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

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Abstract

This paper investigates how companies can utilise Twitter social media-derived sentiment as a method of generating short-term corporate value from statements based on initiated blockchain-development. Results indicate that investors were subjected to a very sophisticated form of asymmetric information designed to propel sentiment and market euphoria, that translates into increased access to leverage on the part of speculative firms. Technological-development firms are found to financially behave in a profoundly different fashion to reactionary-driven firms which have no background in ICT technological development, and who experience an estimated increased one-year probability of default of 170bps. Rating agencies are found to have under-estimated the risk on-boarded by these speculative firms, failing to identify that they should be placed under an increased degree of scrutiny. Unfiltered market sentiment information, regulatory unpreparedness and mis-pricing by trusted market observers has resulted in a situation where investors and lenders have been compromised by direct exposure to an asset class becoming known for law-breaking activity, financial losses and frequent reputational damage.

Keywords: Investor Sentiment; Blockchain; Leverage; Idiosyncratic Volatility; Social Media.

Highlights

- We test for corporate effects instigated by blockchain-related technological development
- Social media response is found to be a significant propellant of financial response
- Rating agencies under-priced the risk on-boarded by speculative non-technological 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 whether social media attention, in conjunction with underlying corporate financial health and prior technological experience have significantly contributed to the development of short-term profits and abnormal sentiment-driven pricing behaviour associated with rumours and official announcements of blockchain development projects. Online public attention and sentiment directly create a euphoric environment through which the corporate entity and shareholders could realise rapid equity price rises and improved access to leverage. Purposefully generating this unwarranted social media "hype" is ethically and legally questionable. After the consideration of one hundred and fifty-six individual cases between January 2017 and July 2019, there remains limited evidence of the complete operational delivery of these rumoured or announced blockchain-development projects. Moreover, some of the studied 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' (Cheng et al. [2019]; Sharma et al. [2020]; Akyildirim et al. [2020]; Cahill et al. [2020]). While not making accusation of illicit behaviour, we highlight abnormal financial performance and evaluate the extent to which financial pressures or social media campaigns were responsible for it.

The underlying motivations for these tactics are not singular. Some publicly traded companies 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 new digital technologies, such as blockchain. These motivations, while explicable, are not necessarily in keeping with existing ethical or regulatory principles, therefore it would not be unwarranted that regulatory bodies placed such announcements of blockchain and cryptocurrency projects under increased scrutiny, especially when considering corporations with no previous historical experience of ICT research and development[1]. It is important to note that this paper focuses on a period of time when this technology was at its most euphoric and novel level, between 2017 and 2019. Regulatory agencies had yet to establish the initial boundaries and definitions that tempered this euphoria. Our results show how the impact of sentiment weakened over time, which aligns to the increase in advisories from the Securities and Exchange Commission and FBI investigations becoming public knowledge. This paper's conclusions that regulators place blockchain announcements under more scrutiny is to encourage vigilance and to highlight the magnitude of the manipulation that took place and could take place again with another novel technological application.

Following Chen et al. [2019], who identify the internet of things (IoT), robo-advising, and

[1]Within the context of this research, such a company that has recently announced corporate development of blockchain projects, with no prior, publicly denoted experience, or evidence of delivery of such ICT research and development projects, is hereafter identified as a 'reactionary-driven' entrant. Such a firm is defined to be that which has identified an opportunity to react in response to the development of blockchain technology and take advantage without any provided evidence of actual, physical blockchain development project delivery.

blockchain as the most valuable digital innovation types, we focus on the latter in order to capture a technology which has already generated very high levels of attention and was at the peak of its "hype curve". Building upon the work of Akyildirim et al. [2020], who present evidence of cryptocurrency shifting price discovery based on a limited set of cases, we develop significant additional insights by increasing the number of analysed firms to one hundred and fifty six and expanding the dimensions of analysis to include social media attention, sentiment and underlying corporate fragility. We find significant shifts in price discovery associated with each of these additional factors.

The novelty of this paper is to be found in the synthesis of sentiment analysis, as derived from Twitter, with the behaviour of firms with respect to blockchain development. While previous papers have highlighted the role of blockchain hysteria in equity pricing [Jain and Jain, 2019] and the role of sentiment on pricing [Cioroianu et al., 2020], here we combine both aspects and link that to corporate behaviour. We are therefore able to derive a specific quantum of error. The excessive positivity of the ratings agencies is on the order of a one grade improvement over the true credit rating. Blockchain announcement companies with speculative intent also present an average one-year probability of default of 2.2% of classification error on the part of ratings agencies brought about by firms bootstrapping performance based on this market euphoria. In order to highlight that, we use abnormal returns to identify the corporate effect of Twitter and split our firms into "strategic" firms with a long history of ICT development, and those who are "speculative" and lack any history in ICT development, even if they have previously operated in a technological manufacturing sector. This distinction is important because it enables a precise analysis of how erroneous ratings agency statements have been.

From a regulatory perspective, we ask whether such project announcements have shrouded, or cloaked true probability of default estimates, and if such risks have been identified and adequately reflected by credit rating agencies. Distinctly, we investigate a number of issues that are within the scope of current regulatory and policy-making concern. Primarily, 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. Secondly, through a variety of methodological techniques for improved robustness, we attempt to quantify the key financial characteristics of corporate entities that have announced their intentions to develop significant blockchain projects. Within this context, we specifically observe the use of leverage and other types of debt by these companies and 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 evaluate whether the true risks of these investments were observed in warnings to investors. We pay particular attention to companies initiating blockchain-development projects with no prior technological development experience (reactionary-driven entrants).

Regulators have a mixed relationship with blockchain, as it offers great opportunity for security and to facilitate transactions, but recent evidence also suggests that it harbours the capacity to be used for money laundering and criminal activity [Canhoto, 2020, Corbet et al., 2020]. This is in addition to ongoing concerns about announcement effects related to blockchain and initial coin offerings that have attracted the interest of the Federal Reserve, Securities and Exchange

Commission, Federal Bureau of Instigation and the US Treasury. This paper highlights the financial effects of corporate misbehaviour based on blockchain technology, both directly and indirectly [Byrne, 2011].

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, internal financial positions, probability of default, and the role of rating agencies. Specifically, we argue the views that both companies in natural decline and those of smaller magnitude (such as small cap and penny stocks) are most likely to benefit from channels incorporating the use of blockchain and cryptocurrency projects to generate both abnormal returns, profits and public exposure. Such arguments are developed with the knowledge that social media rumours are also central to the news dissemination process in the period before the official announcement. We control for this through a thorough review of the 'first' mention on social media of such blockchain projects, with a comparable analysis of corporate performance in the period both before the rumour, and that of the official announcement.

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 while also being 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, but can also bolster or sway it by generating and promoting social media content. 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 and the 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 dramatically 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 should have been 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 potential illicit activity, financial losses and reputational damage.

The paper is structured as follows: previous research that guides our selected theoretical and methodological approaches are summarised in Section 2. Section 3 presents a thorough explanation of the wide variety of data used in our analyses along with the specific hypotheses tested, 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 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. Previous Literature

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 sentiment-influenced abnormal returns that existed across these trades, inclusive of derivatives markets where they existed. 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]).

With regards to research on cryptocurrency, White et al. [2020] identified that Bitcoin, somewhat representative 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 of mechanisms through which cryptocurrencies can influence corporate entities and markets and 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 they lack the ability 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 due to the widespread evidence of substantial growth in the share price of 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 - analysed with Facebook data used as a proxy - subconsciously influences investor perception of potential merger synergies and risks, 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. When informed traders also observe prices, uninformed traders generate reversals by engaging in contrarian trading, and 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 as well as currency returns, Bruguier et al. [2010] hypothesise that Theory of Mind (ToM) 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, showing 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, but also 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.

This paper contributes to this wider literature on behaviour of cryptocurrencies and blockchain by analysing the ways in which sentiment driven by association with this technology and initiated by social media can have a material impact on corporate performance, especially for firms in decline or distress, encouraging the misconduct and ratings agency confusion highlighted in the literature above. The starting point of the paper is the existence of significant abnormal returns from trading arising from these conditions of asymmetric information and moral hazard induced and exacerbated by the attention and sentiment of the online and social media environment. 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 280 characters. Under such conditions it is easy for firms with speculative motivations or a lack of background in blockchain technology to easily associate themselves with the market euphoria surrounding Bitcoin and blockchain development in the 2017-19 period with minimal scrutiny [Hu et al., 2020]. 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. The section below describes the multiple sources used in the analysis.

3. Data Description

We collect data from multiple sources, primarily developing a concise list of corporate announcement that specifically constitute a news release relating to blockchain or 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[2] 1 January 2012 and 30 June 2019. We develop on a combined search of LexisNexis, Bloomberg and Thomson Reuters Eikon, searching for relevant keywords[3] under traditional corporate announcements. To obtain a viable observation, a single data observation must be present across the three search engines and the source must have been 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. The timing and geographic location of each of the announcements are presented in Figure 1. 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

[2] The corporate announcement period covers from 1 January 2017 to 30 March 2019 to perform adequate pre-and post-announcement analyses (announcement data for traded companies was not present in a robust manner prior to January 2017).

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

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.

Insert Figure 1 about here

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 collected[4]. 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 are 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 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 is conducted 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 dictionary[5]. 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

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

[5]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

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[6]. 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[7]. 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 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.

When considering previous research surrounding corporate blockchain development in conjunction with theoretical and methodological support based on the relationship between social media exposure, blockchain development and corporate performance structures a number of distinct hypotheses are determined. Due to 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.

- *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* h_2: Corporate desperation[8], as evidenced by a weak firm cash reserve and/or high leverage position, instigates the decision to incorporate blockchain technology.

[6]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.

[7]The variable representing interest of social media is found to be significantly related with the size of the company, while the effects of sentiment in relation to market capitalisation do not appear to present a clear relationship.

[8]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 investigates 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. The coefficient on the independent variables reflects the net cost (negative coefficient) or benefit (positive coefficient) to equity holders of expansion into blockchain.

- *Hypothesis* h_3: Companies who instigate blockchain development projects present evidence of increased probability of default should they have no prior technological development experience (reactionary-driven entrants)
- *Hypothesis* h_4: Credit ratings have adapted and segregated their consideration of the additional corporate risk associated with speculative and strategic blockchain development

Specifically, h_1 develops a novel investigation of the influence of social media on financial performance based on blockchain or blockchain-related technology. Firm fundamentals are then 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 h_2 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. Next, through the use a probit technique, we investigates the behaviour of the selected companies as again separated by strategic and speculative use, but further considering as to whether such companies can be identified as possessing previous experience of technological development (reactionary-driven entrants). Hypothesis h_3 focuses on specific effects within reactionary-driven corporations with no previous evidence of technological experience but with publicly stated entrance to blockchain-development projects[9]. Hypothesis h_4 considers the risk differential and potential under-pricing of the true risks inherent in such projects and blockchain-based decisions. 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.

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. To complete such a task, we revisit models similar to that presented by Akyildirim et al. [2020] and Cahill et al. [2020] that have focused on abnormal returns, however, in

[9]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. These companies have been earlier defined to be reactionary-driven entrants to the blockchain development sector. 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.

addition we control for the role of social media response. 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[10].

To examine 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-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:

[10] 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 or release of corporate accounts within five days either side of the blockchain-related 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.

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

$$= \frac{1}{1 + exp\left[\alpha + X_{i,t}\beta + Z_{i,c,t}\delta + \gamma_c + \gamma_j\right]} \tag{2}$$

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. 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.

The firm-level variables include leverage or its components, that is, trade, current, and non-current. These are, respectively, the ratios of total leverage, trade payables, and current and non-current liabilities to total assets (as per Cathcart et al. [2020]). 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 obtained 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 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 are presented as:

$$\frac{\vartheta P_t(y_{i,c,j,t+1}=1)}{\vartheta_x} = \beta_x \Phi'(\alpha + X_{i,t}\beta + Z_{i,c,t}\delta + \gamma_c + \gamma_j) \tag{3}$$

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

$$\frac{\vartheta P_t(y_{i,c,j,t+1}=1)}{\vartheta_x} = (\beta_x + \beta_{x.Spec}Spec)\beta_x \Phi'(\alpha + X_{i,t}\beta + Z_{i,c,t}\delta + \gamma_c + \gamma_j) \tag{4}$$

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 blockchain-development 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 whether the effects of leverage and other internal dynamics of corporations who have taken both strategic and speculative decisions to develop blockchain have been effectively considered by credit rating agencies' estimates. To complete this task, we reconstruct estimates similar to those previously described by Metz and Cantor [2006]. 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:

$$w_z = exp\left\{a_z + b_z lev_t^i\right\} \tag{5}$$

where the final weighting of W_z is calculated as:

$$W_z = \frac{W_z}{1 + \sum_{k=1}^{6} W_k} \tag{6}$$

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 Online Appendices), we 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,

$$FR = w_1 R_{CV} + w_2 R_{LV} + w_3 R_{RoA} + w_4 R_{RS} + w_5 R_{vLV} + w_6 R_{AT} + w_7 R_{CVxAT} \tag{7}$$

$$\tilde{R} = FR + n + n(t) + n(I) + \delta \left(\frac{\sigma(LV)}{\mu(LV)} \right) \tag{8}$$

$$R = max \left\{ 5, min \left\{ 20, \bar{R} \right\} \right\} \tag{9}$$

R is our estimate of the final issuer credit rating. The free parameters are estimated by minimising the log absolute notch error plus one[11]. We utilised 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 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. In Table 3 we separate the data into four distinct blocks. Twitter and equity activity on the day of announcement and thirty days before both the rumour or official announcement and then for the three days period after the rumour or official announcement. This is entirely descriptive data as collected from the social media sources. Reactionary-driven 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 reactionary-driven firms.

Insert Table 3 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 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 2 continues,

[11]This places 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.

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 2. 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 2 about here

As in Figures 3 and 4, 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 pre-rumour conditions by day three. Official announcements follow the same pattern as in Figures 2 and 3, 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 3 and 4 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[12]. Therefore, we provide further validation

[12] The degree in which the misuse of social media data and, in particular, fake data has been estimated to have been quite 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. Shao et al. [2018] performed k-core decompositions on a diffusion network obtained from the 2016 US Presidential Elections, providing a first look at the anatomy of a massive online misinformation diffusion network, where similarly, Grinberg et al. [2019] found that 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.

of Hypothesis h_1, by re-estimating a similar baseline cumulative abnormal return model to that used by Akyildirim et al. [2020] and Cahill et al. [2020], with significant novelty added through the addition of sentiment. In Table 4, we observe the sentiment adapted cumulative abnormal returns for a rumour and official statement for period surrounding each announcement. The highlights of this table relate to the response of equities at AR0. Here, we identify 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, sentiment adapted abnormal returns reaching 12% and 18% in 2017 but are moderated to less 1% for rumours and 3% for official statements in 2019.

Insert Table 4 about here

Separating the analysis based on speculative versus the strategic firms for rumour and official announcement responses, we find that 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 5, the substantiative response of speculative firms is observed again but strategic firms also have the appearance of sentiment adapted abnormal returns, but much smaller in magnitude[13].

Insert Figure 5 about here

Separating results by "reach" of the social media as measured by quartiles of tweets, retweets and likes, ranked from lowest through to highest, we find that firms with the highest reach, exhibited the strongest results with respect to official announcements. We further analyse the impact of sentiment as expressed by Twitter statements that have been indexed to positive, negative and neutral sentiment. Strong and persistent sentiment adapted 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

[13]Further results are available from the authors on request relating to time varying effects. Though outside the scope of this research, results indicate an influence from a changed 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, especially for rumours.

or blockchain technology is understood to be overwhelmingly positive for a firm, even if it receives a negative welcome from social media commentators.

Insert Tables 5 through 6 about here

In both of the Tables 5 and 6, we observe direct abnormal pricing performance at the time period specifically surrounding both the date of the rumour and the official announcement, focusing on the period thirty days before, the period inclusive of the day both before and after, and the day of respectively. Firms with speculative motivations to embark on blockchain work during a rumour will have a large proportion (0.14%) of their price movement explained exclusively by sentiment. 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. This is consistent with the view 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, 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 on the day of the announcement but it is still less important than the status of a firm being speculative for both rumour and official announcements. The large explanatory power of speculative firm status continues to confirm our hypothesis that firms seek to exploit this premium via "bandwagon" effects. 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.

Importantly, and where this paper contributes to the literature, we must also ask whether corporate desperation potentially instigated 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. One particular shared characteristic is quite noticeable when considering particular cohorts of the sample of speculatively-denoted companies: their company and sector have been in long-term decline.

In Figure 6, 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[14].

Insert Figure 6 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 sentiment adapted 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 reactionary-driven 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.

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

To investigate Hypothesis h_2 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

[14]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.

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 7. 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 7 and 8 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 8, 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 strategic blockchain announcements, the risks 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. Have reactionary-driven firms presented differential use of leverage?

One of the key red flags surrounding the identification of unlawful behaviour within the context of blockchain development has focused on the why reactionary-driven 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. Using the division between strategic and speculative blockchain announcements, we investigate Hypothesis h_3, adding a further taxonomy 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 9 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 9 and 10 about here

Considering the significant effects of leverage, we next analyse the marginal effects of technological experience with results provided in Table 10. 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. Reactionary-driven 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, 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 reactionary-driven 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 reactionary-driven companies who instigate blockchain-development projects with no previous technological experience are found to present increased probability of default.

5.4. 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 behave, 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 risky set of companies for 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. It is important that we investigate whether investors 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_4 which analyses 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 11 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 11 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 12 about here

When focusing specifically on credit ratings, a similar pattern emerges. In Table 12 we present the average credit rating per company as separated by each type of blockchain-development announcement, 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. 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 evaluating 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 12. 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.

An estimated downgrade from Baa1 to Baa3 was identified in the average speculative blockchain company. When further classifying groups on the basis of ICT experience (as identified earlier to be reactionary-driven companies), results indicate that even those experienced companies should be considered to be of junk status at Ba1. Further, reactionary-driven 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 strategically-indicative blockchain announcements, the average company in the sample is found to warrant a one-grade downgrade from A2 to A3 in circumstances where 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 it 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. Some of 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 split firms into those that are speculative and strategic in their actions. An additional division is between firms 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 specific ICT technological development. However, Facebook and Apple are examples of firms with extensive experience in ICT. Reactionary-driven firms with no prior technological experience are found to generate significant returns during the 'rumour phase' of blockchain announcements, while further presenting differential behaviour in their use of leverage. This reflects the desire of these firms that are traditionally non-technologically-based to act in a speculative manner, to evolve into a "risk-on" asset and where the underlying desire of these firms appears to surround taking advantage of blockchain and cryptocurrency bandwagon effects.

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 as blockchain.

All blockchain related activity is understood to increase risk to the firm that is undertaking it. Reactionary-driven 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 non-artificial 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 fed 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 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.

Even if the role of sentiment is limited to its importance to rumour statements by firms, it still has the power to drive equity prices. This is especially true for firms engaged in speculative objectives. Speculative firms 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. 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 time regulation cannot be so tough that is creates fear of entry that stifles technological development [Corbet et al., 2020]. 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 is 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 have the potential to mislead investors and generate substantial repercussions throughout unsuspecting portfolios.

The analysis from our sentiment and default probability methodologies 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, and 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

This research specifically investigates whether social media attention, when controlling for underlying corporate financial health and previous technological development experience, has significantly contributed to abnormal financial performance, elevated use of leverage, and the shrouding of both actual and perceived risk of default associated with rumours and official announcements relating to blockchain-development projects. First, the level of social media activity is found to be significantly dependent on the type of blockchain announcement. We identify that speculatively-driven announcements, those of reactionary-driven companies with no prior technological development experience, generate abnormal pricing performance of approximately 35%, when compared to 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 price 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.

Secondly, we find that firms with technological experience illustrate less idiosyncratic risk when compared to companies engaged in other sectors. Those reactionary-driven companies that lack experience in technological development, are found to be substantially leveraged in comparison to those with substantial development experience. Such a result indicates that not only are such companies making high-risk decisions, but they are using borrowed funds to take such risks. Thirdly, 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.

Finally, reactionary-driven 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 latter result provides significant evidence that investors have not been appropriately advised of the true risks inherent in such speculative corporate decisions. 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, algorithmic and sentiment-driven computer-aided trading can specifically seek and benefit from short-term momentum driven by hysteria relating to blockchain and cryptocurrencies, irrespective of the ethical or moral issues inherently attached.

In a developing sector increasingly plagued by issues surrounding 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 a priority. To do so, regulators must ensure that those aspiring to take advantage of misinforming investors must be adequately disincentivised. At the same time, 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.

The ability of companies to advertise the creation of instruments with almost any self-determined parameters implies that there are few limits on the complexity of design of these technological solutions. The substantiative, repeated price appreciation without project delivery should generate regulatory concern. Investors cave been therefore forced to base their decisions on improper information and social media hysteria, both, as evidence in ongoing investigations have shown, influenced by artificial sources. This information also possesses the ability to trigger automated trading systems that act as a potential accelerant of abnormal performance. 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. 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 advertisements further exploit these marketing schemes, adding to the hysteria and acting as a propellant of abnormal price performance.

For those companies in desperate economic situations, it might be their only route to profits, hence the need to be particularly beware of reactionary-driven corporations making announcements with no prior technological-development experience. Further investor education and increased regulatory enforcement, particularly of corporate entities with no previous technological development experience announcing speculative blockchain-development projects, might be 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.

References

Acharya, V., Y. Amihud, and S. Bharath (2013). Liquidity risk of corporate bond returns: Conditional approach. *Journal of Financial Economics 110*(2), 358–386.

Acharya, V., S. A. Davydenko, and I. A. Strebulaev (2012). Cash holdings and credit risk. *The Review of Financial Studies 25*(12), 3572–3609.

Aitken, M., D. Cumming, and F. Zhan (2015). Exchange trading rules, surveillance and suspected insider trading. *Journal of Corporate Finance 34*, 311–330.

Aktas, N., C. Louca, and D. Petmezas (2019). Ceo overconfidence and the value of corporate cash holdings. *Journal of Corporate Finance 54*, 85–106.

Aktas, N., G. Xu, and B. Yurtoglu (2018). She is mine: Determinants and value effects of early announcements in takeovers. *Journal of Corporate Finance 50*, 180 – 202.

Akyildirim, E., S. Corbet, D. Cumming, B. Lucey, and A. Sensoy (2020). Riding the wave of crypto-exuberance: The potential misusage of corporate blockchain announcements. *Technological Forecasting and Social Change 159*, 120191.

Akyildirim, E., S. Corbet, A. Sensoy, and L. Yarovaya (2020). The impact of blockchain related name changes on corporate performance. *Journal of Corporate Finance*, 101759.

Albuquerque, R., E. De Francisco, and L. Marques (2008). Marketwide private information in stocks: Forecasting currency returns. *Journal of Finance 63*(5), 2297–2343.

Alsakka, R., O. ap Gwilym, and T. N. Vu (2014). The sovereign-bank rating channel and rating agencies' downgrades during the european debt crisis. *Journal of International Money and Finance 49*, 235–257.

Arnold, M. (2014). Managerial cash use, default, and corporate financial policies. *Journal of Corporate Finance 27*, 305–325.

Basile, P., S. Kang, J. Landon-Lane, and H. Rockoff (2017). An index of the yields of junk bonds, 1910-1955. *Journal of Economic History 77*(4), 1203–1219.

Beck, T. (2008). *Bank competition and financial stability: friends or foes?* The World Bank.

Becker, B. and T. Milbourn (2011). How did increased competition affect credit ratings? *Journal of Financial Economics 101*(3), 493–514.

Bloomfield, R., W. Tayler, and F. Zhou (2009). Momentum, reversal, and uninformed traders in laboratory markets. *Journal of Finance 64*(6), 2535–2558.

Bruguier, A., S. Quartz, and P. Bossaerts (2010). Exploring the nature of "trader intuition". *Journal of Finance 65*(5), 1703–1723.

Byrne, E. F. (2011). Business ethics should study illicit businesses: To advance respect for human rights. *Journal of Business Ethics 103*(4), 497.

Cahill, D., D. G. Baur, Z. F. Liu, and J. W. Yang (2020). I am a blockchain too: How does the market respond to companies' interest in blockchain? *Journal of Banking & Finance 113*, 105740.

Cai, J. and Z. Zhang (2011). Leverage change, debt overhang, and stock prices. *Journal of Corporate Finance 17*(3), 391–402.

Campbell, J. Y., J. Hilscher, and J. Szilagyi (2008). In search of distress risk. *The Journal of Finance 63*(6), 2899–2939.

Canhoto, A. I. (2020). Leveraging machine learning in the global fight against money laundering and terrorism financing: An affordances perspective. *Journal of Business Research*.

Carlin, B. I. (2009). Strategic price complexity in retail financial markets. *Journal of financial Economics 91*(3), 278–287.

Cathcart, L., A. Dufour, L. Rossi, and S. Varotto (2020). The differential impact of leverage on the default risk of small and large firms. *Journal of Corporate Finance 60*, 101541.

Chen, M. A., Q. Wu, and B. Yang (2019). How valuable is fintech innovation? *The Review of Financial Studies 32*(5), 2062–2106.

Cheng, S. F., G. De Franco, H. Jiang, and P. Lin (2019). Riding the blockchain mania: public firms' speculative 8-k disclosures. *Management Science 65*(12), 5901–5913.

Choe, C. (2003). Leverage, volatility and executive stock options. *Journal of Corporate Finance 9*(5), 591–609.

Cioroianu, I., S. Corbet, and C. Larkin (2020). Guilt through association: Reputational contagion and the boeing 737-max disasters. *Economics Letters*, 109657.

Corbet, S., D. J. Cumming, B. M. Lucey, M. Peat, and S. A. Vigne (2020). The destabilising effects of cryptocurrency cybercriminality. *Economics Letters 191*, 108741.

Corbet, S., C. Larkin, B. Lucey, A. Meegan, and L. Yarovaya (2020). Cryptocurrency reaction to fomc announcements: Evidence of heterogeneity based on blockchain stack position. *Journal of Financial Stability 46*, 100706.

Corbet, S., B. Lucey, A. Urquhart, and L. Yarovaya (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis 62*, 182–199.

Cresci, S., R. Di Pietro, M. Petrocchi, A. Spognardi, and M. Tesconi (2015). Fame for sale: Efficient detection of fake twitter followers. *Decision Support Systems 80*, 56–71.

Cumming, D., R. Dannhauser, and S. Johan (2015). Financial market misconduct and agency conflicts: A synthesis and future directions. *Journal of Corporate Finance 34*, 150–168.

Cziraki, P., P. De Goeij, and L. Renneboog (2014). Corporate governance rules and insider trading profits. *Review of Finance 18*(1), 67–108.

Danbolt, J., A. Siganos, and E. Vagenas-Nanos (2015). Investor sentiment and bidder announcement abnormal returns. *Journal of Corporate Finance 33*, 164–179.

Dermine, J. (2015). Basel iii leverage ratio requirement and the probability of bank runs. *Journal of Banking & Finance 53*, 266–277.

D'Mello, R., M. Gruskin, and M. Kulchania (2018). Shareholders valuation of long-term debt and decline in firms' leverage ratio. *Journal of Corporate Finance 48*, 352–374.

Easley, D. and M. O'Hara (2004). Information and the cost of capital. *Journal of Finance 59*(4), 1553–1583.

Faulkender, M. and R. Wang (2006). Corporate financial policy and the value of cash. *The Journal of Finance 61*(4), 1957–1990.

Fidrmuc, J. P., M. Goergen, and L. Renneboog (2006). Insider trading, news releases, and ownership concentration. *The Journal of Finance 61*(6), 2931–2973.

Gabaix, X. and D. Laibson (2006). Shrouded attributes, consumer myopia, and information suppression in competitive markets. *The Quarterly Journal of Economics 121*(2), 505–540.

Gandal, N., J. Hamrick, T. Moore, and T. Oberman (2018). Price manipulation in the Bitcoin ecosystem. *Journal of Monetary Economics 95*, 86–96.

Griffins, J. and A. Shams (2018). Is Bitcoin really un-Tethered? *Available at SSRN, http://dx.doi.org/10.2139/ssrn.3195066*.

Grinberg, N., K. Joseph, L. Friedland, B. Swire-Thompson, and D. Lazer (2019). Political science: Fake news on twitter during the 2016 u.s. presidential election. *Science 363*(6425), 374–378.

Henderson, B. and N. Pearson (2011). The dark side of financial innovation: A case study of the pricing of a retail financial product. *Journal of Financial Economics 100*(2), 227–247.

Hillier, D., A. Korczak, and P. Korczak (2015). The impact of personal attributes on corporate insider trading. *Journal of Corporate Finance 30*, 150–167.

Ho, T. S. and R. Michaely (1988). Information quality and market efficiency. *Journal of Financial and Quantitative Analysis 23*(1), 53–70.

Hu, Y., Y. G. Hou, L. Oxley, and S. Corbet (2020). Does blockchain patent-development influence bitcoin risk? *Journal of International Financial Markets, Institutions and Money*, 101263.

Huson, M. and G. MacKinnon (2003). Corporate spinoffs and information asymmetry between investors. *Journal of Corporate Finance 9*(4), 481–503.

Iannotta, G., G. Nocera, and A. Resti (2013). Do investors care about credit ratings? an analysis through the cycle. *Journal of Financial Stability 9*(4), 545–555.

Jain, A. and C. Jain (2019). Blockchain hysteria: Adding "blockchain" to company's name. *Economics Letters 181*, 178–181.

Jeng, L. A., A. Metrick, and R. Zeckhauser (2003). Estimating the returns to insider trading: A performance-evaluation perspective. *Review of Economics and Statistics 85*(2), 453–471.

Lee, I., M. Lemmon, Y. Li, and J. M. Sequeira (2014). Do voluntary corporate restrictions on insider trading eliminate informed insider trading? *Journal of Corporate Finance 29*, 158–178.

Marin, J. and J. Olivier (2008). The dog that did not bark: Insider trading and crashes. *Journal of Finance 63*(5), 2429–2476.

Metz, A. and R. Cantor (2006). Moody's credit rating prediction model. *Special Comments, Credit Ratings, Moody's Investors Service, Global Credit Research*.

Moeller, T. and C. Molina (2003). Survival and default of original issue high-yield bonds. *Financial Management 32*(1), 83–107.

Ou, S., S. Irfan, Y. Liu, and K. Kanthan (2017). Annual default study: Corporate default and recovery rates, 1920-2016. *Data Report-Moody's Investor Services*.

Rashes, M. S. (2001). Massively confused investors making conspicuously ignorant choices (mci–mcic). *The Journal of Finance 56*(5), 1911–1927.

Shao, C., P.-M. Hui, L. Wang, X. Jiang, A. Flammini, F. Menczer, and G. Ciampaglia (2018). Anatomy of an online misinformation network. *PLoS ONE 13*(4).

Sharma, P., S. Paul, and S. Sharma (2020). What's in a name? a lot if it has "blockchain". *Economics Letters 186*, 108818.

Van Bommel, J. (2002). Messages from market to management: The case of ipos. *Journal of Corporate Finance 8*(2), 123–138.

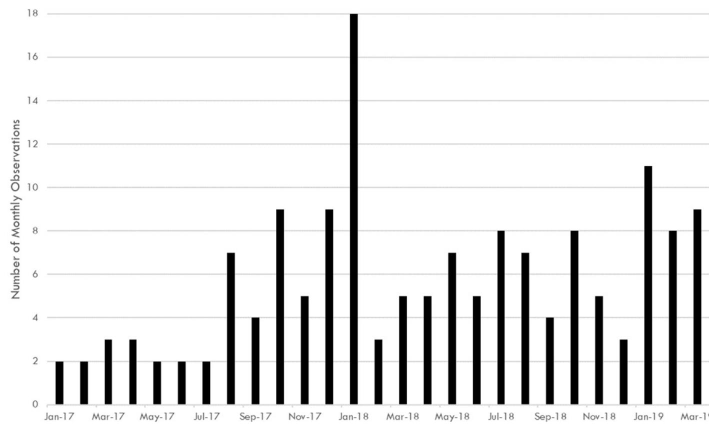
Van Der Walt, E. and J. Eloff (2018). Using machine learning to detect fake identities: Bots vs humans. *IEEE Access 6*, 6540–6549.

White, R., Y. Marinakis, N. Islam, and S. Walsh (2020). Is bitcoin a currency, a technology-based product, or something else? *Technological Forecasting and Social Change 151*, 119877.

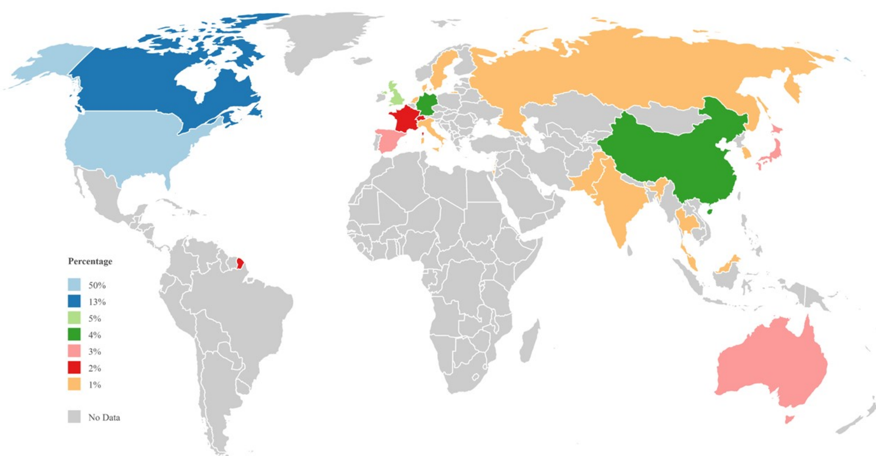
Zhou, M., L. Lei, J. Wang, W. Fan, and A. Wang (2015). Social media adoption and corporate disclosure. *Journal of Information Systems 29*(2), 23–50.

Figure 1: Frequency and geographical location of identified blockchain-development projects

a) Time-varying representation of corporate announcement of blockchain development



b) Geographical representation of corporate announcement of blockchain development

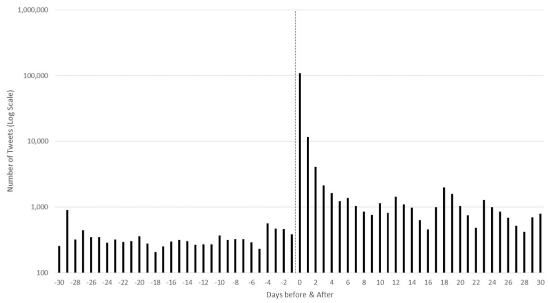


Note: The corporate announcement period covers from 1 January 2017 to 30 March 2019 (announcement data for traded companies was not present in a robust manner prior to January 2017). We develop on a combined search of LexisNexis, Bloomberg and Thomson Reuters Eikon, search for the keywords including that of: "cryptocurrency", "digital currency", "blockchain", "distributed ledger", "cryptography", "cryptographic ledger", "digital ledger", "altcoin" and "cryptocurrency exchange". 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.

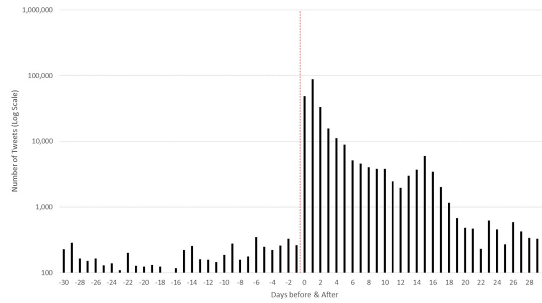
Figure 2: Tweets relating to corporate blockchain announcements

a) Speculatively-defined corporate blockchain announcements

i) Rumour

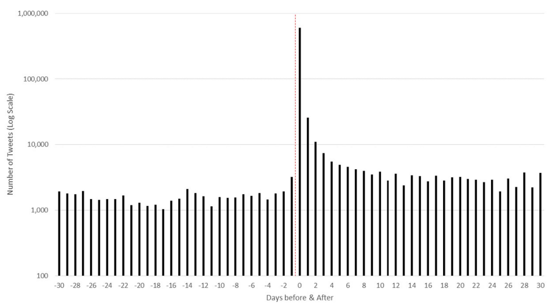


ii) Official

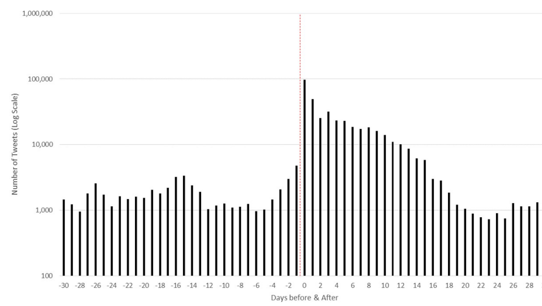


b) Strategically-defined corporate blockchain announcements

i) Rumour

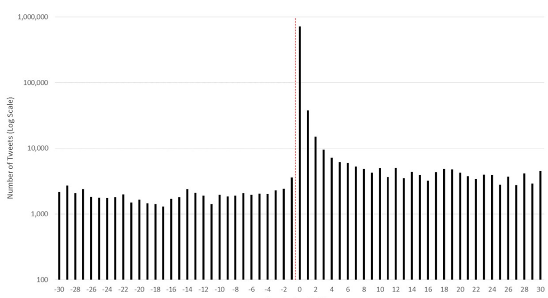


ii) Official

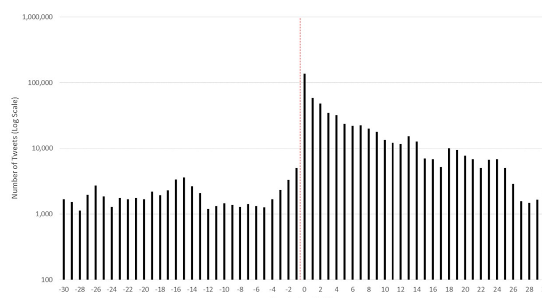


c) Total Twitter activity surrounding corporate blockchain announcements

i) Rumour



ii) Official

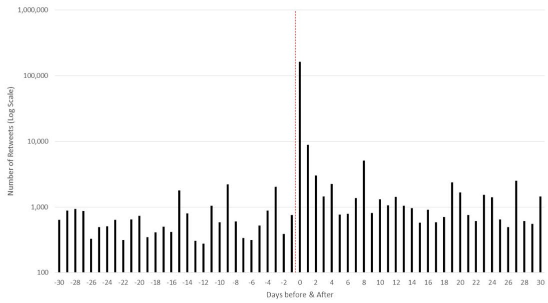


Note: Twitter data was collected for a period between 1 January 2017 and 31 March 2019 for a list of 156 companies. All tweets mentioning the name of the company plus either of the terms 'crypto', 'cryptocurrency' or 'blockchain' were computationally collected through the Search Twitter function on https://twitter.com/explore 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.

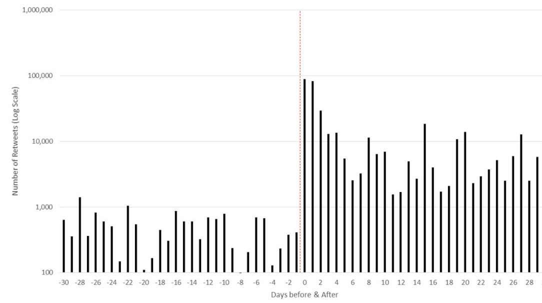
Figure 3: Twitter-based 'Retweets' relating to corporate blockchain announcements

a) Speculatively-defined corporate blockchain announcements

i) Rumour

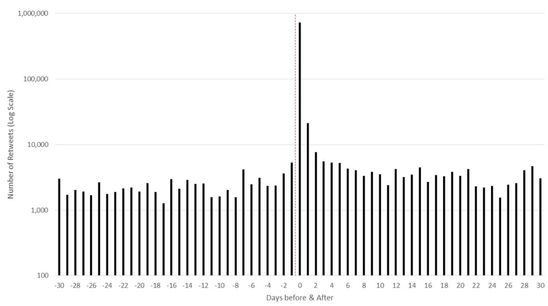


ii) Official

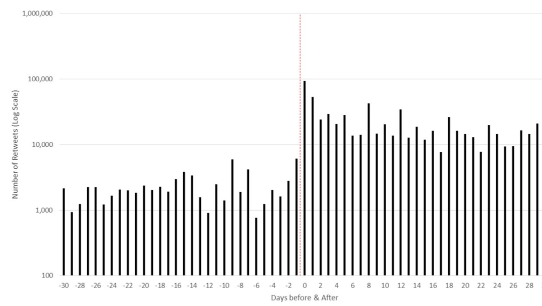


b) Strategically-defined corporate blockchain announcements

i) Rumour

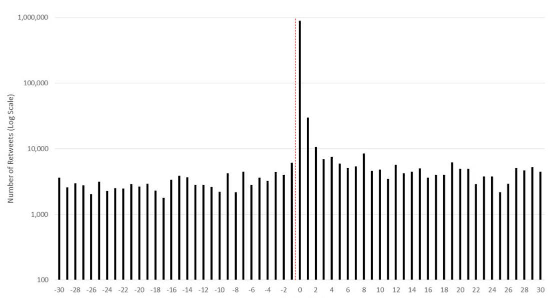


ii) Official

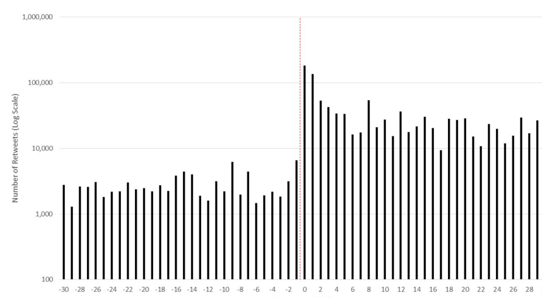


c) Total Twitter activity surrounding corporate blockchain announcements

i) Rumour



ii) Official

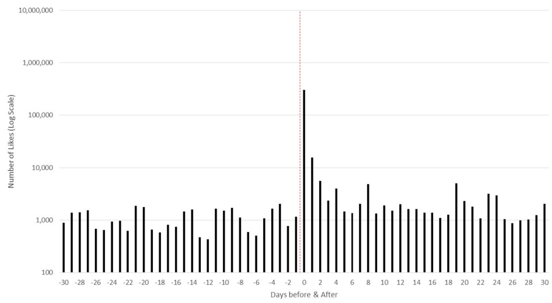


Note: Twitter data was collected for a period between 1 January 2017 and 31 March 2019 for a list of 156 companies. All tweets mentioning the name of the company plus either of the terms 'crypto', 'cryptocurrency' or 'blockchain' were computationally collected through the Search Twitter function on https://twitter.com/explore 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.

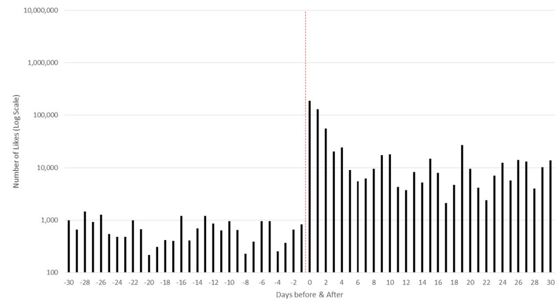
Figure 4: Twitter-based 'Likes' relating to corporate blockchain announcements

a) Speculatively-defined corporate blockchain announcements

i) Rumour

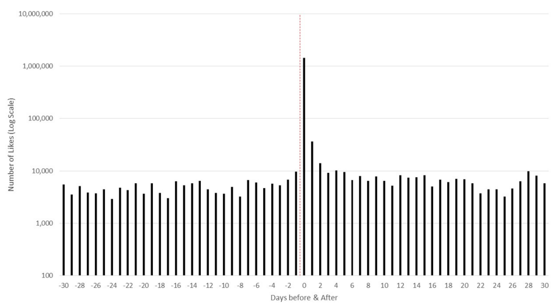


ii) Official

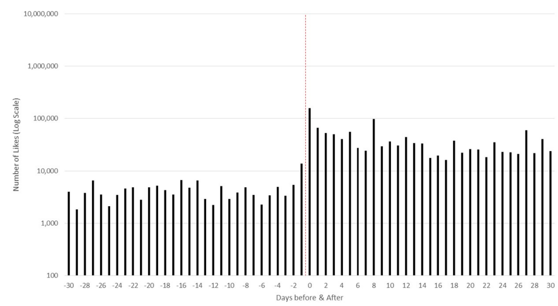


b) Strategically-defined corporate blockchain announcements

i) Rumour

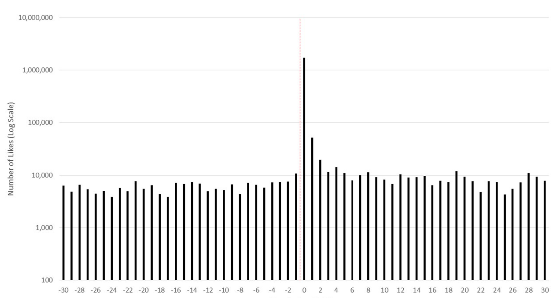


ii) Official

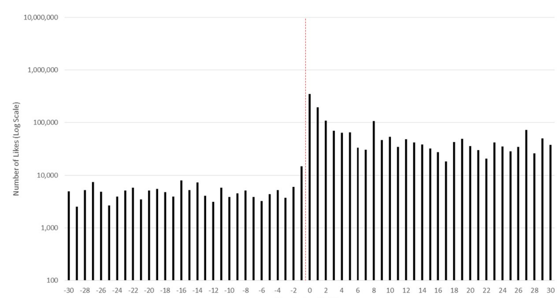


c) Total Twitter activity surrounding corporate blockchain announcements

i) Rumour



ii) Official

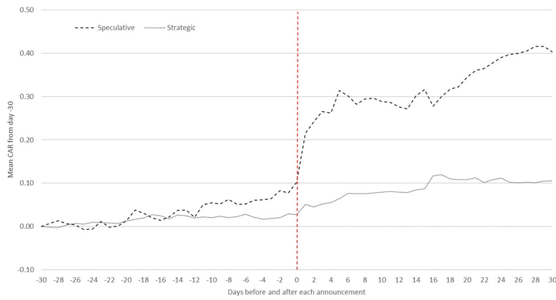


Note: Twitter data was collected for a period between 1 January 2017 and 31 March 2019 for a list of 156 companies. All tweets mentioning the name of the company plus either of the terms 'crypto', 'cryptocurrency' or 'blockchain' were computationally collected through the Search Twitter function on https://twitter.com/explore 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.

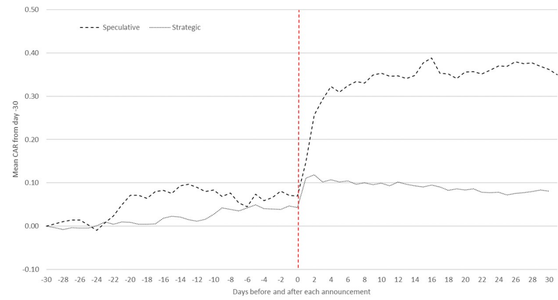
Figure 5: Sentiment adapted cumulative abnormal returns

i) Separated by type of blockchain announcement

a) Defined 'rumour'

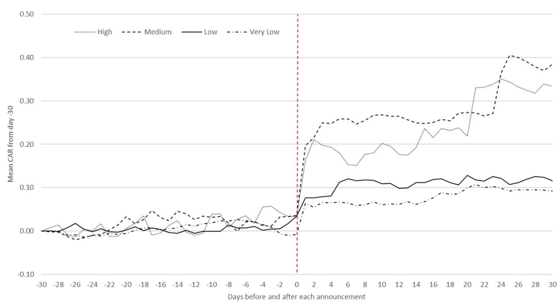


b) Defined 'official announcement'

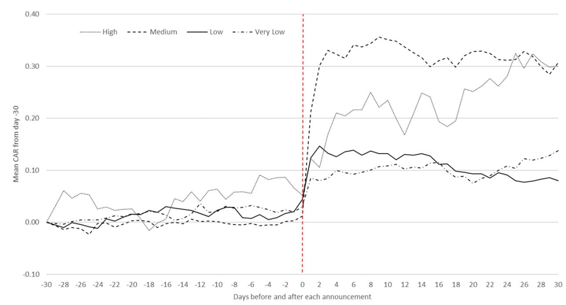


ii) Separated by the defined reach of social media

a) Defined 'rumour'

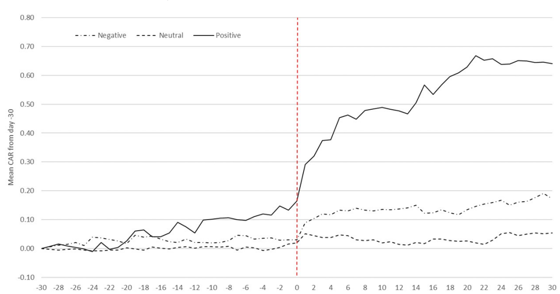


b) Defined 'official announcement'

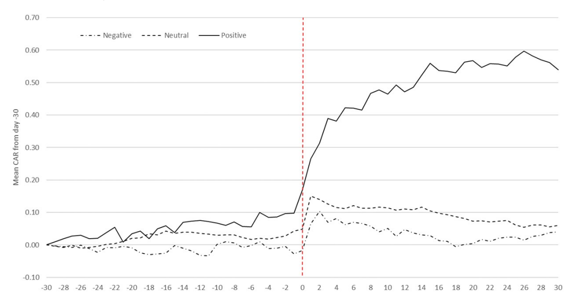


iii) Separated by defined sentiment

a) Defined 'rumour'



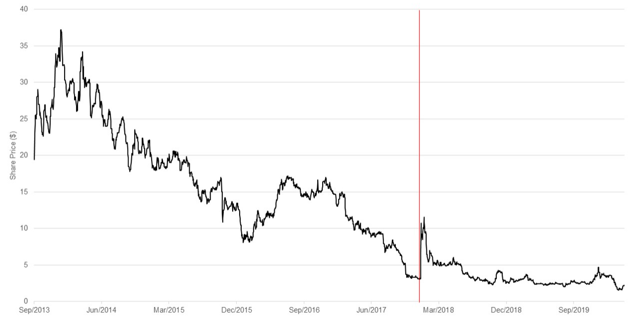
b) Defined 'official announcement'



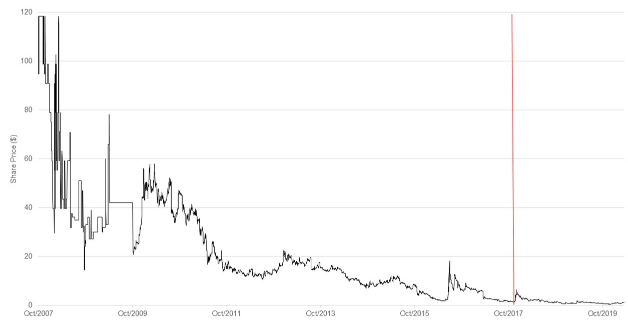
Note: This figure shows the average sentiment adapted cumulative abnormal returns by type of announcement for a 61-day window [30,+30]. Within this context, and building on the work of Akyildirim et al. [2020], speculative announcements are found to be those relating to the change of corporate identity 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'. Reach is 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 6: Selected corporate performance after blockchain-development announcements

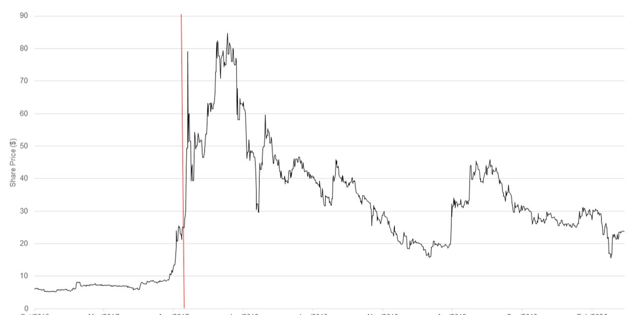
a) Kodak



b) Future Fintech Group



c) Bitcoin Group SE



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).

Table 1: Summary statistics of Twitter activity and corporate size

	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
Speculative	2.785	2.717	12.229	13.564
Strategic	2.137	1.955	122.486	6.233
By 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
By Twitter Activity (Ranked by quintile)				
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
By Company Size (Ranked by 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

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.

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

	Mean	Median	Std. Dev.	Min	Max
			Total		
	Mean	Median	Std. 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
			Speculative		
	Mean	Median	Std. 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
			Strategic		
	Mean	Median	Std. 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

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; 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.

Table 3: Social media statistics for selected periods as denoted by type of denoted blockchain development announcement

[-30,-1]	Rumour						Official					
	Speculative		Strategic		Total		Speculative		Strategic		Total	
	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

[0,3]	Rumour						Official					
	Speculative		Strategic		Total		Speculative		Strategic		Total	
	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

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’.

Table 4: Sentiment adapted cumulative abnormal returns as at the point of both 'rumour' and 'official' announcement relating to corporate blockchain announcements

	Rumour			Official Announcement		
	[-30,-1]	[AR0]	[0,3]	[-30,-1]	[AR0]	[0,3]
Motivation						
Speculative	0.1397	0.1132	0.0465	0.1444	0.1086	0.0527
Structural	0.0171	0.0238	0.0040	0.0757	0.0674	-0.0034
Reach						
High	0.1785	0.1601	0.0516	0.0438	0.0798	0.0028
Medium	0.1775	0.1296	0.0303	0.0519	0.0702	0.0881
Low	0.0624	0.0714	0.0013	0.0300	0.0547	0.0146
Very Low	0.0426	0.0423	0.0048	0.0918	0.2098	0.0214
Sentiment						
Negative	0.0747	0.0599	0.0275	-0.0169	0.0822	0.0155
Neutral	0.0251	0.0314	-0.0130	0.0682	0.0821	-0.0344
Positive	0.1568	0.1276	0.0856	0.1695	0.0963	0.1155

Note: The table shows regression estimates of Sentiment adapted cumulative abnormal returns 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. 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.

Table 5: OLS Regressions for the period inclusive of the day before to the day after each event

	'Rumour'					'Official Announcement'				
	Spec1	Spec2	Spec3	Spec4	Spec5	Spec1	Spec2	Spec3	Spec4	Spec5
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)
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

Note: The table shows regression estimates of Sentiment adapted 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'. 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.

Table 6: OLS Regressions for the day of each type of announcement

	'Rumour'					'Official Announcement'				
	Spec1	Spec2	Spec3	Spec4	Spec5	Spec1	Spec2	Spec3	Spec4	Spec5
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)
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

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'. 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.

Table 7: Default probability: regression results

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				0.426***
				(0.031)
Noncurrent			0.327***	0.231***
			(0.024)	(0.027)
Noncurrent*IMP				0.296*
				(0.175)
DEF	1.548***	1.592***	1.590***	1.008***
	(0.152)	(0.166)	(0.152)	(0.223)
GDP	-0.041***	-0.041***	-0.040***	-0.044***
	(0.001)	(0.001)	(0.001)	(0.001)
Bond	0.052***	0.053***	0.051***	0.054***
	(0.001)	(0.001)	(0.001)	(0.001)
CDS	0.094***	0.094***	0.102***	0.102***
	(0.002)	(0.002)	(0.004)	(0.004)
NITA	-0.113***	-0.113***	-0.080***	-0.129***
	(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***
	(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

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; 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. Independent variables are lagged. ***, ** and * indicate level of significance at 1%, 5%, and 10% respectively.

Table 8: Default probability: average marginal effects

	Leverage	Trade	Current	Noncurrent	Observations
Speculative	0.022***	0.024***	0.031***	0.015***	4,642
	(0.001)	(0.002)	(0.002)	(0.001)	
Strategic	0.003***	0.004***	0.005***	0.004***	6,507
	(0.000)	(0.000)	(0.000)	(0.000)	

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 7. Average marginal effects of trade payables, and current and non-current liabilities to total assets are computed using specification (4) of Table 7. Statistical significance is calculated using the Wald test. ***, ** and * indicate level of significance at 1%, 5%, and 10% respectively.

Table 9: Default probability based on previous technological experience: regression results

	Speculative				*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***
	(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

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; 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. Independent variables are lagged. ***, ** and * indicate level of significance at 1%, 5%, and 10% respectively.

Table 10: Default probability: average marginal effects of previous technological experience

	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***

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 9. Average marginal effects of trade payables, and current and non-current liabilities to total assets are computed using specification (4) of Table 9. Statistical significance is calculated using the Wald test. ***, ** and * indicate level of significance at 1%, 5%, and 10% respectively.

Table 11: 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.

Table 12: Re-estimated credit ratings due to leverage use on corporate blockchain-development projects as defined by previous technological experience

		Restimated Credit Rating								
		Actual Credit Rating			Previous Technological Experience			No Previous Technological Experience		
		Ave	Max	Min	Ave	Max	Min	Ave	Max	Min
Speculative	Pre-	Baa1 (8.4)	Aa2 (3.0)	Caa1 (17.0)						
	Post-	Baa3 (9.7)	A1 (5.0)	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-	A2 (6.0)	Aaa (1.0)	Ba2 (12.0)						
	Post-	A2 (6.4)	Aa1 (2.0)	Ba3 (13.0)	A3 (7.2)	Aa2 (2.5)	B1 (13.5)	Baa1 (8.4)	Aa3 (3.7)	B2 (14.7)

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.

Appendices

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

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

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.

Table A2: Linear Transformation Scale for Credit Ratings

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

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.