development projects. When considering that the average size of speculatively-denoted companies is approximately 1/10th that of their

 $^{^{8}}$ The Harvard General Inquirer IV-4 dictionary is available at the following link and the Loughran and McDonald Financial Sentiment dictionary is available at the following link

strategically-developing counterparts, the reduced corporate size and structure should theoretically produce an increased probability of more stringent planning and information security (Zhou et al. [2015]), however, in preliminary testing, this does not appear to be the case.

4. Empirical Methodology

Our selected methodological form builds upon four separate techniques through which our established hypotheses can be tested. These techniques address the core hypotheses. First, we focus on the impact of social media on both the differences of response to 'rumours' and 'official' firm statements of forthcoming blockchain projects and then testing for significant influence that it could have on market sentiment. This is reflected in cumulative abnormal returns in comparison to the official corporate announcements of such intentions, building on the work of Corbet et al. [2020]. Once we establish the scale of such effects, we then focus on the second technique for the corporate behaviour of such companies within three separate scopes of analysis. We first examine this through the differential effects of leverage as designed by Cathcart et al. [2020], examining default risk relating to structural changes in leverage and cash holding behaviour of such companies in the period prior to blockchain-related rumours announcements. We then employ a third technique to assess whether investors valued variations of long-term debt and changes in their respective leverage ratios in a manner inspired by the work of D'Mello et al. [2018]. Finally, using the methodology provided by Metz and Cantor [2006], we estimate a probability of default methodology to add further robustness to the estimated default risks generated from our analysis of leverage. Within this context, we can then re-estimate and compare to the time-series of credit rating announcements at the times surrounding both rumours and official blockchain-development announcements. By completing such as task, we can estimate as to whether the idiosyncratic risks associated with such decisions are fully comprehended by analysts

After identification of the specific dates surrounding the 'rumour' and 'official announcement', we first establish as to whether there exist significant differentials in cumulative abnormal returns surrounding both types of events events as described in Section 3. Since the news feed gives time and dates in local time, we first changed all times of announcements and market data to GMT, thereby accounting directing for differences in time zones for international firms. We further check the data to account for the broad variation in market opening times as generated through differences in exchange close times, weekends and public holidays. If the announcement occurs between market close and the following market opening time, the next available trading day is taken as the announcement day. To mitigate the effects of simultaneous response to financial announcements, we exclude any company that has an earnings announcement. For added methodological robustness, we extended this filter for a variety of time horizons up to ten days either side of the announcement and our results remain unchanged. We calculate the natural logarithm of returns as $R_{i,t} = ln \frac{P_{i,t}}{P_{i,t-1}}$ for each company and use the market model to estimate abnormal returns as follows:

$$AR_{i,t} = R_{i,t} - \alpha_i - \beta_i(R_{m,t}) \tag{1}$$

and $R_{m,t}$ is representative of the US market (S&P 500 Index) return. We also computed abnormal returns through the use of the selected companies' local stock market index, as well as the MSCI world index⁹. β_i is estimated using returns from the pre-event window [-120, -30] of each stock i and the market index as per Corbet et al. [2020]. We calculate abnormal return (AR_0) as the return for company i on the event day and cumulative abnormal return (CAR) for the preannouncement window [-30,-1], event windows [-1,+1] and [AR0], the post-announcement windows [0,+3], [+4,+30] and the entire period under observation [-30,+30]. This analysis is calculated first for the 'rumour' and then for the 'official announcement' For each company i, the CAR for an event interval [T_1 , T_2] is computed as:

$$CAR_{i;T_1,T_2} = \sum_{t=T_1}^{T_2} AR_{i,t}$$
(2)

Further, the abnormal and cumulative returns averaged over all firms (N) are given by:

$$\bar{AR}_t = \frac{\sum_{i=1}^N AR_{i,t}}{N} \tag{3}$$

$$CA\bar{R}_{T_1,T_2} = \frac{\sum_{i=1}^{N} CAR_{T_1,T_2}}{N}$$
(4)

We then regress the event day abnormal returns and CARs around the announcement against the natural logarithm of Bitcoin prices for the period inclusive of 30 days prior to the announcement (BTC Price Lag30). Additionally, given the high volatility in Bitcoin, we use 30-day past cumulative Bitcoin returns (BTC CAR[-30,-1]) to proxy for investor attention toward blockchain¹⁰. We control for the year effects with year dummies for each year of analysis. We specifically investigate as to whether this methodological structure changes when comparing for whether the blockchain development was deemed a 'rumour' or 'official' announcement; whether it was deemed high or low risk; whether it is denoted to have experienced high or low social media attention; or whether it received positive or negative social media attention.

To examine the next hypotheses investigating as to whether there exists evidence of internal structural changes in the use of leverage, the structure in which such leverage is obtained, or indeed changes in cash holdings of these companies in the periods surrounding both rumours and announcements of blockchain-development. One particular perception surrounding such decision-

⁹Results remained unchanged to those obtained using different market indices

 $^{^{10}}$ We use these variables to capture the past performance of and attention to Bitcoin, and we examine whether the abnormal returns identified earlier are associated with the market's perception of Bitcoin.

making processes surrounds the fact that some companies that have been making the decision to announce their intentions to incorporate blockchain have already been in substantial decline. There are a number of particular methodologies in which we can identify such substantial changes in the use and design of such leverage. Our analysis builds on the work of Cathcart et al. [2020] who specifically investigated the differential impact of such leverage on the default risk of firms of varying size. We design a structured methodological approach to investigate as to whether companies who announce their intentions to develop blockchain present evidence of a variation of their usage and sources of leverage based on pre-defined speculative and strategic announcements of corporate blockchain-development. Further specific hypotheses surrounding differentials based on the timing of rumours and official announcements, social media outreach and associated sentiment, and corporate size, as measured by market capitalisation, add explanatory benefits.

To investigate the effects of leverage, we estimate a default probability using a discrete hazard model in the form of a multi-period logit, similar to the previous work of Campbell et al. [2008], which can be used to analyse unbalanced data using time-varying covariates. The logit model is given by:

$$P_t(y_{i,c,j,t+1} = 1) = \Phi(\alpha - X_{i,t}\beta + Z_{i,c,t}\delta - \gamma_c - \gamma_j)$$
(5)

$$=\frac{1}{1+\exp\left[\alpha+X_{i,t}\beta+Z_{i,c,t}\delta+\gamma_{c}+\gamma_{j}\right]}\tag{6}$$

where subscripts i, c, j, and t vary according to firms, countries, industries and years, respectively. The y variable is a dummy that indicates corporate default; it takes a value of 0 if the firm is active and a value of 1 if the firm is insolvent or bankrupt. Within our selected sample of companies that have announced intentions of blockchain development, a number have already been declared bankrupt or insolvent such those described in Section 1. Firms that remain in default for more than 1 year are retained in the sample used to estimate the model as depicted in the above equation until the year they first migrate to the default state. The parameter α is the constant; γ_c and γ_j are country and industry fixed effects, respectively; X is a vector of time-varying firm-level variables, and Z is a vector of time-varying control variables. Covariates are lagged and refer to the previous accounting year relative to the dependent variable.

As per Cathcart et al. [2020], the firm-level variables include leverage or its components, that is, trade, current, and noncurrent. These are, respectively, the ratios of total leverage, trade payables, and current and non-current liabilities to total assets. Controls that vary at the country level include a set of macroeconomic variables. We employ the natural logarithm of GDP growth (GDP), the yield of 3-month government bonds (Bond) and the logarithm of sovereign credit default swap (CDS) spreads to capture the business cycle, interest rate effects, and sovereign risk, respectively. The information on GDP is from the Eurostat Database, interest rates are collected from the IMF-World Economic Outlook Database and CDS spreads are obtained from Markit. Firm-level control

variables include the ratio of net income to total assets (NITA), the ratio of current assets to total assets (CATA), the number of years since a firm's incorporation (Age). Summary statistics for each of these respective variables are presented in Table 2 The A dummy variable is introduced to the logit methodology (IMP) to denote as to whether the firm is active and not under regulatory investigation, while it receives a value of one if it is insolvent, bankrupt or under regulatory investigation. Within this structure, we attempt to compare our sample and sub-sample of corporate institutions to groupings of companies that have been already proven to have caused significant issues with regards to blockchain development (as being currently investigated by regulatory authorities), or the institution has simply become insolvent or has gone bankrupt.

Insert Table 2 about here

To understand as to how corporate leverage interacted as separated by both speculative and strategic blockchain-development, we calculate the marginal effects on the probabilities of default across different levels of the independent variables, particularly as the selected methodology is non-linear and we cannot directly interpret the sign, magnitude and statistical significance of the coefficients of the logit covariates when they are interacted with dummy variables. The marginal effects where the corporate blockchain-development is defined as strategic is presented as:

$$\frac{\vartheta P_t(y_{i,c,j,t+1}=1)}{\vartheta_x} = \beta_x \Phi'(\alpha + X_{i,t}\beta + Z_{i,c,t}\delta + \gamma_c + \gamma_j) \tag{7}$$

Whereas, marginal effects in the same methodological specifications with companies who have signalled their intention to develop blockchain for purely speculative reasons is modelled as:

$$\frac{\vartheta P_t(y_{i,c,j,t+1}=1)}{\vartheta_x} = (\beta_x + \beta_{x.Spec}Spec)\beta_x \Phi'(\alpha + X_{i,t}\beta + Z_{i,c,t}\delta + \gamma_c + \gamma_j)$$
(8)

where x is the variable of interest and Φ is the logit function. The marginal effect of the variable of interest is a function of all the covariates including the value of the speculation dummy which allows us to have separate marginal effects for companies who incorporate blockchain-development for strategic purposes (when the dummy equals 0) and for companies who incorporate blockchaindevelopment for speculative purposes (when the dummy equals 1). To compute the marginal effects we take the mean value of the covariates' observations that pertain each set of companies.

In the final stage of our analysis, we set out to establish as to whether the effects of leverage and other internal dynamics of corporations who have taken both strategic and speculative decisions to develop blockchain has been effectively considered by credit rating agencies estimates. To complete this task, we reconstruct estimates as described by Metz and Cantor [2006] While the calculated marginal effects of leverage provide a basis point estimate of differential implied probability which can be then compared to the actual point-in-time international credit ratings to which inferences can be drawn. The authors parameterised the weighting functions for each credit metric z, where the

financial metrics we consider are coverage (CV), leverage (LV), return on assets (ROA), volatility adjusted leverage (vLV), revenue stability (RS), and total assets (AT), while defining w_z as the exponential of the linear function of the issuer's leverage as described by:

$$w_z = exp\left\{a_z + b_z lev_t^i\right\} \tag{9}$$

where the final weighting of W_z is calculated as:

$$W_z = \frac{W_z}{1 + \sum_{k=1}^{6} W_k}$$
(10)

The weights are assumed to be a function of an issuer's leverage ratio. Through the use of a 20 point linear transformation scale for cross-corporation credit ratings as described in Table A2 (in the Appendices), are then able to scale the estimated credit rating through adjustments to this weighted average rating. First, we add a constant notching adjustment n simply to absorb rounding biases and give us a mean zero error in sample. Secondly, we then adjust for fiscal year with fixed effects n(t), and finally, we adjust for industry with fixed effects n(I). To consider the effects of blockchain announcements, we make an adjustment proportional to the volatility of leverage in the period since the official blockchain-development announcement. Therefore,

$$FR = w_1 R_{CV} + w_2 R_{LV} + w_3 R_{RoA} + w_4 R_{RS} + w_5 R_{vLV} + w_6 R_{AT} + w_7 R_{CVxAT}$$
(11)

$$\tilde{R} = FR + n + n(t) + n(I) + \delta\left(\frac{\sigma(LV)}{\mu(LV)}\right)$$
(12)

$$R = max\left\{5, \min\left\{20, \bar{R}\right\}\right\} \tag{13}$$

R is our estimate of the final issuer credit rating. We estimate the free parameters by minimising the log absolute notch error plus 1. This puts much less weight on reducing very large errors and much greater weight on reducing small errors, which more closely corresponds to how a user would make such trade-offs. In practice, the results are almost the same as an iterated least squares approach: minimise squared errors, drop the large errors from the dataset, and re-minimise squared errors. We build upon an ordered probit methodology to determine the probability that the company under observation possesses the rating allocated as calculated by the above structure. We then compare the credit ratings over the time period analysed, investigating as to whether the true effects of the use of leverage for blockchain-development were appropriately accounted for.

5. Results

5.1. Understanding the hype surrounding blockchain announcements

We begin our analysis by testing Hypothesis H_1 , which investigates as to whether blockchain announcements generate observable and significant changes in the perception of the firm to which the declaration or news is related: there exist significant differentials in both timing and market response as measured by social media sentiment to both the 'rumour' and the 'official announcement' of corporate blockchain development. It is well understood how news impacts the prices of equities in the market. The source of that information has changed over time, with social media playing as important a role as traditional media such as newspapers, television, radio and new wires. Twitter is a more continuous, non-edited internet version of a news wire and the information that it circulates is incorporated into the decision making processes of investors. Twitter does not discern between rumour and fact. This is important as firms may seek to impose their own editorial policies by minimising leaks from their organisation and ensuring that official statements are properly disseminated via social media. Other firms may seek to encourage rumours, especially as rumours generated in Twitter do not follow the same conventions of traditional business journalism, seeking a "second source" for verification or adding nuance as the communication is limited to between 140 and 280 characters. Under such conditions it is In this analysis we look at the behaviour of the different markets to see how twitter information easy for firms with speculative motivations or a lack of background in blockchain technology to easily associate themselves with the market euphoria that was associated with Bitcoin and blockchain technology in the 2017-19 period with minimal scrutiny. We therefore investigate how Twitter information is processed by market actors and how the different motivations of firms will result in varied equity price responses.

As observed in Tables 1 through 3, companies that are larger garner greater news interest in their blockchain activities. Smaller companies, though not associated with great levels of news interest, make up for that in long duration rumours and are more likely to be speculative in motive. Companies involved in name changes, blockchain partnerships and coin creations are those with the longest rumour periods prior to the official announcement. Companies that are larger and are creating internal value via technological or security improvements or investment motivations have a much shorter rumour duration and reflects the desire of those firms to have a controlled communications policy that protects reputation and shareholder value.

Rumours are powerful drivers of interest in a company and can generate abnormal returns as indicated by Chauvin and Shenoy [2001], Palomino et al. [2009], Jindra and Walkling [2004] and Aktas et al. [2018]. Given the role of rumours, it is plausible to see that companies that are smaller and more speculative in motive pursuing a high risk/high reward strategy that will generate rapid equity price responses. More strategically-minded companies avoid this strategy and minimise their rumours. In Table 3 we break the data into four blocks. Twitter and equity activity 30 days before to 1 day after the announcement and 4 days to 30 days after the rumour or official announcement.

This is descriptive data as collected from the social media sources. The important highlight is that there is a clear volume different speculative and strategic firms. This is interesting as the strongest cumulative abnormal returns are exhibited by speculative firms. Consistently in the data and the statistical analysis the performance of strategic firms will be fundamentally different to that of speculative firms.

Insert Table 3 about here

In Table 4 we separate the data into four distinct blocks. Twitter and equity activity on the day of announcement and 30 days after the rumour or official announcement and then for the entire sample period of 30 days before to 30 days after the rumour or official announcement. This is entirely descriptive data as collected from the social media sources. There is a clear volume different with respect to strategic firms, this once again reinforces the outcomes from Table 4 even in the conditions of the full sample period. Speculative firms experience a stronger lift from rumours as opposed to official announcements as they actively are seeking to exploit bandwagon effects associated with Bitcoin and blockchain. The statistical modelling found below provides further significant evidence for the high risk behaviours of these speculative firms.

Insert Table 4 about here

The number of Tweets issued in both speculatively and strategically orientated blockchain announcements supports the increases in the volume of attention afforded to a firm upon statement. The interesting observation is the decay rate of the that interest. While speculative firms exhibit "flash-in-the-pan" interest, strategic firms have a much longer duration of interest, most especially after they make an official company announcement. The general phenomenon from Figure 1 continues, this time with retweets, with the strategic firms exhibiting a much slower decay rate following an official announcement. This prolonged interest in news from strategic companies may reflect the technical background of these companies and the desire on the part of investors to evaluate the new products and how those investments sustain value creation. In retweets, the decay rate across speculative and strategic firms is much slower after the official announcement when compared to the overall number of tweets issued, as indicated in Figure 1. The most interesting artefact of the data is that for retweets, the initial rumour is the most powerful driver of activity, resulting in an acute but very brief (two days) period of interest.

Insert Figure 1 about here

As in Figures 2 and 3, we present the number of 'Retweets' and 'Likes' respectively. The presented number of 'Likes' follows a similar pattern to the retweets, with rumour being the most

powerful driver of activity, this time with a very rapid decay rate, with a near full return to prerumour conditions by day 3. Official announcements follow the same pattern as in Figures 1 and 2, with strategic firms having a slower decay rate and maintaining a permanently higher level of 'Likes' after the official announcement. Speculative firms have a much more rapid decay rate than strategic firms, but they also permanently increase their 'Likes' after the official announcement. This further confirms the hypothesis that firms seek to use blockchain as a method of acquiring interest in their firms, even if that interest is relatively fleeting. 'Likes', as an indication of interest and approval, in the activities of both the speculative and strategic firms, making an official announcement is a clearly positive action to increase the visibility, interest and approval of the firm.

Insert Figures 2 and 3 about here

It is important to note that Twitter is not an entirely transparent medium for registering interest. The presence of 'bots' (automatic programmes) can manipulate the readers of Tweets as these bots can emulate the behaviour of actual followers and mimic human interaction (so-called 'socialbots'). This can result in an artificial increase in the number of tweets, retweets and likes attached to a particular news announcement. Countermeasures can be taken by firms that have online security support, most especially those with a deep knowledge of the technology behind bots. These firms would typically fall into our strategic categorisation. The degree in which the misuse of social media data and, in particular, fake data has been estimated to have been guite profound. Van Der Walt and Eloff [2018] discussed the many examples that exist of cases where fake accounts created by bots or computers have been detected successfully using machine learning models dependent on employing engineered features, such as the 'friend-To-followers ratio' which have been developed on attributes such as 'friend-count' and 'follower-count,' which are directly available in the account profiles on social media platforms. Shao et al. [2018] performed k-core decompositions on a diffusion network obtained from two million retweets produced by several hundred thousand accounts over the six months before the 2016 US Presidential Elections, providing a first look at the anatomy of a massive online misinformation diffusion network. Grinberg et al. [2019] examined exposure to and sharing of fake news by registered voters on Twitter during the same elections and found that engagement with fake news sources was extremely concentrated, where only 1% of individuals accounted for 80% of fake news source exposures, and 0.1% accounted for nearly 80% of fake news sources shared. Cresci et al. [2015] specifically investigated fake followers on Twitter, pointing out the explicit dangers as they may alter concepts like popularity and influence. The authors show that most of the rules proposed by media provide unsatisfactory performance in revealing fake followers, while features proposed in the past by academia for spam detection provide good results. The authors revise the classifiers both in terms of reduction of over-fitting and cost for gathering the data needed to compute the features. The final result is a novel Class A classifier, that is able to correctly classify more than 95% of the accounts of the original training set where an information

fusion-based sensitivity analysis was performed, to assess the global sensitivity of each of the features employed by the classifier.

5.2. Abnormal returns surrounding social media rumours and official announcements

Next, we investigate Hypothesis H_2 , which analyses as to whether blockchain-based Twitter rumours and announcements influence market sentiment and financial valuation, and as to whether such announcements differ significantly. In Table 5, we observe the cumulative abnormal return for a rumour and official statement pre-announcement window [-30,-1], announcement windows [-1,1; [0,3]; and [-30,30], and post-announcement window [4, 30] for the sample as broken down by motivation to speculative or structural, year, reach (as defined by the natural log of the number of tweets, retweets and likes and broken into quartiles) and sentiment categorised as positive, negative and neutral using existing psychological and financial lexicons definitions. The highlights of this table relate to the response of equities at AR0. Here you see that speculative investments have an 11% higher return in both rumour and official announcement. Equities with a positive sentiment will have a 13% and 8% respectively higher return and importantly, given regulatory responses in recent years, abnormal returns reaching 12% and 18% in 2017 but are moderated to less 1% for rumours and 3% for official statements in 2019. Further, we observe significant differentials between the point of rumour and official announcement when considering both reach and sentiment. Companies that experienced substantially elevated levels of social media tweets surrounding their proposed projects experienced substantially elevated levels of estimated abnormal returns. Further, similar elevated estimates are uncovered where such news dissemination is found to be postive, when compared to both neutral and negative states.

Insert Table 5 about here

Using a similar methodology to that of Cahill et al. [2020], we use a model of cumulative abnormal returns to investigate the behaviour of firms that are associated with blockchain announcements. In this model, the focus of the analysis in on the speculative versus the strategic firms for rumour and official announcement responses. Here strategic firms have little equity market price responses to rumour, whereas speculative firms have very clear and persistent responses to rumour announcements. In the case of official announcements as presented in Figure 4, the dramatic response of speculative firms is observed again but strategic firms also have the appearance of abnormal returns, but much smaller in magnitude.

Insert Figure 4 about here

In the next investigation of abnormal returns in Figure 5, the sample is broken into different years, 2017, 2018 and 2019. The most striking difference is the evidence of abnormal returns

between 2017 and subsequent. This may reflect a dramatic change in the regulatory environment with respect to blockchain technology and the treatment of the "initial coin offering" (ICO) by the US Securities and Exchange Commission (SEC) and the Federal Bureau of Investigation (FBI). The SEC began the process of investigating ICOs in the second half of 2017, making their first investor bulletin in July 2017 and then an enforcement sweep in March 2018 with the FBI making a public announcement of the sentencing of a virtual currency fraudster to 21 months in prison in February 2019. Given these regulatory response, it is not surprising that evidence of abnormal returns reduces in 2018 and is muted in 2019, most especially for rumours.

Insert Figure 5 about here

In Figure 6 we look at the "reach" of the social media. Here you see that in both rumour and official announcements that there is strong response by equities. As expected, the responses reflect the relative "reach" of Twitter as measured by tweets, retweets and likes and broken into quartiles. Those firms with the highest reach, exhibited the strongest results with respect to official announcements. These higher returns remain persistent after the initial announcement for high and medium reach firms. In the case of rumours, which the initial response by high and medium reach firms is the same, the persistence is more pronounced in medium reach firms. In both cases low and very low reach firms respond with an increase in abnormal returns but those are much lower relative to high and medium reach firms. Interestingly they are persistent over the post announcement period of 30 days.

Insert Figure 6 about here

Next, in Figure 7 we look at the impact of sentiment as expressed by Twitter statements that have been indexed to positive, negative and neutral sentiments. In a not unsurprising result, strong and persistent cumulative abnormal returns are associated with positive sentiment information from social media. This is consistent for rumour and the official announcement. The impact of negative sentiment is still positive for both circumstances, and interestingly, more powerful than a neutral social media sentiment for rumours. In the case of official announcements, the expected order of positive, neutral and negative holds but even negative sentiments will still result in an improvement in returns. The only explanation that can be associated with such a response is that overall effect of being associated with a blockchain initiative or blockchain technology is understood to be overwhelmingly positive for a firm, even if it receives a negative welcome from social media commentators.

Insert Figure 7 about here

Table 6 presents CAR regression estimates for 30 to 1 day prior to announcement [AR0] cumulative abnormal returns over a sample of blockchain-related listed firms between 2017 and 2019. Year 2017 and Year 2018 are dummies that are 1 if the announcement is made in 2017 and 2018, respectively, and 0 otherwise. Bitcoin is the natural logarithm of the bitcoin price level 30 days prior to the announcement day. Bitcoin CAR [-30,-1] is the cumulative bitcoin return 30 days prior to the rumour and official announcement day. Non-Speculative is a dummy that takes the value of 1 if the announcement is non-speculative and 0 otherwise. US is a dummy if the firm is traded on a US exchange and 0 otherwise. Market Cap (log) is the natural logarithm of the market capitalisation in USD 30 days prior to the announcement day. Duration is a measure of distance in time between the rumour announcement and the official announcement. Reach is the measure of the volume of tweets, retweets and likes log normalised and broken into quartiles. Sentiment is a measure of positive or negative sentiment with a dummy that takes a value of 1 if the announcement is associated with a positive sentiment. When considering these results, we can clearly identify that US market effects dominate, while the rumour effects are most powerful in 2017, consistent with the regulatory developments. Notably, the Bitcoin price effects, which reflected that of the overall trend in cryptocurrency market impacts, are found to be insignificantly related to the movement of blockchain, presenting evidence of decoupling, or little interaction between the sample of companies and cryptocurrencies prior to either the rumour or official announcement of blockchain development.

Insert Table 6 about here

In both of the Tables 7 and 8, we observe the direct CARs at the time period specifically surrounding both the date of the rumour and the official announcement, focusing on the period [-1,+1], and the day of [AR0] respectively. First, considering the period inclusive of the day-before and the day-after each event, a number of interesting observations are made. The effects identified in 2017 are much stronger for rumours relative to official announcements and interestingly, while 2018 effects are reduced relative to 2017 during the rumour period, they are negative for official statements. This again is consistent with changes in the regulatory environment with respect to blockchain. Bitcoin, in price effects and cumulative abnormal returns are near equal to the announcement taking place during 2017. While immediately pre- and post-announcement there is a distinct different between rumour and official announcement with respect to the behaviour of speculative firms. Firms with speculative motivations to embark on blockchain work during a rumour will have a large proportion (0.14) of its price movement explained exclusively by sentiment. Further, the US market effects are the dominate effect in this period, while from the empirical evidence we can identify that firms with strong responses to rumour do so most actively when they are speculative and in the period prior to 2019. This is consistent with our hypotheses that firms that are engaged in blockchain for speculative purposes are seeking to take advantage of an existing premium in the market associated with cryptocurrencies and that regulatory responses have reduced

that opportunity over time. Importantly, these effects are most pronounced for rumours as opposed to official statements. When focusing specifically on the day of, that is the absolute return at T_0 , or [AR0], at the point of an announcement the most important explanatory factor is clearly Bitcoin prices, and this is most powerful for official statements by firms. Sentiment is found to play a more important role at [AR0] but it is still less important than the status of a firm being speculative for both rumour and official announcements. The US market effects remain persistent across all the time periods but do not explain as much of the price movement. In the case of rumours, they are large but do not dominate, Bitcoin CARs explain most of the movement of prices from rumours. In the case of official announcements those effects are present but are dwarfed by Bitcoin prices and speculative status. Further, the estimate results at [AR0] are indicative of the importance of Bitcoin and the premium on cryptocurrencies reflected in the market and the desire for firms to exploit that premium. The large explanatory power of speculative firm status continues to confirm our hypothesis that firms seek to exploit this premium via "bandwagon" effects.

Insert Tables 7 through 9 about here

In Table 9 we observe regression estimates for the announcement day [AR0] and 3 days after the announcement [AR0] cumulative abnormal returns over a sample of blockchain-related listed firms between 2017 and 2019. Sentiment plays a much larger role in explaining the price movements at and immediately following a rumour or official announcement. While Bitcoin prices and Bitcoin abnormal returns continue to be the most important explanatory factors in the equity price movement, it is notable that sentiment outweigh the status of the firm as a speculative firm in this estimation. US market effects continue to hold sway over rumours but are now less important for official statements. Official statements are driven by Bitcoin prices and Bitcoin CARs and then supplemented by sentiment and speculative firm status. In the [0,+3] time window it is clear that the cryptocurrency premium is the driving factor and that perceptions of firm behaviour and decisions do matter.

Table 10 shows regression estimates for the period of 4 to 30 days after the announcement [AR0] cumulative abnormal returns over a sample of blockchain-related listed firms between 2017 and 2019. Bitcoin CAR [+4,+30] is the cumulative bitcoin return for the period of 4 to 30 days subsequent to the rumour and official announcement day. During the extended period after a rumour announcement the main explanatory variable is if the rumour took place in 2017 and is followed Bitcoin CARs. The changes to regulations and enforcement by the SEC and FBI after 2017 make it clear that firms that were seeking to obtain an equity price premium through an association with blockchain technology were subject to greater Federal scrutiny. Further, the explanatory power of US market movements continues to be strong for both rumours and official statements. While the official statement price movements are explained by slightly different factors to a rumour. Not being a speculative firm tends to improve price performance. Sentiment overall has an explanatory effect

but one that operates in the opposite direction than expected, with a negative impact on cumulative abnormal returns. This in combination with the negative effect for speculative firm status may be indicative of the importance of strategic firms making announcements about blockchain technology that is compliant with regulatory requirements and that sentiment will amplify the negative market response that speculative firms will incur following the market's evaluation of their official statement on a new blockchain product or cryptocurrency.

Insert Tables 10 and 11 about here

Finally, in Table 11, we observe the regression estimates for the entire sample of 30 days prior and 30 days after the announcement [AR0] cumulative abnormal returns over a sample of blockchainrelated listed firms between 2017 and 2019. Year 2017 and Year 2018 are dummies that are 1 if the announcement is made in 2017 and 2018, respectively, and 0 otherwise. Bitcoin is the natural logarithm of the bitcoin price level 30 days prior and 30 days subsequent to the announcement day. Bitcoin CAR [-30, +30] is the cumulative bitcoin return 30 days prior and 30 days subsequent to the rumour and official announcement day. Non-Speculative is a dummy that takes the value of 1 if the announcement is non-speculative and 0 otherwise. US is a dummy if the firm is traded on a US exchange and 0 otherwise. Market Cap (log) is the natural logarithm of the market capitalisation in USD 30 days prior and 30 days subsequent to the announcement day. Duration is a measure of distance in time between the rumour announcement and the official announcement. Reach is the measure of the volume of tweets, retweets and likes log normalised and broken into quartiles. Sentiment is a measure of positive or negative sentiment with a dummy that takes a value of 1 if the announcement is associated with a positive sentiment. Considering the final sample in its entirety presents a number of key observations. There exists a very distinct different between the behaviour of the rumour announcement and the official announcement, such that it is apparent for official announcements that US market effects and Bitcoin CARs drive the price movement for an official announcement. It is also important to note that 2018 is a driver of price movement for official statements. This is important as it reflects the changing regulatory environment that made it more difficult for firms to make unsubstantiated announcements for the purposes of recruiting investors over the time between 2017 to the end 2019. Rumour announcement behaviour is consistent with a high-risk asset. 2017 effects are the most explanatory, reflecting the highly laxed regulatory environment that existed at that time. US market effects are strong but are accompanied by strong sentiment and speculative firm status effects. Bitcoin prices and Bitcoin CARs again are power explanatory variables for movements of firms as a result of rumours. Finally, the estimated model makes it clear that there are firms which seek to exploit the market premium for blockchain technology as it is associated with the creation and distribution of cryptocurrencies, the most notable being Bitcoin, and are as such speculative in market motivation and as such flourish in a weak regulatory environment sensitive to exogenous factors such as sentiment. The strong bifurcation between official statements and rumours only acts to reinforce this assessment as official statements by technologically focused firms engaged in strategic decisions will be taken into account by Federal authorities and be disseminated by the traditional media as well as social media.

5.3. Did corporate desperation instigate the decision to incorporate blockchain technology?

While strategic usage of blockchain-development is of particular interest, there is a concerning issue surrounding companies that have decided to proceed with speculative blockchain development. The first, which we will focus on in the following section, surrounds evidence of an increased use of leverage, that is, companies have borrowed substantial levels of assets from which they can draw upon to take the speculative attempt at rapid growth. Should the situation not manifest in a successful outcome, the company will face even harsher financial conditions. Secondly, to date, and almost three years after some official announcements, there is no evidence of project initiation in some scenarios. This is particularly astonishing. However, one particular shared characteristic is quite noticeable when considering particular cohorts of the sample of speculativelydenoted companies: their company and sector have been in long-term decline. In Figure 8, we present evidence of three particular companies from our sample that merit particular attention due to the unique nature of their decisions to incorporate blockchain technology. First, we present evidence of Kodak, a company who has struggled to transition in the age of mobile technology. Secondly, Future Fintech Group, an unprofitable Chinese company formerly known as 'SkyPeople Fruit Juice' who have now changed their business focus to utilise "technology solutions to operate and grow its businesses' while 'building a regional agricultural products commodities market with the goal to become a leader in agricultural finance technology.' Finally, we observe the performance of Bitcoin Group SE, a holding company focused on innovative and disruptive business models and technologies in the areas of cryptocurrency and blockchain.

Three distinct scenarios are presented in the performance of these companies: 1) observing Kodak, we identify a company in long-term sectoral decline, who through the announcement of KODAKOne, described as a revolutionary new image rights management and protection platform secured in the blockchain created a scenario where at 5.00pm (GMT) on 9 January, Kodak shares were worth \$3.10, while at 2.40pm (GMT) on 10 January, shares were trading at \$12.75; 2) Future Fintech Group who had previously received a written warning from NASDAQ on 1 December 2017 for failing to maintain a market value above \$5 million and risked being de-listed if it did not pass the threshold by May 2018, according to public filings. The rapid boost in market value shortly after this warning mitigated this issue; and 3) Bitcoin Group SE, a company formerly known as AE Innovative Capital SE, a Germany-based investment who changed their corporate identity to re-establish itself with one sole raison d'être, to provide speculative venture capital to companies with a focus on business concepts and technology.

Insert Figure 8 about here

It would not be considered excessive for more sceptical market participants to ask of these and similar cases: 1) had these companies just unveiled a novel and genius evolutionary use for blockchain; or 2) had they just attempted to ride the wave of a potential cryptocurrency bubble? The nature and rationale underlying these decisions is of particular interest. While we have established interactions with regards to sentiment and cumulative abnormal returns, it is central to our research to focus on whether internal corporate structures presented evidence of changing structure in the form of excessive use of leverage in anticipation of such speculative projects? And such important questions such as whether such increased use of borrowed capital reflected in increased corporate probability of default and as to whether corporate ambitions had been identified by credit rating agencies? Further, one very interesting question remains unanswered: had investors, policy-makers and credit rating agencies alike considered it curious that companies with no previous technological development experience had now signalled their intentions to change their corporate identity and enter a sector with little or no experience? Such dramatic decisions would not only incorporate risks from a exceptionally high-risk sector into the corporate structure, but might not have been fully appreciated and valued by investors and regulatory authorities alike.

5.3.1. Did the selected companies increase their leverage and cash reserves in the period before blockchain incorporation?

To investigate Hypothesis H_3 we set out to investigate as to whether the corporate decision to initiate speculative blockchain-development projects coincided with two specific characteristic changes: significantly weak cash holdings and elevated levels of corporate leverage in comparison to industrial peers. Both are characteristics of companies who are in a particularly vulnerable financial positions (Aktas et al. [2019]; Dermine [2015]; Cai and Zhang [2011]; Choe [2003]; Acharya et al. [2012]; Arnold [2014]; Aktas et al. [2018]). To test for such effects, we build on the work of Cathcart et al. [2020] and estimate a logit regression estimates for the four specifications as presented in Table 12. The coefficient of representing leverage is positive and strongly significant, indicating that it is a central force in the methodological structure when considering the baseline estimation compared to companies that are either in liquidation or have been under SEC investigation for fraudulent behaviour since announcing their intentions to develop blockchain. Further, for methodological robustness, the leverage components in specification (2) are also positive and strongly significant. The relationships between the estimations of trade-payables to total assets, and both current and non-current liabilities to current assets respectively are presented in specifications (3) and (4). We identify a significantly positive relationship between all variables and the logit-calculated structure. However, the influence of the estimated leverage effect is significantly stronger across each estimated methodology. We can therefore confirm that when controlling our sample for companies who have defaulted or have become the focus of SEC or other legal and regulatory scrutiny, increased leverage and reduced cash holdings were both significant characteristics of such companies.

Insert Tables 12 and 13 about here

Considering both the sign and significance of leverage and leverage components interactions with blockchain-developing corporations, we next examine the marginal effects of such interactions as per Cathcart et al. [2020]. We therefore estimate the default probability as separated by type of corporate blockchain-developing type as denoted to be speculative or strategic. In Table 13, we find that the marginal effect of leverage for strategic blockchain-developing corporations is 0.003, while for speculative blockchain-developing corporations is 0.022. These estimates and their differences are economically significant. It is widely considered that an increase in the average default rate from 0 to 9 basis points would cause a substantial downgrade from Aaa to A (Ou et al. [2017]; Cathcart et al. [2020]). When considering this estimate, we can identify that the estimated coefficient for speculative blockchain-developing firms could generate enough default risk to downgrade an investment-grade company (approximately A3 as per Moody's credit ratings), as denoted to possess strong payment capacity, to fall to junk-grade status (Ba1, Moody's). For strategicallydenote blockchain announcements, the risk are relatively minimal and would be estimated to be approximately one grade based on a one standard deviation change. While Cathcart et al. [2020] state that their results relating to SMEs and large corporations surrounds the fact that large financially constrained firms are able to raise bank finances more easily than are small firms, especially during crisis periods (Beck [2008]), our results follow the same vein of thought. After considering the summary statistics presented in Table 2, we identified that companies that had taken part in speculative blockchain-development were most likely to be substantially younger (26.4 years old), almost three times more leveraged (total liabilities divided by total assets equals 0.750) and have substantially less income and current assets as a proportion of total assets. Such specific characteristics would also support the view that financial constraints had hindered an ability to obtain leverage as smaller, younger firms were more likely to take the decision to carry out highly speculative tasks such as creating a cryptocurrency or changing the corporate identity of the company, similar to the moves made by companies such as Long Island Iced Tea and SkyPeople Fruit Juice.

5.3.2. Did such companies have previous experience with similar technological release and development?

One of the key red flags surrounding the identification of illicit behaviour within the context of blockchain development has focused on the why companies with no prior experience of technological development in any form would consider shifting their primary business practice to blockchain development? While an exceptionally high-risk and complex change in corporate identity, a large number of companies have attempted to carry out such strategy changes since 2017. Continuing to separate our methodological structure to analyse the differences between strategic and speculative blockchain announcements, to specifically investigate Hypothesis H_4 , we add a further separating characteristic to denote as to whether our sample of companies are identified as technologically proficient. Therefore, we identify companies in their respective domestic indices that operate within the communications, information technology and financial sectors to be technologically proficient as development within this context is consider a core operational function. Using this structure we estimate a similar logic regression, we again set the y variable to be a dummy that indicates corporate default or regulatory investigation; taking a value of zero if the firm is active and a value of one if the firm is insolvent, bankrupt or under investigation. Table 14 presents the estimates of the methodological structure used to calculate the representative probability of default. We identify that leverage is once again a significant explanatory variable with regards to both speculative and strategic methodological structures.

Insert Tables 14 and 15 about here

Considering the significant effects of leverage, we next analyse the marginal effects of technological experience with results provided in Table 15. We separate the estimates not only by intention underlying announced blockchain-development intention, but also whether each company has been defined to possess previous technological experience. When considering speculatively-driven blockchain-development, companies with prior experience present a significant marginal effect of leverage of 0.023, which compared to the benchmark estimates represents a two-grade fall in credit rating. However, speculative blockchain announcements by companies that are found to possess no technological experience are found to be capable of generating between a four and five grade fall in credit rating due to significant leverage effects. When considering strategically-driven blockchain announcements, those companies with previous technological experience generate less than half of a one-grade credit rating decline due a marginal effect of leverage of 0.004, while those companies with no technological experience is found to generate a significant marginal effect of 0.015. This would lead approximately a one grade decline in credit rating. The results of this marginal effect analysis therefore support the hypothesis that companies who instigate blockchain-development projects with no previous technological experience are found to present increased probability of default.

5.3.3. Have credit ratings reflected the inherent risk of speculative blockchain development?

While conclusively finding evidence that there exist significant differential effects between strategic and speculative blockchain-development announcements for corporations in the manner of which news is disseminated, the response of investors, and indeed, the manner in which underlying fundamental corporate structures, we further find conclusive evidence of significant differentials in behaviour considering whether the corporation had prior experience in the area of technological development. This reflects considerable evidence that there exists a somewhat exceptionally exceptionally risky set of companies through which the nature of their intention does not appear to be fully valued within standard risk metrics when considering their excessive use of leverage to take on exceptionally risky projects that appear to be fundamentally based on 'bandwagon effects' such as changing long-standing corporate identity, or creating a cryptocurrency for no explicit structural rationale whatsoever. It is important that we investigate as to whether investor's possess a true representation of the risk that they are adding to their portfolios through investment in these companies. We test this through an investigation of Hypothesis h_5 which analyses as to whether credit ratings have been adapted and present evidence of risk segregation when considering the additional corporate risk associated with speculative and strategic blockchain development.

In Table 16 we observe two distinct measures of risk, as separated by type of blockchain announcement. The first is a combined global ranking measure based on structural and text mining of credit rating risk into one concise, time-varying estimate for each company. The higher the value of the measure, the lower the estimated probability that each company will enter bankruptcy or default on their debt obligations over the forthcoming twelve months. Secondly, we present estimated values per company of the one-year estimated probability of default during the periods under investigation.

Insert Table 16 about here

A number of interesting observations are presented when observing the companies in this manner. Primarily, there is a clear separation between the credit scores and actual presented probability of default by type of blockchain-announcement. When considering strategically-denoted blockchain development, companies that announce their intentions to use blockchain for purposes such as technological and security enhancement, or indeed the announcement of partnerships and investment funds present evidence of superior control of their ability to repay creditors, with further support of this finding provided through substantially and significantly compressed one-year probability of default rates. While the average company in the sample presents a one-year PD of 0.8%, strategically positioned companies are found to be 0.5%. When comparing companies that are defined as instigating speculative blockchain announcements, while companies that announce their intentions to create cryptocurrency are not necessarily distinguishable from those who have announced blockchain-development for strategic purposes when considering ability to repay creditors. However, in comparison, companies that announce their intentions to change their names also present quite insurmountable challenges within the forthcoming twelve months as evidenced in their significantly suppressed credit rating scores. Such companies also present an average one-year probability of default of 2.2%.

Insert Table 17 about here

When focusing specifically on credit ratings, a similar pattern emerges. In Table 17 we present the average credit rating per company as separated by each type of blockchain-development announcement, while further separated by period both before and after the official date. A linear transformation scale for S&P, Moody's and Fitch is presented in Table A2. We use Moody's rating

scale as the selected metric to present and compare our results. Further, using the earlier described logit methodology, we re-estimate ratings based on the average marginal effects of leverage. While credit rating agencies present evidence of only a nominal downgrade of the average company who utilised speculative blockchain announcements from Baa1 to Baa3 in the period thereafter. Further, strategic blockchain announcements are found to remain unchanged at A2 between the periods both before and after. When considering the significant marginal effects of leverage as considered within the previous section, we reconstruct leverage-adjusted credit ratings (Metz and Cantor [2006]), as presented in Table 17. A number of significant observations are identified. While credit rating agencies appear to have somewhat distinguished and identified the risk associated with speculative behaviour, evidence suggests that it fails to truly reflect inherent idiosyncratic risks. While an estimated downgrade from Baa1 to Baa3 was identified in the average speculative blockchain company, when further separating groups to either possess or not to possess previous technological experience, results indicate that even those experienced companies should be considered to be of junk status at Ba1. Further, companies without previous experience are estimated to be positioned at B1. Even under the most optimistic circumstances, speculative blockchain developing companies with no previous evidence of technological development do not exceed junk investment status of B1. This result provides significant evidence that investors have not been appropriately advised of the true risks inherent in such speculative corporate decisions. When considering strategicallyindicative blockchain announcements, the average company in the sample is found to warrant a one-grade downgrade from A2 to A3 in circumstances whether evidence suggests previous technological experience, while a further one-grade downgrade to Baa1 is suggested should no previous technological experience be identified.

6. Discussion

We find in our investigations that firms are aware of the price premium placed on blockchain, reflecting the price premia experienced by some cryptocurrencies, namely Bitcoin. Cryptocurrencies are an application of blockchain technology but blockchain can be used for a wide variety of security and contracting business applications. During the period under observation, January 2017 to July 2019, Bitcoin experienced a price rally that saw prices move from \$800 a coin to a peak of \$19,783 on 17 December 2017 to a price of \$3,300 in late December 2018 and a price \$9,503 in July of 2019. This rally attracted many firms to take advantage of the exuberance and associate themselves with the powerful upward price movement of Bitcoin. The novelty of the technology and the inherent information asymmetries that brings afforded an opportunity for firms that exclusively seek a rapid increase in equity prices or seek to rebuild market capitalisation. An association with blockchain is a method of bootstrapping bandwagon effects. These firms are distinctively speculative in behaviour and the empirical analysis highlights that speculative firms performed differently to strategic firms, which undertake blockchain projects for value creation purposes.

This incentive to exploit market euphoria consistently appears in our findings. At the highest level, we spit firms into those that are speculative and strategic in their actions. An additional division is to divide firms into those with and without technological experience. Firms with technological experience illustrate less idiosyncratic risk when compared to companies engaged in other sectors. Using our earlier example firms, Kodak and Long Blockchain are firms with no background in ICT technology. Facebook, Apple are examples of firms with extensive experience in ICT. Firms that lack experience in technology and are speculative in nature are high-risk firms and indicate that in the form of their CARs. CARs are most prevalent in these risky firms during the rumour phase as opposed to the official announcement. Non-technological firms also exhibit strong CARs with an official announcement. This reflects the desire of these firms that are non-technological to act in a speculative manner, to evolve into a "risk-on" asset and the underlying desire of these firms to take advantage of blockchain and cryptocurrency bandwagon effects as evidenced by the explanatory power of Bitcoin and Bitcoin CARs in these firms estimated CARs.

While our results illustrate how firms have attempted to take advantage of the market conditions surrounding Bitcoin to advantage their equity position, the internal corporate financial position can also be manipulated by an association with blockchain. Firms that are engaged in blockchain announcements that are speculative in nature tend to dramatically expand their leverage position. This naturally changes their idiosyncratic risk position. Blockchain activity attracts investors which extend credit to the firm to develop the new application or product. This has several interesting outcomes. First, a dramatic increase in the probability of default in firms that undertake this course of action. Second, the increase in idiosyncratic risk is sufficiently large to warrant a significant downgrade of that firm's credit rating, a downgrade that is currently underestimated by informed market actors. Third, it highlights yet a further difference between strategic and speculative firms, as the large cash position of strategic firms can be seen as a prerequisite to undertaking high-risk product development projects such of blockchain. All blockchain related activity is understood to increase risk to the firm that is undertaking it. Firms with prior experience of the technology sector and large cash reserves will minimise the increase in their idiosyncratic risk and therefore have a much lower increase in their probability of default. Given the importance of blockchain technology to operational security for high tech firms, a common application outside of cryptocurrencies, the financial benefit of maintaining a store of ready cash to finance product development is apparent and explains in part the desire for technology sector firms to hold their noted large cash reserves.

Given these observed and estimated conditions, the most obvious investment strategy is to buy these companies equities based on rumours and sell in the days after official announcement. This is a strategy that can only be undertaken in a circumstance of a information being based on nonartificial sources. The reality of Twitter communication and computer-aide algorithmic trading is that information, sentiment, interest can all be manipulated quickly and cheaply and then feed into trading activity driven by sentiment-driven rule-based computer-aided trading further compounding the cycle of trades. Setting that cycle of information manipulation aside, there exists a social media-based strategy through which investors can profit based on investment should their source of information be non-bot. The ethical and legal implications of this strategy are substantial. There is nothing to mitigate the effects of false statements to the market, i.e. 'fake news'. The quality of such news is only as good as the source that has generated the Tweet, which will not typically abide by the conventions of traditional journalism. Still, if the information is of high or low quality, it has the capacity to generate sentiment, sentiment that can be read and understood by human and machine learning alike. The use of automated programmes to generate interest can generate positive returns should sufficient attention and reach of social media interaction take place. While the role of sentiment is limited to its importance to rumour statements by firms but it still has the power to drive equity prices. This is most especially true for firms engaged in speculative objectives. Speculative firms clearly improve their equity returns and access to leverage as a result of associating with blockchain but also become highly risky firms with a high probability of default and cease to be investment-grade assets. This matters for those that direct those firms, investor guides and for investors themselves as it takes a set of bad asymmetric information conditions and generates the optimal conditions for moral hazard.

Given these opportunities to manipulate investors and market watchers, there exists a new channel through which a hypothetical firm, desperate and in sectoral decline, or a young start-up with ambiguous morals, can obtain artificial 'followers', 'retweets' and 'likes' on social media can be easily recruited and purchased via the darknet¹¹ and in an incredibly efficient manner attention can be artificially stirred. This presents another layer of complexity through which regulators and policy-makers must attempt to navigate. The company can therefore quickly gain through increased share value and market capitalisation. There are particular avenues of value addition for corporations who obtain particular value from marketability, or in an ethically-flawed and illicit vein, would like to quickly increase the value of their respective corporations for the purpose of increased sale-ability, or perhaps to mitigate threats such as de-listing. The research provided presents clear evidence that speculative firms use blockchain announcements or the declaration of an intention to develop cryptocurrency or a change in corporate identity incorporating blockchain and cryptocurrency-naming similarities should at best greeted with investor scepticism and regulator inquiries. Removing the layer of digital complexity, there is fundamentally little difference between these techniques and a textbook definition of a 'pump-and-dump'. Evidence suggests that smaller companies, that experience substantial 'rumours' for prolonged periods of time, to date, have presented almost zero proof of a successful speculative project coming to completion and/or generating a positive net cash-flow. Despite the obvious lack of fundamental value creation, the share prices of these firms have remain elevated after the substantial marketing action that coincides with such behaviour.

¹¹The darknet is a portion of the internet that is dedicated to illegal activities and operates mainly off of peer-topeer networks. The most notable was the global drugs bazaar Silk Road, which notably relied heavily upon Bitcoin for payment in transactions.

While some participants argue that those with better quality information should be rewarded (Ho and Michaely [1988]; Rashes [2001]) for their efforts when obtaining quality information, the real difficult task for policy-makers and regulators is the identification of 'questionable' cases. Regulators have been slow to address the space of cryptocurrencies as the legislative frameworks they rely upon are based on older technologies and practices, which at the most fundamental level generate problems of definition and jurisdiction. The regulatory environment with respect to blockchain was underdeveloped with lax enforcement prior to the second half of 2017. Regulators, most importantly the Securities and Exchange Commission and the Federal Bureau of Investigation began the process of investigating potentially fraudulent cryptocurrency companies and subsequently released investor guidelines. At the same regulation cannot be so tough that is creates fear of entry that stifles technological development. Regulation does not operate best when perceived to be so 'laissez faire' that a new, incredibly-easy channel to generate illicit profits by deeply unethical behaviour exists. This is perhaps where a direction of future research in this emerging area should focus. In the meantime, timely and unobstructed investigations of such announcements should be carried out by regulators so as to minimise the probability of illicit activity. The argument supporting this should centre upon the need to protect uninformed investors from such channels of manipulation. This is even more necessary considering the identified mis-pricing of risk in our research. There appears to be a substantial risk associated with this questionable behaviour as surrounds contagion and if investors have truly quantified the relationship between these companies and their exceptional risk-taking behaviour. This is evidenced by the exceptional levels of leverage used in the high-risk categories of firms. Revising recent credit ratings, and continuing to assume that investors observe and obtain information within these metrics (Alsakka et al. [2014]; Becker and Milbourn [2011]; Iannotta et al. [2013]), our logit-calculated revised credit ratings that consider the sentiment and speculative nature of blockchain-development ambitions present evidence of both substantial and significant mis-pricing of risk. Those companies who partake in speculative blockchain development are found to possess an average actual credit rating of Baa2, which is of an investment grade. Considering companies with both experience and no experience of technological development, leverage-adjusted re-estimated credit ratings find that the average grade should be no higher than junk status (Ba1 with technological experience and B1 without). Re-evaluating those companies who use blockchain-development for strategic purposes are found to have their risk correctly identified when possessing previous technological experience, while only receiving a one-sub-grade announcement with no previous technological experience. This finding presents evidence that the underlying behavioural aspects of these companies has the potential to mislead investors and generate substantial repercussions throughout unsuspecting portfolios. Ultimately the analysis from sentiment, CARs and default probability ensures that firms that desire to move into blockchain fall into two categories: a high-risk, high-default probability speculative firm or a firm that is in decline seeking to regain market capitalisation and investor attention or a cash-rich technology firm that is seeking to develop a new product or service. Given such conditions, there are clear policymaker

implications as more stringent oversight and enforcement has reduced the attraction for the latter but market actors continue to under-price the risk associated with an expansion into blockchain.

7. Conclusions

We focus on the role of speculative blockchain-development announcements and their differential impacts on the probability of default of corporate institutions, particularly those with no previous experience of technological development. Two of the most speculative techniques observed to date include developing a corporate cryptocurrency or changing an entire corporate identity to incorporate words such as 'blockchain' and 'cryptocurrency', sometimes phrased as "initial coin offerings" or ICOs copying the traditional equity market initial public offering (IPO). Particular examples include an orange juice producer and an iced tea sales company changing their identities to become blockchain-centred companies. Such actions drew substantial attention from national regulatory authorities. Through a number of robust methodological approaches, we find that blockchain announcements generate observable and significant changes in the perception of the firm to which blockchain-development announcements have been made. There are found to exist significant abnormal returns at both the time of the first social media rumour and again at the point in time of the official announcement.

The level of social media activity is found to be significantly dependent on the type of blockchain announcement. In the thirty-day period after a speculative rumour, cumulative abnormal returns are found to exceed 40% compared to 10% for strategic-based announcements. During the time of an official announcement, speculatively-driven announcements generate abnormal returns of approximately 35%, again considerably more than similar strategically-denoted projects. These effects have been found to diminish over time. When considering the ability of some companies to use social media sources to generate product-based interest with substantial positive sentiment, companies that generate the largest amount of interest are found to experience the largest abnormal returns. This specific result generates an added layer of regulatory complexity given the difficulty in discerning if that digital interest is artificially manufactured. Theoretically, significant abnormal profits exist through the generation of added social media activity. These firms are distinctively speculative in behaviour. The empirical analysis highlights that speculative firms experience different performance to strategic firms, which undertake blockchain projects for value creation purposes. Firms with technological experience illustrate less idiosyncratic risk when compared to companies engaged in other sectors. Those that lack experience in technology and are speculative in nature are high risk firms and indicate that in the form of their CARs and tend to dramatically expand their leverage position.

After presenting evidence of significant and substantial levels of leverage usage in such companies that instigate speculative blockchain-development projects, we identify clear separation between the credit scores and actual presented probability of default by type of blockchain-announcement. Speculative companies are found to present an added 1.7% one-year probability of default when compared to strategically-denoted companies. Companies with no previous technological experience that take on additional leverage, when considered in the light of the estimated one-grade downgrade using a leverage-adjusted credit rating methodology, should be considered to be no better than junk investment status. This result provides significant evidence that investors have not been appropriately advised of the true risks inherent in such speculative corporate decisions.

We observe that credit rating agencies misconstrued the rationale for the use of leverage by these companies, particularly for the purposes of highly speculative blockchain-development plans. Credit rating agencies undervalued how firms jeopardise their status as going concerns by using such a substantial level of borrowed funds to undertake a high risk product development, therefore investors that obtain information through such sources have been placed at a disadvantage. Companies that signal their intentions to instigate strategic blockchain-development do not appear to present evidence of the same elevated short-term probability of default or discrepancy in leverage-adjusted credit ratings. While some informed investors will observe the internal structural discrepancies, there are many which will seek out such movements. Algorithmic and sentiment-driven computeraided trading specifically seek short-term momentum driven by hysteria relating to blockchain and cryptocurrencies irrespective of the ethical or moral issues inherently attached and will advantage firms that undertake such high risk strategies, at least in the very short run.

In a developing sector ripe with issues with fraud and cybercriminality, policy-makers must tread carefully between over-regulation, potentially stifling credible technological development, and counter-balancing such activity through ensuring the presence of market integrity and corporate credibility. Given the exogenous conditions and speed of technological evolution, protecting unsuspecting and uniformed investors should be considered to be a priority. To do so, regulators must ensure that those aspiring to take advantage of misinforming investors must be adequately disincentivised. Consider that many of the companies that have indicated this product development course of action are in long-term sectoral decline, or have been established simply to take advantage of a short-term profit opportunity. To date, almost no viable corporate cryptocurrency has been developed, although in each scenario examined, a substantial long-term share premium persisted along with significant underestimation of leverage risks.

This research has presented evidence of a dark side to the corporate ability to create instruments that generate substantial social media attention and abnormal returns, but to date, do not generate corporate revenue. Asymmetric information disadvantages some investors as they misunderstand financial markets or suffer from cognitive biases that cause them to assign incorrect probability weights to events or the viability of certain blockchain-projects. Financial institutions can exploit this asymmetric information by creating corporate projects that build on investors' potential excessive expectancy and irrational exuberance with regards to perceptions of the viability projects that might appear to have profitability similar to cryptocurrencies such as Bitcoin. These entities fail to adequate explain the true risks involved, such as the incredibly high level of illegality in blockchain markets and the realistic assertion that many of these projects not only fail but also many do not even begin. This leads investors to value the new instruments more highly than they would if they understood financial markets and correctly evaluated information about the probabilities of future events. The ability to create instruments with almost any parameters implies that there are few limits on the complexity of design of these technological solutions. Investors must therefore base their decisions on improper information and social media hysteria, both, as evidence in ongoing investigations show, influenced by artificial sources. This information also possesses the ability to trigger automated trading systems that act as a potential accelerant of abnormal returns. Such shrouding of information relating to blockchain-development by corporate entities will substantially influence an investment system with myopic investors who are being driven by social media hysteria and other sources of noise. Shrouding creates a significant inefficiency that policymakers and regulators have an incentive to eliminate by educating investors as to the inherent risks that such high-risk projects possess and result in corporate losses. Corporate institutions operating this strategy should only expect to attract the same risk-loving investors that have been the source of the price-increases in cryptocurrency markets. Therefore, optimising companies will continue to exploit myopic consumers through such speculative announcements that shroud blockchain-development as a source of future corporate revenues. In turn, sophisticated social media advertisement further exploit these marketing schemes, adding to the hysteria and acting as a propellant of abnormal returns.

It is not possible to drive away the speculative sophisticated social media advertisement. As evidenced in diminished abnormal returns since 2017 in line with moderate regulatory advancement. Further investor education and increased regulatory enforcement, particularly of corporate entities with no previous technological development experience announcing speculative blockchaindevelopment projects, is a particularly successful solution. Ultimately, investors and regulators will be required to become more vigilant and sophisticated as digital tools take a traditional market story of irrational exuberance in the face of a new technology and layer it with the complexity of social media communication.

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Figure 1: Tweets relating to corporate blockchain announcements

a) Speculatively-defined corporate blockchain announcements

Note: Twitter data was collected for a period between 1 January 2017 and 31 March 2019 for a list of 156 companies. All tweets mentioning the name of the company plus either of the terms 'crypto', 'cryptocurrency' or 'blockchain' were computationally collected through the Search Twitter function on https://twitter.com/explore using the Python 'twitterscraper' package. A total number of 954,765 unique tweets were collected. The data was then aggregated by company and by day, taking the sums of the variables. In a provisional methodology, we determine the very first tweet as identified on Twitter that was correctly based (identified as the 'rumour' hereafter) on the forthcoming corporate blockchain announcement (identified as the 'official announcement'). In the above figure, we present evidence of average the total number of Tweets in the 30 days both before and after the identification of both the date of the 'rumour' and the 'official announcement'. The vertical axis represents a logarithmic scale so as to best represent the scale of the number of tweets in the days surround each event, which is indicated with a line.



Figure 2: Twitter-based 'Retweets' relating to corporate blockchain announcements

a) Speculatively-defined corporate blockchain announcements

Note: Twitter data was collected for a period between 1 January 2017 and 31 March 2019 for a list of 156 companies. All tweets mentioning the name of the company plus either of the terms 'crypto', 'cryptocurrency' or 'blockchain' were computationally collected through the Search Twitter function on https://twitter.com/explore using the Python 'twitterscraper' package. A total number of 954,765 unique tweets were collected. The data was then aggregated by company and by day, taking the sums of the variables. In a provisional methodology, we determine the very first tweet as identified on Twitter that was correctly based (identified as the 'rumour' hereafter) on the forthcoming corporate blockchain announcement (identified as the 'official announcement'). In the above figure, we present evidence of average the total number of Retweets in the 30 days both before and after the identification of both the date of the 'rumour' and the 'official announcement'. The vertical axis represents a logarithmic scale so as to best represent the scale of the number of retweets in the days surround each event, which is indicated with a line.



Figure 3: Twitter-based 'Likes' relating to corporate blockchain announcements

a) Speculatively-defined corporate blockchain announcements

Note: Twitter data was collected for a period between 1 January 2017 and 31 March 2019 for a list of 156 companies. All tweets mentioning the name of the company plus either of the terms 'crypto', 'cryptocurrency' or 'blockchain' were computationally collected through the Search Twitter function on https://twitter.com/explore using the Python 'twitterscraper' package. A total number of 954,765 unique tweets were collected. The data was then aggregated by company and by day, taking the sums of the variables. In a provisional methodology, we determine the very first tweet as identified on Twitter that was correctly based (identified as the 'rumour' hereafter) on the forthcoming corporate blockchain announcement (identified as the 'official announcement'). In the above figure, we present evidence of average the total number of 'Likes' in the 30 days both before and after the identification of both the date of the 'rumour' and the 'official announcement'. The vertical axis represents a logarithmic scale so as to best represent the scale of the number of likes in the days surround each event, which is indicated with a line.





a) At the point of the defined 'rumour'



b) At the point of the defined 'official announcement'

Note: This figure shows the average cumulative abnormal returns by type of announcement for a 61-day window [30,+30]. Within this context, and building on the work of Akyildirim et al. [2020], speculative announcements are found to be those relating to the change of corporate identity to include words such as 'blockchain' and 'cryptocurrency', and the development of corporate cryptocurrencies. Alternatively, structural-development includes announcements relating to internal security, and internal process, system and technological development. The following analysis will be sub-categorised within these sub-groups throughout. The analyses are repeated for the two defined windows of analysis, the first surrounding the 30-day period before the first social media 'rumour', the second based on the same time frame surrounding the 'official announcement'.

Figure 5: Cumulative abnormal returns as separated by the year in which each announcement was made



a) At the point of the defined 'rumour'



b) At the point of the defined 'official announcement'

Note: This figure shows the average cumulative abnormal returns by year in which the official announcement was made for a 61-day window [30,+30]. The analyses are repeated for the two defined windows of analysis, the first surrounding the 30-day period before the first social media 'rumour', the second based on the same time frame surrounding the 'official announcement'.

Figure 6: Cumulative abnormal returns as separated by the defined reach of social media



a) At the point of the defined 'rumour'





Note: This figure shows the average cumulative abnormal returns by type of social media (Twitter) sentiment for a 61-day window [30,+30] as separated by reach (as defined by the natural log of the number of tweets, retweets and likes). 'Very Low' defines the group of companies in the lowest 25th percentile as ranked by tweets in the period 30 days prior to the announcement in our sample. Low represents the 26th through 50th percentile, while medium reach is defined as the 51st through 75th percentile. High social media reaching companies represent the top 25th percentile by market capitalisation 30 days prior to the announcement. The analyses are repeated for the two defined windows of analysis, the first surrounding the 30-day period before the first social media 'rumour', the second based on the same time frame surrounding the 'official announcement'.

Figure 7: Cumulative abnormal returns as separated by defined sentiment



a) At the point of the defined 'rumour'





Note: This figure shows the average cumulative abnormal returns by type of social media (Twitter) sentiment for a 61-day window [30,+30] as separated by positive, neutral and negative. Sentiment in this context is separated based on _pos and _neg as defined in Table A1. Resulting insignificant notation of average sentiment for the period under observation is treated as neutral. The analyses are repeated for the two defined windows of analysis, the first surrounding the 30-day period before the first social media 'rumour', the second based on the same time frame surrounding the 'official announcement'.



Figure 8: Selected corporate performance after blockchain-development announcements

a) Kodak

Note: The above figure presents evidence of the respective share price performance of Kodak, Future Fintech Group and Bitcoin Group SE, for all daily closing prices on dates since the incorporation of each respective company. The horizontal line in each individual graph represents the date of a significant speculative-blockchain announcement. For Kodak, this represents the date of the first official announcement of KODAKOne (9 January 2018). For Future Fintech Group, this represents the date on which the corporate identity changed from that of SkyPeople Fruit Juice (19 December 2017). While for Bitcoin Group SE, this date represents the beginning of a period of sharp growth in the price of Bitcoin where the company held 100% of the shares in Bitcoin Deutschland AG, which operated Germany's only authorised trading place for the digital currency Bitcoin under Bitcoin.de (9 October 2017).

	Interest	Sentiment	Company Size	Rumour Duration
By announcement type				
Blockchain Partnership	1.985	2.768	41.590	12.750
Coin Creation	2.899	2.017	12.229	12.564
Investment Fund	2.282	1.672	65.831	8.417
Name Change	2.942	2.894	15.452	15.482
Security Improvements	2.143	2.044	239.239	5.800
Technological Improvement	2.403	2.249	118.994	5.315
Creating	0 795	0.717	19 990	19 EG4
Speculative	2.700	2.717	12.229	15.004
Strategic	2.137	1.955	122.480	0.233
Bu year				
2017	2.240	2.031	65.363	13.188
2018	2.238	2.164	98.140	11.719
2019	2.412	2.158	101.548	10.548
Bu Twitter Activity (Ranked	hu avintile	»)		
Some Interest	-	1 720	35 442	15 412
Low Interest	_	1 990	64 761	11 791
Average Interest	_	2 679	69 238	7 667
High Interest		2.568	155 167	10 529
Very High Interest	_	2.683	370.029	8 000
very mgn merest		2.000	010.020	0.000
By Company Size (Ranked b	y quintile)			
Very Small	1.752	1.800	-	15.909
Small	2.061	2.350	-	19.150
Medium	2.178	2.060	-	6.522
Large	2.514	2.055	-	10.231
Very Large	2.643	2.313	-	11.143

Table 1: Summary statistics of Twitter activity and corporate size

Note: In the table above, we observe the key statistics as presented from the scale of interest and sentiment of the associated Twitter activity. Interest is sub-divided by quintile of the number of identified tweets, which are further separated as per type of blockchain-announcement, the year in which the announcement was made, and by company size. Further, we have included a final column that specifically investigates the average time difference, as measured in days, of the time between the first identified tweet, denoting the establishment of the 'rumour' and the 'official' announcement.

		1	Total		
	Mean	Median	Standard Dev.	Min	Max
NITA	0.017	0.005	1.831	-0.908	1.147
CATA	0.258	0.595	0.299	-0.045	1.000
Age	35.912	23.603	32.731	16.658	120.047
Leverage	0.463	0.136	0.196	0.005	5.703
Trade	0.116	0.100	0.094	0.003	0.996
Current	0.201	0.181	0.150	0.009	4.507
Noncurrent	0.115	0.085	0.645	0.000	2.632
		Spec	culative		
	Mean	Median	Standard Dev.	Min	Max
NITA	-0.012	0.014	0.049	-0.050	0.000
CATA	-0.476	0.616	0.012	-0.001	0.991
Age	29.437	21.523	26.969	16.658	119.532
Leverage	0.750	0.139	0.304	0.074	5.703
Trade	0.125	0.100	0.120	0.025	0.996
Current	0.429	0.194	0.236	0.129	4.507
Noncurrent	0.235	0.100	1.019	0.000	2.632
		Str	rategic		
	Mean	Median	Standard Dev.	Min	Max
NITA	0.059	0.002	2.894	-0.908	1.147
CATA	1.356	0.528	0.471	-0.045	1.000
Age	40.237	23.651	35.431	22.329	120.047
Leverage	0.271	0.134	0.045	0.005	0.670
Trade	0.110	0.100	0.070	0.003	0.426
Current	0.049	0.175	0.005	0.009	0.147
Noncurrent	0.036	0.079	0.018	0.000	0.051

Table 2: Summary statistics for the probit methodology and marginal effects regression variables

Note: The above table reports the summary statistics of the estimated coefficients based on the companies identified within our sample and subsequently used in the following logit regressions. The dependent variable takes a value of zero if the firm is active and not under regulatory investigation, while it receives a value of one if it is insolvent, bankrupt or under regulatory investigation. Similar to the methodology used by Cathcart et al. [2020], GDP is the 1-year GDP growth rate; bond is the 3-month government bond interest rate; CDS is the logarithm of the CDS price of government bonds; NITA is the ratio of net income to total assets; CATA is the ratio of current assets to total assets; AGE is the number of days since incorporation divided by 365; IMP is a dummy variable that takes a value of one if the identified company is impaired as defined as to be 'insolvent, bankrupt or under regulatory investigation'. Lev is the ratio of total liabilities to total assets; Tarde is the ratio of trade payables to total assets; Curr is the ratio of current liabilities (minus trade payables) to total assets; and Noncurr is the ratio of non-current liabilities to total assets.

[-30,-1]			Rur	nour			Official					
	Specu	ilative	Strat	egic	Tot	al	Specu	ılative	Stra	tegic	Tot	tal
	Total	Average	Total	Average	Total	Average	Total	Average	Total	Average	Total	Average
Tweets	130,790	4,087	677,103	21,159	807,893	25,247	19,385	606	68,989	2,156	88,374	2,762
Retweets	192,817	6,026	823,857	25,746	1,016,674	31,771	186,715	5,835	216,718	6,772	403,433	12,607
Likes	351,655	10,989	1,614,424	50,451	1,966,079	61,440	340,219	10,632	358,076	11,190	698,295	21,822
Replies	29,936	936	133,147	4,161	163,083	5,096	30,834	964	23,889	747	54,723	1,710
Interest		2.369		2.669		2.596		2.159		2.772		2.560
Positive/Negative		1.847		2.288		2.180		1.802		2.306		2.132
Max Polarity		4.042		5.249		4.930		4.972		9.102		7.701
Min Polarity		-0.333		0.013		-0.069		0.042		2.295		1.513
Max Subjectivity		1.546		1.734		1.673		1.937		3.838		3.192
Min Subjectivity		0.267		0.338		0.319		0.323		0.687		0.563
'Blockchain' Mentions	65,716	2,054	513,210	16,038	578,926	18,091	8,682	271	53,321	1,666	62,003	1,938
'Cryptocurrency' Mentions	82,239	2,570	226,014	7,063	308,253	9,633	13,660	427	22,479	702	36,139	1,129
[4,30]			Rur	nour			•		Of	ficial		
	Specu	ılative	Strat	egic	Tot	al	Specu	ılative	Stra	tegic	Tot	tal
	Total	Average	Total	Average	Total	Average	Total	Average	Total	Average	Total	Average
Tweets	26,538	983	89,900	3,330	116,438	4,313	13,324	493	33,218	1,230	46,542	1,724
Retweets	34,260	1,269	93,258	3,454	127,518	4,723	164,560	6,095	465,320	17,234	629,880	23,329
Likes	52,430	1,942	180,098	6,670	232,528	8,612	264,030	9,779	884,250	32,750	1,148,280	42,529
Replies	4,334	161	14,975	555	19,309	715	25,720	953	66,160	2,450	91,880	3,403
Interest		2.915		3.051		3.023		2.324		2.753		2.598
Positive/Negative		2.140		2.824		2.683		1.697		2.395		2.145
Max Polarity		4.309		6.664		6.193		2.081		6.248		4.756
Min Polarity		-0.833		0.311		0.072		-0.536		1.150		0.550
Max Subjectivity		2.478		2.321		2.353		1.483		2.571		2.176
Min Subjectivity		0.630		0.485		0.515		0.310		0.473		0.414
'Blockchain' Mentions	15,935	590	67,849	2,513	83,784	3,103	8,250	306	24,484	907	32,734	1,212
'Cryptocurrency' Mentions	14,216	527	30,205	1,119	44,421	1,645	7,205	267	11,678	433	18,883	699

Table 3: Social media statistics for the periods both before and after each type of denoted blockchain development announcement

Note: The above table presents the estimated Twitter data in the identified periods as separated by the date of the 'rumour' and the date of the 'official announcement'.

[0,3]			Rur	nour					Off	icial		
	Specu	lative	Strat	egic	Tot	al	Speci	ilative	Strat	egic	Tot	al
	Total	Average	Total	Average	Total	Average	Total	Average	Total	Average	Total	Average
Tweets	126,600	31,650	646,736	161,684	773,336	193,334	18,546	4,637	20,410	5,103	38,956	9,739
Retweets	175,772	43,943	765,026	191,257	940,798	235,200	214,040	53,510	200,770	50,193	414,810	103,703
Likes	326,274	81,569	1,488,686	372,172	1,814,960	453,740	394,880	98,720	328,940	82,235	723,820	180,955
Replies	27,037	6,759	121,544	30,386	148,581	37,145	38,330	9,583	21,080	5,270	59,410	14,853
Interest		3.545		3.886		3.805		2.919		3.402		3.230
Positive/Negative		3.721		4.195		4.084		3.509		3.081		3.234
Max Polarity		24.453		23.502		23.543		32.086		24.647		27.297
Min Polarity		-0.548		3.122		2.287		0.652		7.364		4.972
Max Subjectivity		9.766		7.272		7.749		14.630		7.545		10.069
Min Subjectivity		1.391		1.291		1.302		1.972		1.256		1.511
'Blockchain' Mentions	62,696	15,674	498,753	124,688	561,449	140,362	7,768	1,942	16,540	4,135	24,308	6,077
'Cryptocurrency' Mentions	80,773	20,193	208,065	52,016	288,838	72,210	13,882	3,471	6,479	1,620	20,361	5,090
[-30.30]			Rur	nour					Off	icial		
	Specu	lative	Strat	egic	Tot	al	Specı	ılative	Strat	egic	Tot	al
	Total	Average	Total	Average	Total	Average	Total	Average	Total	Average	Total	Average
Tweets	163,521	2,681	785,463	12,876	948,984	15,557	37,580	616	107,952	1,770	145,532	2,386
Retweets	231,522	3,795	930,307	15,251	1,161,829	19,046	393,635	6,453	735,488	12,057	1,129,123	18,510
Likes	412,037	6,755	1,817,900	29,802	2,229,937	36,556	679,979	11,147	1,345,326	22,055	2,025,305	33,202
Replies	35,199	577	149,674	2,454	184,873	3,031	65,364	1,072	96,409	1,580	161,773	2,652
Interest		2.654		2.884		2.831		2.258		2.779		2.596
Positive/Negative		2.053		2.598		2.477		1.835		2.370		2.182
Max Polarity		4.553		6.266		5.882		3.967		7.950		6.564
Min Polarity		-0.506		0.246		0.083		-0.179		1.828		1.125
Max Subjectivity		2.128		2.107		2.100		1.920		3.308		2.827
Min Subjectivity		0.460		0.423		0.429		0.348		0.591		0.507
'Blockchain' Mentions	85,005	1,394	596,021	9,771	681,026	11,164	19,298	316	81,839	1,342	101, 137	1,658
'Cryptocurrency' Mentions	100,318	1,645	261,400	4,285	361,718	5,930	24,231	397	36,507	598	60,738	996

Table 4: Social media statistics for selected periods as denoted by type of denoted blockchain development announcement

Note: The above table presents the estimated Twitter data in the identified periods as separated by the date of the 'rumour' and the date of the 'official announcement'.

	Rumour						Official Announcement					
	[-30, -1]	[-1,1]	[AR0]	[0,3]	[4, 30]	[-30, 30]	[-30,-1]	[-1,1]	[AR0]	[0,3]	[4, 30]	[-30, 30]
Motivation												
Speculative	0.1021	0.1397	0.1132	0.0465	0.0734	0.3875	0.1480	0.1444	0.1086	0.0527	0.0311	0.3550
Structural	0.0275	0.0171	0.0238	0.0040	0.0498	0.1143	0.0432	0.0757	0.0674	-0.0034	-0.0222	0.0798
Time												
2017	0.1087	0.1321	0.1172	0.0289	0.1747	0.4679	0.1688	0.1991	0.1786	0.0416	0.0723	0.4850
2018	0.0775	0.0551	0.0474	0.0236	0.0095	0.1810	0.0803	0.0609	0.0448	-0.0200	-0.0809	0.0087
2019	-0.0001	0.0057	0.0094	0.0208	-0.0135	0.0089	-0.0015	0.0455	0.0354	0.0055	-0.0609	-0.0113
Reach												
High	0.0363	0.1785	0.1601	0.0516	0.1196	0.3779	0.0438	0.1026	0.0798	0.0028	-0.0565	0.0790
Medium	0.0337	0.1775	0.1296	0.0303	0.1746	0.3550	0.0519	0.0534	0.0702	0.0881	0.0948	0.2991
Low	-0.0077	0.0624	0.0714	0.0013	0.0280	0.0950	0.0300	0.0496	0.0547	0.0146	0.0375	0.1330
Very Low	0.0339	0.0426	0.0423	0.0048	-0.0042	0.1084	0.0918	0.2094	0.2098	0.0214	-0.0387	0.2761
Sentiment												
Negative	0.0297	0.0747	0.0599	0.0275	0.0448	0.1782	-0.0169	0.1202	0.0822	0.0155	-0.0242	0.0380
Neutral	0.0197	0.0251	0.0314	-0.0130	0.0037	0.0505	0.0682	0.0719	0.0821	-0.0344	-0.0492	0.0630
Positive	0.1640	0.1568	0.1276	0.0856	0.1781	0.6313	0.1695	0.1441	0.0963	0.1155	0.1274	0.5500

Table 5: Cumulative Abnormal Returns (CARs) as at the point of both 'rumour' and 'official' announcement relating to corporate blockchain announcements

Note: The table shows regression estimates of cumulative abnormal returns for the periods [-30,-1], [-1,1], [AR0], [0,3], [4,30] and [-30,30] for each of the denoted blockchain-developing listed firms in the time period surrounding both the 'rumour' and 'official announcement'. Motivation is defined as whether each corporate blockchain-decision is defined to be either speculative or strategic. The years 2017 and 2018 are dummy variables that take a value of unity if the announcement is made in 2017 and 2018, respectively, and 0 otherwise. Both Reach and Sentiment refer to the volume of social media interactions and the estimated sentiment as defined to be either positive, neutral or negative.

			'Rumour'			'Official Announcement'				
[-30,-1]	Spec1	Spec2	Spec3	Spec4	Spec5	Spec1	Spec2	Spec3	Spec4	Spec5
2017	0.065^{***}	0.067***	0.085***	0.067^{***}	0.094^{***}	-0.018*	-0.016	0.012	-0.014	0.028***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.047)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
2018	0.026^{***}	0.021^{***}	0.010	0.023^{***}	0.039^{***}	-0.221***	-0.216^{***}	-0.198^{***}	-0.214^{***}	-0.175^{***}
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
US	0.131^{***}	0.127^{***}	0.137^{***}	0.129^{***}	0.141^{***}	0.344^{***}	0.334^{***}	0.268^{***}	0.328^{***}	0.213^{***}
	(0.042)	(0.041)	(0.044)	(0.041)	(0.031)	(0.124)	(0.121)	(0.097)	(0.119)	(0.077)
Bitcoin	0.081	0.088	0.085^{*}	0.089^{*}	0.087	0.081	0.080	0.086^{*}	0.080	0.083
	(0.066)	(0.068)	(0.067)	(0.068)	(0.220)	(0.077)	(0.075)	(0.060)	(0.073)	(0.068)
Bitcoin CAR	0.015	0.013	0.016	0.013	0.016	0.025^{*}	0.021	0.022	0.021	0.020
	(0.015)	(0.014)	(0.015)	(0.014)	(0.038)	(0.019)	(0.017)	(0.018)	(0.017)	(0.017)
Mkt Cap	-0.017*	-0.018**	-0.020**	-0.016*	-0.016*	-0.015	-0.016	-0.018	-0.012	-0.011
	(0.010)	(0.009)	(0.009)	(0.011)	(0.011)	(0.016)	(0.015)	(0.015)	(0.018)	(0.018)
Duration	0.001^{***}				0.001^{***}	0.001^{***}				0.001^{***}
	(0.000)				(0.000)	(0.000)				(0.000)
Reach		-0.067***			-0.051^{***}		-0.070*			-0.043
		(0.038)			(0.039)		(0.062)			(0.065)
Sentiment			0.103^{**}		0.093^{***}			0.154^{***}		0.150^{***}
			(0.047)		(0.049)			(0.076)		(0.080)
Speculative				0.019	0.050				0.039^{***}	0.083^{***}
				(0.074)	(0.075)				(0.010)	(0.012)
Constant	0.068	0.220^{**}	0.054	0.061	0.123^{***}	0.205^{***}	0.365^{***}	0.183^{***}	0.186^{*}	0.203
	(0.077)	(0.108)	(0.070)	(0.087)	(0.031)	(0.126)	(0.178)	(0.114)	(0.142)	0.215)
Adj R2	0.209	0.209	0.237	0.253	0.246	0.245	0.256	0.281	0.246	0.289

Table 6: OLS Regressions for the period [-30,-1]

Note: The table shows regression estimates of cumulative abnormal returns for the period [-30,-1] for each of the denoted blockchain-developing listed firms in the time period surrounding both the 'rumour' and 'official announcement'. The years 2017 and 2018 are dummy variables that take a value of unity if the announcement is made in 2017 and 2018, respectively, and zero otherwise. Market Cap refers to the the natural logarithm of the firm market capitalisation as measured in US dollars for the time period 30 days prior to the announcement day. Bitcoin and Bitcoin CAR are the natural logarithm of the bitcoin price level 30 days prior to the announcement day and the estimated cumulative bitcoin return 30 days prior to the announcement day refers to the time difference as measured in days between the estimated 'rumour' and the 'official announcement'. Both Reach and Sentiment refer to the volume of social media interactions and the estimated sentiment as defined to be either positive, neutral or negative. Speculative is a dummy that takes the value of one if the announcement is defined to be of a speculative nature and zero otherwise. ***, ** and * indicate level of significance at 1%, 5%, and 10% respectively.

			'Rumour'				'Offic	ial Announc	ement'	
[-1,1]	Spec1	Spec2	Spec3	Spec4	Spec5	Spec1	Spec2	Spec3	Spec4	Spec5
2017	0.134^{***}	0.143^{***}	0.159^{**}	0.154^{**}	0.174^{**}	0.132*	0.128^{*}	0.137^{*}	0.134^{*}	0.147^{*}
	(0.100)	(0.100)	(0.099)	(0.100)	(0.100)	(0.099)	(0.099)	(0.100)	(0.100)	(0.102)
2018	0.059	0.065	0.077	0.091	0.104	-0.031	-0.035	-0.026	-0.026	-0.017
	(0.097)	(0.097)	(0.097)	(0.098)	(0.099)	(0.097)	(0.097)	(0.097)	(0.098)	(0.100)
US	0.221^{***}	0.238^{***}	0.270^{***}	0.285^{***}	0.318^{***}	0.116***	0.107^{***}	0.126^{***}	0.124^{***}	0.149^{***}
	(0.071)	(0.076)	(0.087)	(0.091)	(0.102)	(0.042)	(0.039)	(0.046)	(0.045)	(0.054)
Bitcoin	0.152^{***}	0.147^{***}	0.105^{***}	0.111^{***}	0.124^{***}	0.080***	0.066^{***}	0.049***	0.048***	0.058^{***}
	(0.049)	(0.047)	(0.034)	(0.036)	(0.040)	(0.029)	(0.024)	(0.018)	(0.017)	(0.021)
Bitcoin CAR	0.182^{***}	0.211^{***}	0.151^{***}	0.183^{***}	0.164^{***}	0.132***	0.142^{***}	0.103^{***}	0.121^{***}	0.112^{***}
	(0.058)	(0.068)	(0.048)	(0.059)	(0.052)	(0.047)	(0.051)	(0.037)	(0.044)	(0.040)
Mkt Cap	-0.014	-0.012	-0.013	-0.003	-0.005	-0.013**	-0.013**	-0.014**	-0.012*	-0.011
	(0.011)	(0.011)	(0.011)	(0.012)	(0.013)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Duration	-0.003***				-0.002*	0.001***				0.001^{***}
	(0.001)				(0.002)	(0.000)				(0.000)
Reach		-0.015***			-0.009		0.034^{***}			0.044^{***}
		(0.009)			(0.035)		(0.004)			(0.005)
Sentiment			0.085^{***}		0.090			0.034^{***}		0.053^{***}
			(0.052)		(0.056)			((0.005)		(0.006)
Speculative				0.127^{**}	0.137^{***}				0.030^{***}	0.037^{***}
				(0.084)	(0.086)				(0.008)	(0.009)
Constant	0.050	0.043	0.007	0.079	0.054	0.081	0.018	0.085	0.071	0.061^{***}
	(0.088)	(0.126)	(0.081)	(0.099)	(0.151)	(0.088)	(0.124)	(0.081)	(0.099)	(0.015)
Adj R2	0.240	0.230	0.251	0.249	0.283	0.251	0.256	0.254	0.251	0.266

Table 7: OLS Regressions for the period [-1,+1]

Note: The table shows regression estimates of cumulative abnormal returns for the period [-1,+1] for each of the denoted blockchain-developing listed firms in the time period surrounding both the 'rumour' and 'official announcement'. The years 2017 and 2018 are dummy variables that take a value of unity if the announcement is made in 2017 and 2018, respectively, and zero otherwise. Market Cap refers to the the natural logarithm of the firm market capitalisation as measured in US dollars for the time period 30 days prior to the announcement day. Bitcoin and Bitcoin CAR are the natural logarithm of the bitcoin price level 30 days prior to the announcement day and the estimated cumulative bitcoin return 30 days prior to the announcement day refers to the time difference as measured in days between the estimated 'rumour' and the 'official announcement'. Both Reach and Sentiment refer to the volume of social media interactions and the estimated sentiment as defined to be either positive, neutral or negative. Speculative is a dummy that takes the value of one if the announcement is defined to be of a speculative nature and zero otherwise. ***, ** and * indicate level of significance at 1%, 5%, and 10% respectively.

			'Rumour'			'Official Announcement'					
[0,+3]	Spec1	Spec2	Spec3	Spec4	Spec5	Spec1	Spec2	Spec3	Spec4	Spec5	
2017	0.023	0.025	0.028	0.027	0.031	-0.003	-0.003	0.004	0.008	0.018	
	(0.036)	(0.036)	(0.034)	(0.035)	(0.032)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	
2018	0.012	0.010	0.008	0.006	-0.002	-0.011	-0.011	-0.005	0.006	0.015	
	(0.027)	(0.022)	(0.021)	(0.020)	(0.021)	(0.049)	(0.049)	(0.049)	(0.049)	(0.050)	
US	0.050^{***}	0.050^{***}	0.052^{***}	0.048^{***}	0.042^{***}	-0.020***	-0.020***	-0.002***	0.021^{***}	0.048^{***}	
	(0.016)	(0.016)	(0.017)	(0.015)	(0.013)	(0.007)	(0.007)	(0.001)	(0.008)	(0.017)	
Bitcoin	0.032^{***}	0.035^{***}	0.033^{***}	0.033^{***}	0.027^{***}	0.127***	0.129^{***}	0.144^{***}	0.145^{***}	0.305^{***}	
	(0.010)	(0.011)	(0.011)	(0.011)	(0.009)	(0.046)	(0.047)	(0.052)	(0.052)	(0.110)	
Bitcoin CAR	0.098^{***}	0.087^{***}	0.085^{***}	0.091^{***}	0.076^{***}	0.062^{***}	0.053^{***}	0.018^{***}	0.060^{***}	0.081^{***}	
	(0.031)	(0.028)	(0.027)	(0.029)	(0.024)	(0.022)	(0.019)	(0.006)	(0.022)	(0.029)	
Mkt Cap	-0.003	-0.002	-0.003	0.000	-0.001***	-0.007*	-0.006*	-0.007*	-0.001	-0.001	
	(0.003)	(0.003)	(0.003)	(0.004)	(0.000)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	
Duration	-0.001***				0.000^{***}	0.000				0.000	
	(0.000)				(0.000)	(0.000)				(0.001)	
Reach		-0.010*			-0.008***		0.008^{***}			0.012^{***}	
		(0.005)			(0.001)		(0.002)			(0.023)	
Sentiment			0.021^{***}		0.020			0.032^{***}		0.043^{***}	
			(0.011)		(0.018)			(0.013)		(0.028)	
Speculative				0.024^{*}	0.027^{*}				0.080^{*}	0.088^{***}	
				(0.015)	(0.018)				(0.042)	(0.043)	
Constant	0.017	0.031	0.005	0.007	0.010	0.051*	0.031	0.042	-0.007	0.053	
	(0.028)	(0.040)	(0.026)	(0.032)	(0.048)	(0.044	(0.063)	(0.041)	(0.049)	(0.076)	
Adj R2	0.225	0.225	0.234	0.228	0.249	0.214	0.215	0.227	0.247	0.268	

Table 8: OLS Regressions for the period [AR0]

Note: The table shows regression estimates of abnormal returns for the period [AR0], for each of the denoted blockchain-developing listed firms in the time period surrounding both the 'rumour' and 'official announcement'. The years 2017 and 2018 are dummy variables that take a value of unity if the announcement is made in 2017 and 2018, respectively, and zero otherwise. Market Cap refers to the the natural logarithm of the firm market capitalisation as measured in US dollars for the time period 30 days prior to the announcement day. Bitcoin and Bitcoin CAR are the natural logarithm of the bitcoin price level 30 days prior to the announcement day and the estimated cumulative bitcoin return 30 days prior to the announcement day refers to the time difference as measured in days between the estimated 'rumour' and the 'official announcement'. Both Reach and Sentiment refer to the volume of social media interactions and the estimated sentiment as defined to be either positive, neutral or negative. Speculative is a dummy that takes the value of one if the announcement is defined to be of a speculative nature and zero otherwise. ***, ** and * indicate level of significance at 1%, 5%, and 10% respectively.

			'Rumour'				'Offic	ial Announce	ement'	
[0,3]	Spec1	Spec2	Spec3	Spec4	Spec5	Spec1	Spec2	Spec3	Spec4	Spec5
2017	-0.024***	-0.021***	-0.011*	-0.016***	-0.008***	-0.040	-0.045	-0.032	-0.040	-0.014
	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)	(0.051)	(0.051)	(0.050)	(0.051)	(0.050)
2018	-0.048	-0.048	-0.039	-0.039	-0.034	-0.112***	-0.115***	-0.105^{**}	-0.107^{***}	-0.085***
	(0.049)	(0.049)	(0.049)	(0.050)	(0.050)	(0.049)	(0.050)	(0.049)	(0.050)	(0.049)
US	0.083^{***}	0.079^{***}	0.057^{***}	0.062^{***}	0.048^{***}	0.074***	0.018^{***}	0.016^{***}	0.017^{***}	0.011^{***}
	(0.026)	(0.025)	(0.018)	(0.020)	(0.015)	(0.027)	(0.007)	(0.006)	(0.006)	(0.004)
Bitcoin	0.057^{***}	0.050^{***}	0.039^{***}	0.040^{***}	0.033^{***}	0.120***	0.117^{***}	0.108^{***}	0.107^{***}	0.078^{***}
	(0.018)	(0.016)	(0.013)	(0.013)	(0.011)	(0.043)	(0.042)	(0.039)	(0.039)	(0.028)
Bitcoin CAR	0.119^{***}	0.104^{***}	0.099^{***}	0.093^{***}	0.091^{***}	0.173***	0.159^{***}	0.164^{***}	0.152^{***}	0.139^{***}
	(0.038)	(0.033)	(0.032)	(0.030)	(0.029)	(0.063)	(0.057)	(0.059)	(0.055)	(0.050)
Mkt Cap	-0.005	-0.003	-0.004	-0.001	-0.003***	-0.002***	-0.003***	-0.005***	0.000	0.002^{***}
	(0.006)	(0.005)	(0.005)	(0.006)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Duration	-0.001*				-0.001*	0.002***				0.002^{***}
	(0.001)				(0.001)	(0.000)				(0.000)
Reach		0.019^{*}			0.026		0.011^{***}			0.006^{***}
		(0.012)			(0.023)		(0.002)			(0.002)
Sentiment			0.045^{***}		0.054^{***}			0.067^{***}		0.079^{***}
			(0.024)		(0.028)			(0.027)		(0.013)
Speculative				0.034^{***}	0.034^{*}				0.042	0.069^{***}
				(0.013)	(0.024)				(0.243)	(0.024)
Constant	0.074^{***}	0.013^{***}	0.047^{***}	0.032^{***}	-0.025***	0.065^{*}	0.116^{***}	0.079^{***}	0.063^{*}	0.019
	(0.024)	(0.006)	(0.011)	(0.015)	(0.008)	(0.045)	(0.064)	(0.040)	(0.051)	(0.075)
Adj R2	0.223	0.220	0.238	0.219	0.265	0.277	0.260	0.310	0.266	0.356

Table 9: OLS Regressions for the period [0,+3]

Note: The table shows regression estimates of cumulative abnormal returns for the period [0,+3] for each of the denoted blockchain-developing listed firms in the time period surrounding both the 'rumour' and 'official announcement'. The years 2017 and 2018 are dummy variables that take a value of unity if the announcement is made in 2017 and 2018, respectively, and zero otherwise. Market Cap refers to the the natural logarithm of the firm market capitalisation as measured in US dollars for the time period 30 days prior to the announcement day. Bitcoin and Bitcoin CAR are the natural logarithm of the bitcoin price level 30 days prior to the announcement day and the estimated cumulative bitcoin return 30 days prior to the announcement day refers to the time difference as measured in days between the estimated 'rumour' and the 'official announcement'. Both Reach and Sentiment refer to the volume of social media interactions and the estimated sentiment as defined to be either positive, neutral or negative. Speculative is a dummy that takes the value of one if the announcement is defined to be of a speculative nature and zero otherwise. ***, ** and * indicate level of significance at 1%, 5%, and 10% respectively.

			'Rumour'			'Official Announcement'					
[4,30]	Spec1	Spec2	Spec3	Spec4	Spec5	Spec1	Spec2	Spec3	Spec4	Spec5	
2017	0.126	0.117	0.130	0.107	0.149^{*}	-0.130	-0.124	-0.176	-0.135	-0.221	
	(0.117)	(0.116)	(0.118)	(0.119)	(0.098)	(0.188)	(0.187)	(0.183)	(0.189)	(0.186)	
2018	-0.100	-0.101	-0.095	-0.117	-0.077	0.344^{***}	0.342^{***}	0.307^{***}	0.326^{***}	0.251*	
	(0.114)	(0.113)	(0.115)	(0.117)	(0.066)	(0.183)	(0.183)	(0.178)	(0.186)	(0.182)	
US	0.030^{***}	0.018^{***}	0.040^{***}	-0.011^{***}	0.083^{***}	0.145^{***}	0.149^{***}	0.150^{***}	0.119^{***}	0.134^{***}	
	(0.009)	(0.006)	(0.013)	(0.003)	(0.026)	(0.052)	(0.054)	(0.054)	(0.043)	(0.049)	
Bitcoin	0.019^{***}	0.007^{***}	0.026^{***}	0.018^{***}	0.053^{***}	0.157^{***}	0.297^{***}	0.296^{***}	0.370^{***}	0.022^{***}	
	(0.006)	(0.002)	(0.008)	(0.006)	(0.017)	(0.057)	(0.107)	(0.107)	(0.134)	(0.008)	
Bitcoin CAR	0.064^{***}	0.042^{***}	0.074^{***}	0.067^{***}	0.107^{***}	0.184^{***}	0.156^{***}	0.144^{***}	0.304^{***}	0.069^{***}	
	(0.021)	(0.013)	(0.024)	(0.022)	(0.034)	(0.066)	(0.056)	(0.052)	(0.110)	(0.025)	
Mkt Cap	-0.007***	-0.01^{***2}	-0.013^{***}	-0.014^{***}	-0.007***	0.026^{*}	0.029^{*}	0.034^{***}	0.021^{*}	0.016	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.021)	(0.020)	(0.020)	(0.013)	(0.013)	
Duration	0.005^{***}				0.005^{*}	-0.003***				-0.005*	
	(0.003)				(0.003)	(0.001)				(0.004)	
Reach		-0.100***			-0.076^{***}		0.090^{***}			0.085^{***}	
		(0.051)			(0.025)		(0.028)			(0.034)	
Sentiment			0.091^{*}		0.079^{***}			-0.274^{***}		-0.287***	
			(0.064)		(0.037)			(0.099)		(0.104)	
Speculative				0.034	0.024				-0.110***	-0.199*	
				(0.010)	(0.101)				(0.060)	(0.159)	
Constant	0.006	0.031	0.064	0.105	0.141	0.030	0.054	0.029	0.027	0.016	
	(0.111)	(0.125)	(0.183)	(0.184)	(0.177)	(0.166)	(0.236)	(0.148)	(0.188)	(0.279)	
Adj R2	0.281	0.285	0.270	0.253	0.320	0.304	0.309	0.359	0.303	0.380	

Table 10: OLS Regressions for the period [+4,+30]

Note: The table shows regression estimates of cumulative abnormal returns and abnormal returns for the period [+4,+30] for each of the denoted blockchain-developing listed firms in the time period surrounding both the 'rumour' and 'official announcement'. The years 2017 and 2018 are dummy variables that take a value of unity if the announcement is made in 2017 and 2018, respectively, and zero otherwise. Market Cap refers to the the natural logarithm of the firm market capitalisation as measured in US dollars for the time period 30 days prior to the announcement day. Bitcoin and Bitcoin CAR are the natural logarithm of the bitcoin price level 30 days prior to the announcement day and the estimated cumulative bitcoin return 30 days prior to the announcement day respectively. Duration refers to the time difference as measured in days between the estimated 'rumour' and the 'official announcement'. Both Reach and Sentiment refer to the volume of social media interactions and the estimated sentiment as defined to be either positive, neutral or negative. Speculative is a dummy that takes the value of one if the announcement is defined to be of a speculative nature and zero otherwise. ***, ** and * indicate level of significance at 1%, 5%, and 10% respectively.

			'Rumour'				'Offici	ial Announce	ement'	
[-30,30]	Spec1	Spec2	Spec3	Spec4	Spec5	Spec1	Spec2	Spec3	Spec4	Spec5
2017	0.261	0.265	0.265	0.275	0.370	0.011***	0.012***	0.014^{***}	0.013***	0.015***
	(0.228)	(0.225)	(0.225)	(0.229)	(0.204)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
2018	-0.184	-0.174	-0.174	-0.159	-0.072	0.032^{**}	0.032^{**}	0.034^{**}	0.035^{**}	0.037^{**}
	(0.222)	(0.220)	(0.220)	(0.225)	(0.220)	(0.021)	(0.021)	(0.021)	(0.021)	(0.022)
US	0.164^{***}	0.196^{***}	0.196^{***}	0.248^{***}	0.340^{***}	0.090***	0.094^{***}	0.101^{***}	0.102^{***}	0.216^{***}
	(0.052)	(0.063)	(0.063)	(0.079)	(0.109)	(0.033)	(0.034)	(0.037)	(0.037)	(0.078)
Bitcoin	0.113^{***}	0.125^{***}	0.135^{***}	0.159^{***}	0.133^{***}	0.062^{***}	0.060^{***}	0.070^{***}	0.065^{***}	0.084^{***}
	(0.036)	(0.040)	(0.043)	(0.051)	(0.042)	(0.022)	(0.022)	(0.025)	(0.024)	(0.030)
Bitcoin CAR	0.185^{***}	0.177^{***}	0.202^{***}	0.199^{***}	0.200^{***}	0.137^{***}	0.123^{***}	0.146^{***}	0.128^{***}	0.160^{***}
	(0.059)	(0.057)	(0.065)	(0.064)	(0.064)	(0.050)	(0.044)	(0.053)	(0.046)	(0.058)
Mkt Cap	-0.047*	-0.049**	-0.049**	-0.039*	-0.037*	-0.001***	0.000^{***}	-0.001***	0.001^{***}	0.000^{***}
	(0.025)	(0.024)	(0.024)	(0.028)	(0.028)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Duration	0.001^{*}				0.003^{***}	0.000***				0.000^{***}
	(0.001)				(0.001)	(0.000)				(0.000)
Reach		-0.152*			-0.093		-0.006***			-0.005***
		(0.100)			(0.040)		(0.001)			(0.001)
Sentiment			0.212^{*}		0.342^{***}			0.012^{**}		0.011^{**}
			(0.100)		(0.125)			(0.006)		(0.006)
Speculative				0.130^{***}	0.229^{*}				0.013^{***}	0.015^{***}
				(0.019)	(0.192)				(0.005)	(0.005)
Constant	0.274^{**}	0.622^{***}	0.622^{***}	0.201^{*}	0.229^{**}	0.015	0.006	0.021	0.027	0.018
	(0.120)	(0.128)	(0.128)	(0.123)	(0.134)	(0.019)	(0.027)	(0.018)	(0.022)	(0.033)
Adj R2	0.280	0.300	0.300	0.284	0.366	0.227	0.229	0.234	0.229	0.243

Table 11: OLS Regressions for the period [-30,+30]

Note: The table shows regression estimates of cumulative abnormal returns for the period [-30,+30] for each of the denoted blockchain-developing listed firms in the time period surrounding both the 'rumour' and 'official announcement'. The years 2017 and 2018 are dummy variables that take a value of unity if the announcement is made in 2017 and 2018, respectively, and zero otherwise. Market Cap refers to the the natural logarithm of the firm market capitalisation as measured in US dollars for the time period 30 days prior to the announcement day. Bitcoin and Bitcoin CAR are the natural logarithm of the bitcoin price level 30 days prior to the announcement day and the estimated cumulative bitcoin return 30 days prior to the announcement day respectively. Duration refers to the time difference as measured in days between the estimated 'rumour' and the 'official announcement'. Both Reach and Sentiment refer to the volume of social media interactions and the estimated sentiment as defined to be either positive, neutral or negative. Speculative is a dummy that takes the value of one if the announcement is defined to be of a speculative nature and zero otherwise. ***, ** and * indicate level of significance at 1%, 5%, and 10% respectively.

Specification	(1)	(2)	(3)	(4)
Lev	0.834^{***}	0.943***		
	(0.011)	(0.017)		
Lev*IMP	. ,	1.368^{***}		
		(0.037)		
Trade		. ,	0.227^{***}	0.304^{***}
			(0.066)	(0.068)
Trade*IMP			· · · ·	0.289^{***}
				(0.019)
Curr			0.766^{***}	0.321***
			(0.021)	(0.035)
Curr*IMP			(0.022)	0.426***
our min				(0.031)
Noncurrent			0 327***	0.231***
roncurrent			(0.021)	(0.0251)
Noncurrent*IMP			(0.024)	0.296*
Noneuriene imi				(0.175)
DFF	1 5/8***	1 509***	1 500***	1 008***
DEF	(0.152)	(0.166)	(0.152)	(0.223)
CDP	(0.152) 0.041***	0.041***	0.152)	(0.225)
GDI	(0.041)	(0.041)	(0.040)	(0.044)
Bond	0.052***	0.053***	0.051***	0.054***
Dolld	(0.052)	(0.001)	(0.001)	(0.034)
CDC	(0.001)	(0.001)	(0.001)	(0.001)
CDS	(0.002)	(0.094)	(0.004)	(0.004)
	(0.002)	(0.002)	(0.004)	(0.004)
NIIA	-0.113	-0.113	-0.080	-0.129
CATTA	(0.031)	(0.031)	(0.030)	(0.027)
CATA	0.183	0.182^{++++}	0.633	0.540^{+++}
	(0.047)	(0.047)	(0.215)	(0.221)
Age	-0.025***	-0.025***	-0.024***	-0.024***
a	(0.004)	(0.004)	(0.004)	(0.004)
Constant	-1.798***	-1.831***	-2.330***	-1.990***
	(0.157)	(0.164)	(0.241)	(0.265)
Observations	11,562	11,562	11,559	11,559
Pseudo-R2	0.0901	0.0904	0.0939	0.0944

Table 12: Default probability: regression results

Note: This table reports the estimated coefficients for the logit regressions and their robust standard errors clustered at the firm level (in parentheses). The dependent variable takes a value of zero if the firm is active and not under regulatory investigation, while it receives a value of one if it is insolvent, bankrupt or under regulatory investigation. Similar to the methodology used by Cathcart et al. [2020], GDP is the 1-year GDP growth rate; bond is the 3-month government bond interest rate; CDS is the logarithm of the CDS price of government bonds; NITA is the ratio of net income to total assets; CATA is the ratio of current assets to total assets; AGE is the number of days since incorporation divided by 365; IMP is a dummy variable that takes a value of one if the identified company is impaired as defined as to be 'insolvent, bankrupt or under regulatory investigation'. Lev is the ratio of total liabilities to total assets; and Noncurr is the ratio of non-current liabilities to total assets. Independent variables are lagged. ***, ** and * indicate level of significance at 1%, 5%, and 10% respectively.

Table 13: Default probability: average marginal effects

	Leverage	Trade	Current	Noncurrent	Observations
Speculative	0.022^{***}	0.024^{***}	0.031^{***}	0.015^{***}	4,642
Stratogia	(0.001)	(0.002)	(0.002)	(0.001)	6 507
Struteyte	(0.000)	(0.004)	(0.000)	(0.004)	0,007

Note: The table shows average marginal effects of total leverage, trade payables, and current and non-current liabilities to total assets, and associated marginal effects when companies are denoted to either have, or do not have any previous technological development experience prior to decisions to partake in either speculative and strategic corporate blockchain development. Standard errors are reported in parentheses. Standard errors of marginal effects are calculated using the delta method. Lev is the ratio of total liabilities to total assets; Trade is the ratio of trade payables to total assets; Curr is the ratio of current liabilities (minus trade payables) to total assets; and Noncurr is the ratio of non-current liabilities to total assets. Average marginal effects of leverage are computed using specification (2) as presented in Table 12. Average marginal effects of trade payables, and current and non-current liabilities to total assets are computed using specification (4) of Table 12. Statistical significance is calculated using the Wald test. ***, ** and * indicate level of significance at 1%, 5%, and 10% respectively.

		Speci	lative	Strategic					
Specification	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	
Lev	0.638***	0.842***			0.297***	0.268***			
	(0.010)	(0.009)			(0.022)	(0.023)			
Lev*IMP		0.775^{***}				0.300***			
		(0.121)				(0.092)			
Trade			0.126^{*}	0.136^{***}			0.575^{***}	0.499^{***}	
			(0.073)	(0.073)			(0.253)	(0.237)	
Trade*IMP			. ,	0.379^{*}			. ,	0.929^{***}	
				(0.237)				(0.173)	
Curr			0.079^{***}	0.102^{***}			0.473^{***}	0.316^{***}	
			(0.035)	(0.031)			(0.101)	(0.102)	
Curr*IMP				0.142^{*}			. ,	0.358^{*}	
				(0.080)				(0.234)	
Noncurr			0.293^{***}	0.160***			0.253	0.146**	
			(0.094)	(0.049)			(0.113)	(0.078)	
Noncurr*IMP			. ,	0.397***			· · · ·	0.334^{*}	
				(0.132)				(0.258)	
GDP	0.051^{***}	0.053^{***}	0.057^{***}	0.058^{***}	-0.009***	-0.010***	-0.010***	-0.010***	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
Bond	0.031***	0.031***	0.031***	0.031***	0.043***	0.042***	0.043***	0.043***	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
CDS	0.142***	0.142***	0.144***	0.144***	0.062***	0.062***	0.069^{***}	0.071***	
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	
NITA	-0.052***	-0.066***	-0.036***	-0.092***	-0.068***	-0.036***	-0.125***	-0.082***	
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	
CATA	0.241^{***}	0.305^{***}	0.096***	0.108***	0.090***	0.089***	0.107^{***}	0.071***	
	(0.006)	(0.007)	(0.030)	(0.030)	(0.034)	(0.032)	(0.044)	(0.044)	
Age	0.000***	0.000***	0.000***	0.000***	0.000***	-0.001***	-0.001***	-0.001***	
Q	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Constant	-0.656* ^{**}	-0.671***	-0.929***	-0.130***	-0.619***	-0.797***	-2.206***	-2.478***	
	(0.150)	(0.153)	(0.295)	(0.320)	(0.349)	(0.385)	(0.573)	(0.583)	
	. ,	. ,	. ,	. ,		. ,	. ,	. ,	
Pseudo R2	0.084	0.129	0.121	0.149	0.099	0.108	0.099	0.166	

Table 14: Default probability based on previous technological experience: regression results

Note: This table reports the estimated coefficients for the logit regressions and their robust standard errors clustered at the firm level (in parentheses). The dependent variable takes a value of zero if the firm is active and not under regulatory investigation, while it receives a value of one if it is insolvent, bankrupt or under regulatory investigation. Similar to the methodology used by Cathcart et al. [2020], GDP is the 1-year GDP growth rate; bond is the 3-month government bond interest rate; CDS is the logarithm of the CDS price of government bonds; NITA is the ratio of net income to total assets; CATA is the ratio of current assets to total assets; AGE is the number of days since incorporation divided by 365; IMP is a dummy variable that takes a value of one if the identified company is impaired as defined as to be 'insolvent, bankrupt or under regulatory investigation'. Lev is the ratio of total liabilities to total assets; Curr is the ratio of current liabilities (minus trade payables) to total assets; and Noncurr is the ratio of non-current liabilities to total assets. Independent variables are lagged. ***, ** and * indicate level of significance at 1%, 5%, and 10% respectively.

	Speculative				Strategic				
	Lev	Trade	Curr	Noncurr	Lev	Trade	Curr	Noncurr	
Experience	0.023***	0.019^{***}	0.017^{***}	0.015^{***}	0.004***	0.006^{***}	0.006^{***}	0.005^{***}	
	(0.007)	(0.003)	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	
No Experience	0.042^{***}	0.032^{***}	0.030^{***}	0.034^{***}	0.015***	0.019^{***}	0.017^{***}	0.015^{***}	
	(0.011)	(0.006)	(0.005)	(0.004)	(0.006)	(0.006)	(0.006)	(0.004)	
	Technological differential, no experience								
	0.019^{***}	0.013^{***}	0.013^{***}	0.019^{***}	0.009***	0.013^{***}	0.011^{***}	0.010^{***}	

Table 15: Default probability: average marginal effects of previous technological experience

Note: The table shows average marginal effects of total leverage, trade payables, and current and non-current liabilities to total assets, and associated marginal effects when companies are denoted to either have, or do not have any previous technological development experience prior to decisions to partake in either speculative and strategic corporate blockchain development. Standard errors are reported in parentheses. Standard errors of marginal effects are calculated using the delta method. Lev is the ratio of total liabilities to total assets; Trade is the ratio of trade payables to total assets; Curr is the ratio of current liabilities (minus trade payables) to total assets; and Noncurr is the ratio of non-current liabilities to total assets. Average marginal effects of leverage are computed using specification (2) as presented in Table 14. Average marginal effects of trade payables, and current and non-current liabilities to total assets are computed using specification (4) of Table 14. Statistical significance is calculated using the Wald test. ***, ** and * indicate level of significance at 1%, 5%, and 10% respectively.

Table 16: Credit repayment ability and probability of default and credit ratings due to leverage used on corporate blockchain-development projects by type

	1-yr PD (%)					
		Ave	Max	Min		
Blockchain Partnership	CRGR	23.3	37.0	3.0		
	PD	0.8	1.5	0.4		
Coin Creation	CRGR	31.6	97.0	1.0		
	PD	1.4	14.8	0.0		
Investment Fund	CRGR	49.3	93.0	7.0		
	PD	0.3	0.9	0.0		
Name Change	CRGR	9.5	21.0	1.0		
	PD	4.2	24.3	0.5		
Security Improvements	CRGR	27.7	90.0	1.0		
	PD	0.7	4.0	0.1		
Technological Improvements	CRGR	36.7	91.0	2.0		
	PD	0.5	2.4	0.01		
Speculative	CRGR	23.8	97.0	1.0		
	PD	2.2	24.3	0.0		
Strategic	CRGR	38.4	91.0	1.0		
	PD	0.5	4.0	0.1		
Total	CRGR	34.0	97.0	1.0		
	PD	0.8	24.3	0.0		

Note: In the above table, PD represents the estimated 1-year probability of default as separated by type of company making each corporate blockchain announcement. The CRGR, is the provided rank of Credit Combined Global Rank as provided by Thomson Reuters Eikon. This measure is used to validate and provide robustness to our estimated probability of default. The CRGR is described as a 1-100 percentile rank of a company's 1-year probability of default based on the StarMine Combined Credit Risk model. The combined model then blends the Structural, SmartRatios and Text Mining Credit Risk models into one final estimate of credit risk at the company level. Higher scores indicate that companies are less likely to go bankrupt, or default on their debt obligations within the next twelve month period.

			Restimated Credit Rating							
		Actual Credit Rating			Previous '	Fechnological	Experience	No Previous Technological Experience		
		Ave	Max	Min	Ave	Max	Min	Ave	Max	Min
Speculative	Pre- Post-	$\begin{array}{c} \text{Baa1} \ (8.4) \\ \text{Baa3} \ (9.7) \end{array}$	$\begin{array}{c} \text{Aa2} (3.0) \\ \text{A1} (5.0) \end{array}$	Caa1 (17.0) Caa2 (18.0)	Ba1 (11.4)	A3 (7.3)	Ca/C (20.0)	B1 (14.2)	Ba1 (10.7)	Ca/C (20.0)
Strategic	Pre- Post-	$\begin{array}{c} A2 \ (6.0) \\ A2 \ (6.4) \end{array}$	Aaa (1.0) Aa1 (2.0)	Ba2 (12.0) Ba3 (13.0)	A3 (7.2)	Aa2 (2.5)	B1 (13.5)	Baa1 (8.4)	Aa3 (3.7)	B2 (14.7)

Table 17:	Re-estimated	credit ratings	due to leverage	use on corporate	blockchain-d	evelopment	projects as	s defined b	v previous i	technological	experience
10010 111	ree oberniaeou (creare raeingo	add to reterage	abe on corporate	oro chemann a	overopment	projecto de	aonnoa o	, provious	ocumorogrea.	. onportonico

Note: The above table presents the utilised linear transformation methodology used to compare the respective credit ratings based on the companies analysed. Where possible, the differential point between investment grade and junk grade investment status is used as the separating point between point 10 and point 11. At point 20, companies are treated in same manner should they be considered to be either near default or in default. We have selected Moody's credit ratings as the representative value in the provided analysis. We have used the linear transformation scale provided in Table A2 to transfer ratings from S&P and Fitch to comparative Moody's rating. The provided ratings are based on the actual transformed ratings during the time period under observation and the re-estimated credit ratings based on whether the company under observation has previous technological development experience.

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Appendices

Variable	Description
company	Company name
$company_id$	Company ID
date	Date
number_tweets	Number of tweets
retweets	Number of retweets
likes	Number of likes
replies	Number of replies
blockchain	Number of mentions of the term 'blockchain'
crypto	Number of mentions of the terms 'crypto' or 'cryptocurrency'
hi pos	Number of positive terms based on Harvard General Inquirer dictionary
hi_neg	Number of negative terms based on Harvard General Inquirer dictionary
hi_polarity	Polarity (Pos-Neg)/(Pos+Neg) based on Harvard General Inquirer
hi_subjectivity	Subjectivity (Pos+Neg)/All_words based on Harvard General Inquirer
lm_{pos}	Number of positive terms based on Loughran-McDonald dictionary
lm_neg	Number of negative terms based on Loughran-McDonald dictionary
lm_polarity	Polarity (Pos-Neg)/(Pos+Neg) based on Loughran-McDonald dictionary
lm_subjectivity	Subjectivity (Pos+Neg)/All_words based on Loughran-McDonald dictonary
neg_lm_neg	Negative form of lm_neg (for plots)
neg hi neg	Negative form of hi_neg (for plots)

Table A1: List of variables and variable description defined in Twitter Sentiment Search

Note: Twitter data was collected for a period between 1 January 2017 and 31 March 2019 for a list of 156 companies. All tweets mentioning the name of the company plus either of the terms 'crypto', 'cryptocurrency' or 'blockchain' were computationally collected through the Search Twitter function on https://twitter.com/explore using the Python 'twitterscraper' package. A total number of 954,765 unique tweets were collected. The above list of variables describes the format in which the data was obtained.

			S&P	Moody's	Fitch
Highest Quality		1	AAA	Aaa	AAA
		2	AA+	Aa1	AA+
High Quality		3	AA	Aa2	AA
		4	AA-	Aa3	AA-
	Inv. Crodo	5	A+	A1	A+
Strong Payment Capacity	IIIV. Grade	6	А	A2	А
		7	A-	A3	A-
		8	BBB+	Baa1	BBB+
Adequate payment capacity		9	BBB	Baa2	BBB
		10	BBB-	Baa3	BBB-
		11	BB+	Ba1	BB+
Likely to survive despite uncertainty		12	BB	Ba2	BB
		13	BB-	Ba3	BB-
		14	B+	B1	B+
High Credit Risk	Junk Crodo	15	В	B2	В
	Julik Glade	16	B-	B3	B-
		17	CCC+	Caa1	$\mathrm{CCC}+$
Very High Credit Risk		18	CCC	Caa2	CCC
		19	CCC-	Caa3	CCC-
Near Default or In Default		20	$\rm CC/SD/D$	$\rm Ca/C$	$\rm CC/C/DDD/DD/D$

Table A2: Linear Transformation Scale for Credit Ratings

Note: The above table presents the utilised linear transformation methodology used to compare the respective credit ratings based on the companies analysed. Where possible, the differential point between investment grade and junk grade investment status is used as the separating point between point 10 and point 11. At point 20, companies are treated in same manner should they be considered to be either near default or in default.