8-26-2024

An Event Study Approach to Analyze the Confounding Nature of Bitcoin on Blockchain Disclosures

Venu Bhaskar Puthineedi

Prajwal Eachempati

Ashish Kumar Jha

Praveen Ranjan Srivastava

Pacific Asia Journal of the Association for Information Systems

ISSN 1943-7544

Research Paper doi: 10.17705/1pais.XXXXX Volume XX, Issue X (202X)

An Event Study Approach to Analyze the Confounding Nature of Bitcoin on Blockchain Disclosures

Venu Bhaskar Puthineedi[1], Prajwal Eachempati[2], Ashish Kumar Jha[3,*], Praveen Ranjan Srivastava[4]

[1]Trinity College Dublin, Ireland, puthinev@tcd.ie
[2]Ernst and Young Dublin, Ireland, prajwal.eachempati@ie.ey.com
[3,*]Trinity College Dublin, Ireland, akjha@tcd.ie
[4]Indian Institute of Management Rohtak, India, praveen.ranjan@iimrohtak.ac.in

Abstract

Background: *There is a case to be made that the widely popular and highly valued "Bitcoin" (and other significant cryptocurrencies) has become synonymous with blockchain for many retail investors and other non-informed individuals. This study attempts to answer two important research questions in this space. First, the study aims to understand if companies leverage this proximity in technological awareness of Bitcoin and blockchain to attract more investors and users by riding the Bitcoin wave and strategically timing the disclosures. Second, we aim to compute the value of the confounding effect.*

Method: *To answer these questions, we collected over 4000 blockchain-related announcements from the top 30 NASDAQ-listed firms over the past five years. All announcements are analyzed using text analytics techniques to identify the topic, tone, and complexity. An event study approach adopting a Fama-French four-factor model is developed to detect whether any changes in the market-wide abnormal returns surrounding Bitcoin events influence the company's performance. The relationship between the announcement texts and the abnormal returns is then computed and analyzed.*

Results: *The results evidence a substantial impact of Bitcoin market returns on the abnormal return instances. Further, it is also observed that strategically framing the firm disclosures concerning blockchain announcements has a significant impact on the market returns.*

Conclusion: *This study contributes to the literature on digital business strategies within the emerging purview of cryptocurrency networks. At a practical level, the study aims to alert "not-so-well-informed" investors about the possible misconception of Bitcoin performance as a direct driver of the performance of the technological companies making blockchain announcements.*

Keywords: Blockchain; Bitcoin; Cryptocurrency Market Strategy; Abnormal Returns; Event study.

This research article was submitted on July-2023 and under five revisions, accepted on July-2024.

Citation: Puthineedi, V. B., Eachempati, P., Jha, A. K., & Srivastava, P. R. (in press). An Event Study Approach to Analyze the Confounding Nature of Bitcoin on Blockchain Disclosures. *Pacific Asia Journal of the Association for Information Systems, XX*(X), XX-XX. https://doi.org/10.17705/1pais.XXXXX

Introduction

"*Many people wrongly conflate the two. Do you know the difference*?" (Euromoney, 2022)

This opening quote from Euromoney in 2022 talks about the two terms – "Blockchain" and "Bitcoin." While being related, these terms do not represent the same thing, and the confusion has persisted until now (Euromoney, 2022). Since the inception of blockchain technology in 2008 (Nakamoto, 2008), there has been a significant development in the characteristics governing its practical use case (Agi & Jha, 2022). However, Statista reports that the financial sector currently accounts for more than 60% of blockchains worldwide (Statista, 2022). It is not uncommon for individuals to confound blockchain with cryptocurrencies when presented with such information.

Within the realm of cryptocurrencies, over the past decade, "Bitcoin" has emerged as the most popular cryptocurrency (Yi et al., 2018). At its inception, the monetary value of Bitcoin (BTC) was nearly zero dollars. However, it garnered a substantial amount of traction over the past decade, with the BTC unit touching an all-time high (ATH) of $67,566 in November 2021 (Coinmarketcap, 2021). El Salvador became one of the major adopters of Bitcoin when it announced the adoption of Bitcoin as legal tender in September 2021 (Alvarez et al., 2022). Bitcoin has also gained more traction as various companies, such as Microsoft, Tesla, AT&T, and Twitch, have announced their acceptance of Bitcoin and various cryptocurrencies for transactions (Bhattacharya & Rana, 2021).

All these events and the associated news reporting have ensured that Bitcoin remains the most popular blockchain technology as well as the one most talked about in the popular press. However, over the past decade, the use of blockchain as part of digital business strategy has transcended the financial domain. Due to the advent of digitalization, the need to improve operational efficiency, business agility, privacy, and security has become crucial for organizations and businesses (Jha & Bose, 2013; Kamal, 2020; Masrom & Rahimly, 2015). Businesses require a strong digital business strategy to adapt, compete, and thrive in the current digital economy (Skare et al., 2023; van de Wetering, 2021). With decentralization, transparency, security, and immutability as core features, blockchain technology has become a part of the digital landscape of businesses in the domains of IoT, cybersecurity, real estate, and healthcare (Shao et al., 2022). Blockchain has reformed environments where data privacy and security are of the highest priority. For instance, blockchain technologies are used to enable patients and doctors to share sensitive information (Prokofieva & Miah, 2019) or to design smart contracts in the music industry to track royalties (Darvish & Bick, 2024).

Companies often use traditional media or press releases to announce innovative blockchain applications, keeping stakeholders informed. These announcements cover various topics such as company performance reports, product launches (including blockchain innovations), and organizational restructuring. According to Mitchell and Mulherin (1994) and Stankevičienė and Akelaitis (2014), stock prices are directly correlated with the public announcements made by the companies. Hence, it is reasonable to assert that announcements related to blockchain made by firms could influence the stock price of said firms. However, this study aims to address the fundamental question of whether investors in the firm can discern between the specialized applications of blockchain proposed by these firms and the widely recognized form of blockchain, namely "Bitcoin", when making investment decisions. Therefore, the research focuses on studying the influence of the confoundedness between the terms "Bitcoin" and "Blockchain" on the financial performance of technological firms making blockchain-based announcements. It is crucial to understand if the use of blockchain as a part of digital strategy is misinterpreted as Bitcoin. This leads us to the following set of research questions:

RQ1a: Does any confoundedness exist between the terms Blockchain and Bitcoin (BTC)?
RQ1b: Does the confoundedness reflect in the stock price of companies making Blockchain announcements and Bitcoin prices?

In other words, are the blockchain-based announcements strategically timed to leverage this proximity in technological awareness of bitcoin and blockchain to attract investors and boost financial performance? The second question derived from the above discussion is stated as follows:

RQ2: How can we quantify or measure the extent of confoundedness between the above two terms?

These research questions are answered by implementing an event study methodology (Bose & Leung, 2019) that aims to investigate the relationship between the Bitcoin price movement and blockchain-related announcements of the top NASDAQ-listed companies. The study aims to analyze the possible misconception of Bitcoin performance being a direct driver of the performance of companies making blockchain announcements and urges potential investors to be wary of such business wrongdoings. Investors need to be cautious about hastily misinterpreting highs in the Bitcoin market as optimistic signals to invest in companies, which may subsequently plummet contrary to expectations. Investors should consider all information sources before making a suitable decision.

Literature Review

Blockchain

Distributed data of transactions and block of ledgers are some of the terms used across the literature to define blockchain. To put things into perspective, Rossi et al. (2019) explained blockchain as an append-only distributed database of transactions characterized by high tamper resistance, making it a decentralized system. However, the assumed fundamental characteristics of blockchain are security, transparency, anonymity, and enhanced transactional speeds. These features can only be attained by integrating smart contracts and encryption into blockchain technology. The distributed ledgers are responsible for storing the data in groups defined as blocks. These blocks are stacked in chronological order, giving it a chain-like structure and hence the term blockchain. Each block in the database is protected using timestamps, cryptographic hashes, and data structures, which prevent the information from being overridden or tampered with (Liang et al., 2021).

Blockchain technology, a decentralized system, eliminates the requirement for third-party organizations for data protection and privacy concerns as the databases are verified and processed by multiple actors in the system, minimizing hacking concerns to a great extent (Upadhyay et al., 2021). Despite being such a revolutionary technology that can alter the modus operandi of sectors like fintech, supply chain, IoT, etc., the ability to provide a decentralized and transparent system comes at a price. The demand for substantial computational power to verify blocks leads to increased energy consumption, making it a notable drawback for this technology. Apart from this, double-spending and Sybil attacks are essential issues of concern. These limitations and disadvantages of blockchain technology are identified by Liang et al. (2021).

Blockchain and Cryptocurrencies

The advent of blockchain technology and accompanying programmed protocols (smart contracts) creates disruptive business opportunities (Leewis et al., 2021). In the Fintech sector, blockchain provides the security and privacy required to handle transactional data, supported by other elements that are generally presumed to be the inherent features of blockchain. The combination of distributed ledgers with consensus mechanisms, encryption, smart contracts, and immutable audit trails offers the critical features necessary for the fintech sector (Du et al., 2019).

Acting as the backbone for the fintech industry, blockchain technology has revolutionized the cryptocurrency domain (Ali et al., 2020) with its capacity to record, store, and secure large volumes of transactional data. In over 13 years since the inception of Bitcoin in 2009, more than 19,000 different cryptocurrencies have come into existence reaching an all-time high market value of 2.95 trillion dollars. Mattke et al. (2021) found that, considering the nature of cryptocurrencies as an investment opportunity, factors such as transactional speeds, privacy, and low transactional fees drive the adoption of Bitcoin, in particular.

Other Blockchain Applications

Primarily defined as distributed ledgers, blockchain is commonly considered a technology constrained within the fintech sector (Ng et al., 2023). To put things in perspective, Wang et al. (2020) defined blockchain as an incorruptible digital ledger of economic transactions that can be programmed to record not just financial transactions but virtually everything of value. Blockchain technology has found its place in almost every industry and domain where privacy is of utmost importance (Völter et al., 2023).

Supply chain management is the sector that encompasses the planning and management of all business activities (Council of Supply Chain Management Professionals, 2018). Involving extensive data storage, privacy, and security concerns, the supply chain is one of the sectors where blockchain technology is predominantly used. Erol et al. (2020) identified the powerplant industry, pharmaceutical supply chain, and intelligent transportation systems among the various sectors that have been significantly transformed by integrating blockchain technology. This integration enhances transparency regarding the elements within the supply chain while ensuring security and privacy. Chen et al. (2022) noted the progression of blockchain applications in the healthcare sector. The healthcare sector has large volumes of data, including patients' health records, prescriptions, and information regarding the operations and activities of firms. Such private and sensitive information is prone to cyber-attacks and hacking. With the ability to record and store large volumes of data, a private blockchain can be used to provide limited access based on user-defined conditions. This feature has an impending use case, as patient health records can be shared between healthcare institutions based on the requirement. Prescriptions can be managed by monitoring the pharmaceutical supply chain; this helps solve the drug shortage issues and handle the addiction to prescriptive drugs.

Blockchain vs Bitcoin

Due to the existing confoundedness between Bitcoin and blockchain, there has been significant speculation about the performance of companies based on blockchain or cryptocurrencies. To understand if the companies are trying to leverage the speculative market, Akyildirim et al. (2020) investigated the stock returns of companies that announced the integration of blockchain or cryptocurrencies into their environment. It was found that there were abnormal stock returns for the companies that announced these integrations compared to the other companies in the same domain, class, and geography. This research provides a basis for understanding that firms are leveraging the popularity of blockchain and Bitcoin to boost their financial performance.

The influence of various types of announcements on firm performance, depending on the sector and industry, has been studied extensively. The literature indicates that firm announcements indeed have a significant influence on firm performance. Bose and Pal (2012) studied the influence of Green Supply Chain Management announcements on the short-term change in the firm's stock returns and found a positive correlation between these two factors. Regarding technological announcements, Bose and Leung (2019) provided evidence that Identity Theft Countermeasure (ITC) adoption announcements positively influence firms' short- and long-term market performance.

Similarly, research efforts have been directed to explore the extent of ambiguity regarding blockchain and Bitcoin in the general population (Cahill et al., 2020). Autore et al. (2021) reaffirmed that investors view credible corporate strategies involving blockchain technology favorably. Similarly, a study conducted by Chen and Zahedi (2016) found that blockchain announcements have led to a significant positive increase in firm value by generating more credible and substantial stock returns in technological firms. There is evidence of a positive relationship between the integration of blockchain and firm announcements on the firm's financial performance. This research aspires to understand if firms use these elements to garner higher stock returns and improve their financial performance.

Table 1 – A Non-Exhaustive Summary of Relevant Studies

Research Articles	Research Objective/Theoretical Background	Study Artefact	Research Variable
Cheng et al. (2019)	The ambiguity in the usage of terms “blockchain” and “Bitcoin.”	Bitcoin vs Blockchain	Financial performance
Rossi et al. (2019)	Understanding the core concepts of blockchain.	Blockchain	Theoretical framework
Zhong et al. (2022)	Signaling theory for identifying factors impacting firm valuation- Bitcoin returns, in particular.	Bitcoin	Abnormal returns
Panagiotidis et al. (2019)	Influence of financial markets on Bitcoin returns.	Bitcoin	Bitcoin returns
Akyildirim et al. (2020)	An instance of firms riding a crypto exuberance wave.	Cryptocurrency	Abnormal stock returns
Kashanipoor et al. (2020)	The information disseminated by the firm announcements should accurately provide a roadmap for the firm's future outlook.	Company disclosures	Financial performance
Stevens (2022)	While sentiment is an important factor that can influence abnormal returns, an equally important factor is the complexity of words used in the announcements.	Firm announcements	Financial performance
Choudhury et al. (2019); Eachempati et al. (2021)	It is demonstrated that investors value the addition of strategic keywords/themes over and above numerical information in the report.	Firm announcements	Abnormal returns
Kraus & Feuerriegel (2017)	Influence of company disclosures on abnormal stock returns.	Company disclosures	Abnormal stock returns
Du et al. (2019)	Role of blockchain in cryptocurrencies.	Blockchain and cryptocurrencies	Theoretical framework

Table 1 summarizes the relevant studies that form the structural basis for this research's theory development and operationalization. While prior studies have investigated the consequences of ambiguity in the usage of “Bitcoin” and “blockchain”, none of them have measured the extent to which this ambiguity impacts the abnormal returns of the firm and, in turn, the firm’s performance. Therefore, there is a pressing need to adopt a robust methodology that measures the impact on abnormal returns.

Furthermore, there is a need to identify the various factors/signals from corporate announcements that impact market valuation (such as topics and sentiments in the announcement, complexity of announcements, etc.) and quantitatively measure the extent to which these variables drive abnormal returns. Determining the significance of the variables is essential to ascertain which factors can impact the firm's decision-making strategies.

Theoretical Background: Signaling Theory

The research arguments are built on the concepts of signaling theory. According to Connelly et al. (2011), the signaling theory posits that the information asymmetry between parties in a transaction can be reduced through appropriate signals. The four key elements of signaling theory are the signaler (sender), the receiver, the signal, and the signaling environment. In the context of the study, signalers are the executives or managers of the firm who possess information that is not available to the external parties. The information withheld can include the firm's performance, future plans, or firm announcements, which are the signals that will be released to the receivers. Receivers are the investors who assess the firm's stock value by relying on the signals released through various channels.

The reports or announcements (signals) from the firms are used by the investors (receivers) to reduce the information asymmetry to make investment decisions. However, this may not provide accurate information for decision-making. To reduce this information asymmetry, investors may seek additional direct or indirect signals from the signalers or the signaling environment (Srinivasan et al., 2022). The firms (Signalers) mostly intend to convey positive direct or indirect signals (Kim & Youm, 2017). Nevertheless, the actions of the investors depend on how they interpret the direct and indirect signals from the firm and the external environment (Connelly et al., 2011).

In the context of the study, the firms (signalers) leverage indirect signals from the external environment (such as fluctuations in Bitcoin prices) to convey positive signals. However, these signals are interpreted by the investors (receivers) as a negative indicator due to the volatility of Bitcoin. These arguments form the basis for the hypotheses and are detailed in the hypotheses development section.

Hypotheses Development

The confounding belief between Bitcoin and blockchain that we argue in this paper is based on similar occurrences that have been researched in extant literature. In one of the major studies in this area, Cheng et al. (2019) studied the confounding of 8K filings with the rise in the Bitcoin price. They observed a sharp increase in 8K filing announcements as a co-movement with the rise of Bitcoin prices caused by the novel breakthroughs in blockchain technology at the end of the year. The investors were found to overreact to an announcement stating the advent of blockchain technology. This behavior was attributed to the Bitcoin price bubble. Similarly, Jain and Jain (2019) further observed that when companies changed their names to include terminologies related to "blockchain" or "Bitcoin" in their terms, they experienced significant abnormal positive returns for the next two months. These studies seem to show that individuals, as well as firms, want to ride the Bitcoin wave by aligning themselves with Bitcoin-related announcements and, therefore, gain from that.

In the scope of our investigation, we extend beyond the discoveries articulated by Cheng et al. (2019) by adopting a nuanced and critical perspective. Specifically, our investigation concentrates on discerning whether companies possessing substantial market capitalization, capable of exerting influence on the U.S. market, are strategically aligning their blockchain announcements for the general public with the Bitcoin price fluctuations. Consequently, we posit the hypothesis that companies with significant market capitalization may actively engage in leveraging the Bitcoin trend, thereby influencing their market dynamics. Hence, we hypothesize that:

H1: Companies are timing their blockchain-related announcements acting upon fluctuations in the Bitcoin market movement as vital information signals such that more announcements are made when the Bitcoin prices are at local peaks.

Next, we rely on the signaling theory (Connelly et al., 2011) to analyze the impact of these announcements. Signaling theory provides a framework for making arguments on the use of signals by technological firms to drive investors. According to signaling theory, signaling can be used as a form of communication by the signalers to influence the behavior of the receivers leveraging any circumstances in the external environment. The vital information that prompts receivers' decision-making are the desired signals. The three major stakeholders in the current research scenario are technological firms (signalers) utilizing the Bitcoin price fluctuations (external environment) to influence the investing behavior of the investors (receivers). The technological firms (signalers) leverage the timing of the blockchain-based announcements (signals) following

the Bitcoin price fluctuations to alleviate their financial performance. The announcements include vital information about company events, earnings, disclosures, and product launches (Zhong et al., 2022). These arguments based on signaling theory provide a base for developing hypotheses to examine the factors/signals influencing firms' financial performance.

For H2, we argue that the blockchain-based announcements that firms make are the signals sent to the investors by the firms. As discussed in the preceding paragraph, such signals may relate to various firm activities (Zhong et al., 2022). Extant research has established that investors react to these signals sent by firms as firm announcements. When firms send signals about blockchain-based activities that they are engaging in (or are considering engaging in), investors have the option to support the firm by buying its stock or show disapproval by selling its stocks. When investors sell stocks, it leads to a decline in the market value of the firm. With the building traction of blockchain and Bitcoin over the past decade, there is evidence of cautious wariness in investors for blockchain-related investments as it is seen as a risky venture. Hence, we argue that when firms make blockchain-based announcements, investors will not react positively to that as they confound blockchain with Bitcoin, leading to a loss of market value for the firms. In a related study, Cheng et al. (2019) found that after an initial positive reaction to blockchain announcements, the market value of firms reversed over the next 30 days. This confirms an existing distrust in blockchain announcements that we argue has only grown stronger. Hence, we hypothesize that:

H2: Firms making blockchain-based announcements have a significant decline in their market value.

Signaling theory relies on the signal, type of signal, and content of the signal. The sentiment of the signal is one of the other important metrics that explain the signal's inherent meaning. Srinivasan et al. (2022) argue that the sentiment of the signal is significant in explaining abnormal market returns. It is believed that the sentiment of the signal, i.e., news announcements, has an impact on the market value of the companies making blockchain-based announcements. As stated in H1 and H2, investors are wary of Bitcoin and blockchain news as risky ventures, the more firms are bullish about Bitcoin, investors will be cautious and withdraw from these firms, leading to lower market value for these firms. Therefore, the more positive the sentiment of the firm announcements, the lower the firm market value. Similarly, other studies have evidenced an impact on the managers' tone (Kim et al., 2022) and the style of the language used in the textual component of 10-K filings (Kashanipoor et al., 2020) as factors influencing a firm's future performance. Thus, firm-generated announcements can be subjected to sentiment analysis to decipher whether a firm, in general, is conveying positive (or negative) signals (Kraus & Feuerriegel, 2017). Hence, we hypothesize the following:

H3: The more positive the sentiment of the blockchain-based announcements, the higher the loss of market value of the firm.

Extending the concepts of signaling theory from the above argument, we continue to focus on the other dimensions of signal content. While sentiment is an important factor that can influence abnormal returns, we present an argument that the complexity of words used in the announcements also influences the decision-making capabilities of the investors. Investors may assume that the companies are fudging the financial statements if they are found complex in wording, dissuading them further away from investing in the firm. Investigating this line of argument, Cecchini et al. (2010) observed a relationship between annual report readability and the persistence of the firm's earnings. They found that the higher the readability and clarity of words used in the report, the more confident investors feel about investing in the firm, leading to higher earnings for the firm. Therefore, we hypothesize that:

H4: The complexity of the announcement text impacts the abnormal stock returns significantly.

As hypothesized above in H2, investors perceive announcements as signals for their decision-making. Based on the signaling theory, the reaction to a particular signal depends on its strength. The content, specifically the topic of the announcement, influences the decision-making capability of the investors (Roeder et al., 2022). The topic modelling approach can be used to identify the major topics in these announcements. It is an unsupervised algorithm that clusters the text based on their similarity to identify topics.

We argue that the topic of the announcement varies the perception of the investors, acting as the strength of the signal, implying that certain topics are a stronger negative driver of market value. Huang et al. (2018) and Eachempati et al. (2021) investigated whether drafting the tone and content of disclosures by presenting suitable keywords/topics can influence the firm's market value. Therefore, we hypothesize that:

H5: Topic coverage proportion significantly impacts abnormal stock returns.

Data Collection and Research Methodology

The research aims to investigate if the top technological firms are riding the Bitcoin wave. Specifically, the focus will be on the top 30 NASDAQ-listed companies, which are predominantly technology-focused (Le et al., 2021). This differs from the top 30 US companies, which encompass a variety of sectors. Notably, certain companies within this group, such as Tesla and AT&T, accept cryptocurrencies as a means of payment. Moreover, collectively, these top 30 firms represent a substantial portion, accounting for approximately 35% of the total market capitalization across all NASDAQ-listed companies.

It is also essential to highlight that the frequency of blockchain-related announcements decreases substantially beyond the top 30 companies. In fact, upon closer examination of these announcements, we found that for companies ranked beyond the 30th position, the number of blockchain-related announcements reduces to single digits. Within these 30 firms, we conducted longitudinal data collection spanning as many years as feasible to establish patterns for our analysis. As detailed in the subsequent section, we amassed data for over 4,000 events across these firms.

Data Collection

To investigate the hypotheses, blockchain announcements made by the top 30 NASDAQ-listed companies are collected from the LexisNexis® database. LexisNexis is a widely used news database that collates all news announcements from across the world (Chan et al., 2011; Weitkamp & Eidsvaag, 2014). It is extensively used in most event studies. We took a six-year timeline between January 2015 and October 2021 (when data collection for this study concluded). The timeline was chosen for the following reason: The collection of blockchain announcements began in 2015, primarily because there were relatively few announcements made by companies in the preceding years. To illustrate, the total number of blockchain announcements made in 2014 and 2015 amounted to 21 and 19, respectively. It was only in 2016 that the number of announcements witnessed a substantial increase, reaching a total of 88. Therefore, data collection for these announcements commenced in 2015, just one year before this notable growth in blockchain-related announcements began. On the other hand, data pertaining to Bitcoin was collected starting from 2014. This was because of requirements for event study as we used past financial performance to predict “normal” financial performance on the day of blockchain-related announcements and compared that to the actual performance to find the impact of blockchain-related announcements. This methodology requires the financial data of the period significantly before the public announcements.

As the firms were based in the US and the NASDAQ is also based in the US, we limited our search to English-language publications based in North America. For each announcement, if multiple outlets had covered the same, we took the earliest announcement as the relevant one for our study. The keyword for the search was “blockchain,” and any announcement by the 30 firms in the dataset using this word was considered relevant to the study. We retrieved 4,056 announcements made by the top 30 companies. We found two firms, i.e., Facebook and Microsoft, to dominate the announcements. They had 1,486 and 1,135 blockchain-related announcements, respectively.

In addition to the data on announcements, we collected financial and Bitcoin price data as well. The daily closing stock prices for all the constituent firms of the S&P 500 index were collected from Bloomberg data sources for the period between January 2014 and October 2021. Financial data, such as the firm's revenue, market capitalization, net income, assets, liability, and return on assets, were also collected from Bloomberg. The S&P Market returns (benchmark) were collected for the same period as above. Daily Bitcoin prices are gathered from the publicly available source Yahoo Finance. Firms’ financial parameters like total assets, market capitalization, liabilities, and stock prices are extracted from the Bloomberg database.

To address the research questions, the event study methodology has been adopted to relate the extent to which the blockchain-based firms time the events with the Bitcoin price movement. This extent can be measured by first identifying various factors/signals from corporate announcements that impact market valuation and then regressing the factors such as word count, writing complexity (using the Gunning FOG index), the sentiment of the announcement, and the financial factors of the firms like asset, revenue, and liability on the abnormal returns (a measure of the impact of events on Bitcoin price). The textual indicators and the financial indicators collected above are regressed on the abnormal returns with the detailed implementation procedure for the regression model provided in the subsequent sections.

Since the factors vary in nature and require different pre-processing and extracting procedures, the data analysis has been subdivided into three subsections: Textual Data Analysis, Abnormal Returns Computation, and Regression Analysis. This division allows for a stage-wise analysis procedure to be captured.

Textual Data Analysis

Initially, the textual data analysis was performed to extract the word count, sentiment, and Gunning FOG index from the announcement text using the pre-processing steps described below. This was followed by computing the abnormal returns using the event study procedure detailed below in the Abnormal Returns Computation subsection, which gives the dependent variable for the regression.

We followed robust analytical procedures for this study that were in line with recent developments in the field of event study (Zhang et al., 2021) and text-based analysis (Lee, 2022). Our analytical approach can be summarized in the following steps. First, the collected announcement data from LexisNexis were cleaned following standard text analytic protocols[1]. Then, the variables from the processed text data were extracted. We compute the complexity of the text through the Gunning FOG index (Zhou et al., 2018). The Gunning FOG[2] index is widely used to measure of text complexity in business announcements (Ajina et al., 2016). We employed Latent Dirichlet Allocation (LDA) to extract topics from the text (Ali & Kannan, 2022). Details on the execution of the LDA algorithm and the uncovered topics are provided in the Appendix. We identified 10 topics from the text that represent 10 themes of content in the announcements. We used the software R for LDA and also to compute the sentiment of the text using the bag of words approach (X. Li et al., 2022). As the text analytic techniques described above, work on understanding word frequency and the distance between words, it is important to exclude the common words in English, i.e., stop words, numerical data, memorable characters, and weblinks (Du et al., 2022). All necessary text pre-processing is performed as per the existing best practices (Du et al., 2022). The data from the announcements were then merged with the firms' financial data gathered from Bloomberg and Yahoo Finance.

Abnormal Return Computation

The event study methodology was adopted to check for the change in the market value of firms (Liu et al., 2022), as stated in the Efficient Market Hypothesis (Fama, 1970). The abnormal return AR_{ft} for a firm "f" caused by the occurrence of an event at a particular point of time "t" is the deviation of the actual return on the day of the event and the expected return in an ideal scenario of non-occurrence of an event. In this study, the Fama-French-Carhart five-factor model (FF5) (Martin & Xia, 2022) (equation 1) was adopted to compute expected returns, with S&P 500 index firms considered as the benchmark market index. The FF5 model is considered a more comprehensive model because it controls for factors such as market capitalization, value risk, robust-minus-weak profitability, conservative minus aggressive portfolio returns, and momentum (Foye, 2018).

$$r_{ft} = \propto_f + \beta_f r_{mt} + h_f marketcap_t + s_f value\ risk_t + rm_f profitability_t + c_f portfolio\ returns_t + u_f momentum_t + \epsilon_{it} \quad (1)$$

The parameters for equation 1 are estimated using OLS regression in the estimation window of [-152,-40], i.e., the duration from 152 days and ending 40 days before the event, respectively (Racicot & Rentz, 2017). The significance of the abnormal returns is validated using statistical tests like Mean abnormal return (non-standardized) (%), T-test, Median AR (%), Wilcoxon rank-sum test, Percentage negative, and Binomial sign test(p-values) (depicted in Table 3). Figure 1 explains the complete methodology of the paper in a graphical format.

[1] This included removing emoticons, and emojis, converting text to lowercase and stemming the text, and removing stopwords and punctuations. Please see Jha, A. K., & Shah, S. (2021). Disconfirmation effect on online review credibility: An experimental analysis. *Decision Support Systems*, *145*, 113519. for more details on text preparation.

[2] The FOG index algorithm provides a few different sets of readability indices, among which the "grade" score is extracted and assigned as the FOG index score. This reflects the complexity of the announcements made by companies.

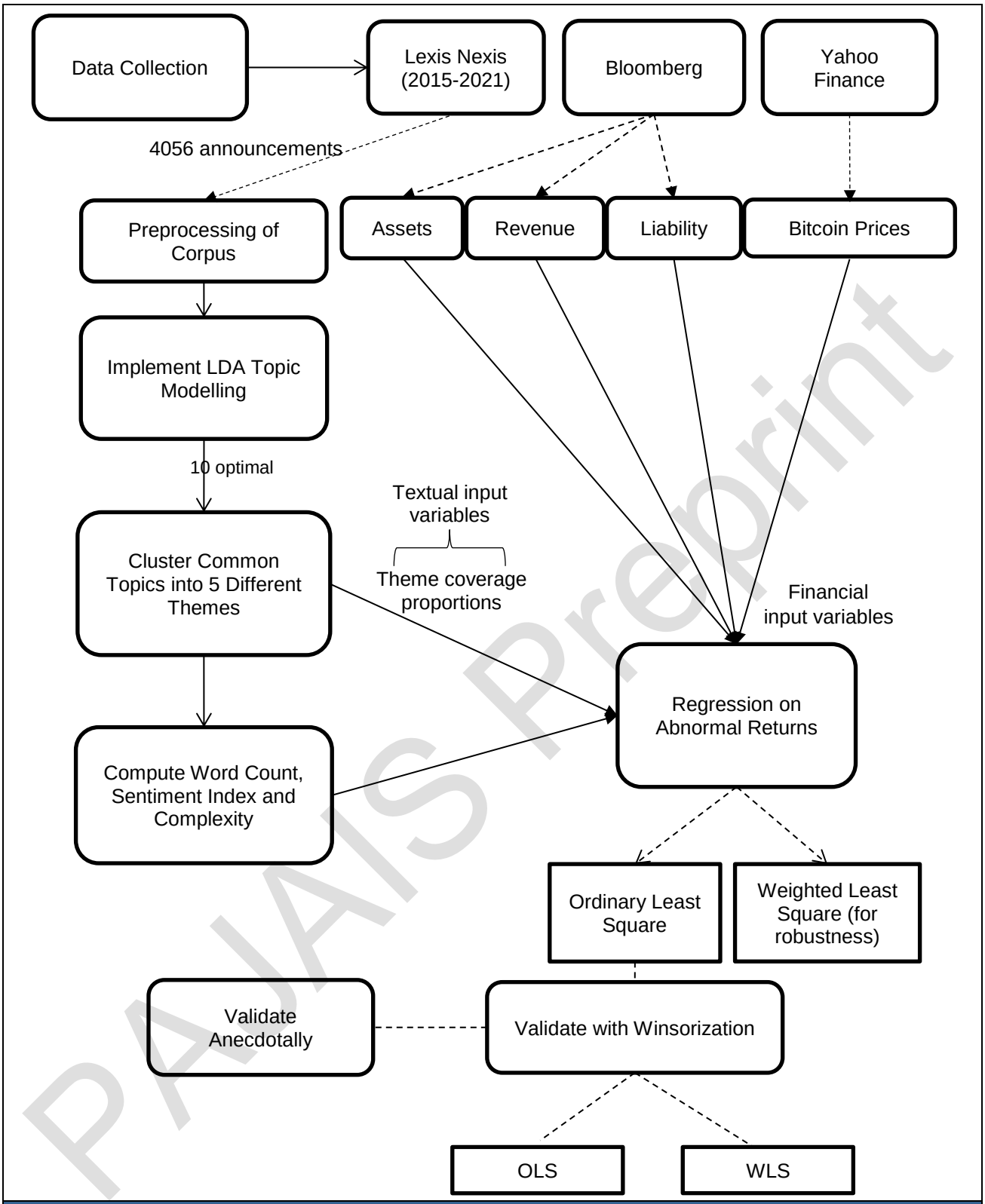

Figure 1 – Data Collection and Research Methodology

Regression Analysis

The abnormal returns computed above are now incorporated as the dependent variable in the regression analysis to determine the impact of Bitcoin market events on a firm's abnormal stock returns. The Weighted Least Squares (WLS) was adopted as the regression technique; however, it was also compared with the standard OLS regression model (Kibekbaev & Duman, 2016). WLS regression controls for group-wise heteroscedasticity by computing the weights from the inverse of the industry group-specific residuals of the OLS regression (Y. Li et al., 2022).

The independent variables for the study were the text features i.e., the topics (Topic one to Topic ten) representing the topic probabilities or top ten topic coverage proportions in the company announcements, topic relevance, i.e., the relevance score of the topics concerning Bitcoin; the sentiment of the content and the complexity.

Besides the top ten topic coverage proportions, sentiment, and FOG index used as parameters, the model is also controlled for multiple firm and industry-related factors. The inherent firm characteristics such as firm size are stated to impact abnormal returns (Palmon & Wald, 2002). There are different ways to quantify the firm size; however, this study considers the market capitalization of each of the top 30 firms (Coën & Desfleurs, 2022). Further, the total assets (Carlini et al., 2022), total liabilities (Fernández-Méndez & Pathan, 2022), and total debt (Gao & Bao, 2022) were also included as control variables. We controlled for the firm's revenue and income, which are dominant factors likely to have a confounding effect on abnormal returns. The impact of the critical independent variable, i.e., Bitcoin returns, is investigated on the abnormal returns.

Analysis and Results

Table 2 shows the descriptive statistics and the Pearson correlation coefficients for the variables. The variables income, stock price, and stocks issued were eliminated (income due to its high correlation with revenue and stock price and stocks issued were removed due to high correlation with market capitalization). Further, only the predominant topic one correlation is depicted due to its high importance over other topic proportion variables, and only the sentiment is presented in the interest of parsimony.

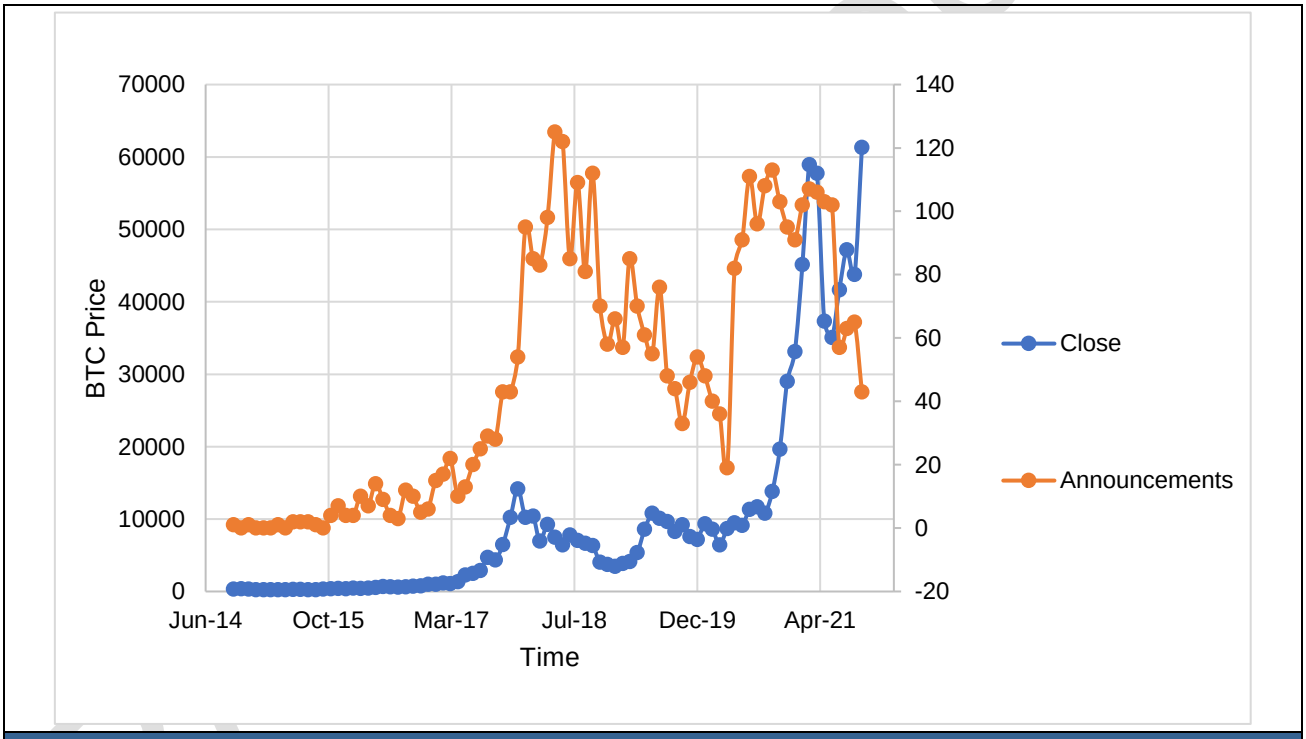

Figure 2 – Bitcoin Market Price vs. Blockchain Company Announcement Patterns

Initially, to investigate hypothesis H1, a procedure is conducted wherein the BTC market closing prices and the number of blockchain firm announcements (aggregated from the compiled cross-sectional dataset of companies and announcement dates) are plotted over the period from 2014 to 2021. Figure 2 illustrates the co-movement patterns of BTC price and blockchain company announcements. We perform the Engle-Granger test for cointegration to test the co-movement of the two-time series data. The Engle-Granger test checks the stationarity of the pair of time series and indicates co-movement. The Engle-Granger statistic for these two data series was -5.357 ($p<0.001$), indicating cointegration and hence establishing the co-movement of the two data series.

Table 2 – Correlation Matrix of Variables in the Dataset														
	Mean	**Std dev**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Length of words (1)	793.5	612.71	1.00	0.001**	-0.10	-0.05	0.04	0.02*	0.06	0.07	-0.01	0.02*	0.04*	0.04*
Revenue (2)	92,342,217	66,858,658.13	0.00	1.00	0.19	0.29	0.38	0.33	-0.01	-0.03	-0.10	0.09	-0.05	0.13
Capitalization (3)	6,392,734	59,872,336.49	-0.10	0.19	1.00	0.96	0.78	0.57	-0.06	-0.01	0.03*	-0.17	0.03*	-0.09
Total assets (4)	176.4	98,632,023.4	-0.05	0.29	0.96	1.00	0.91	0.70	-0.05	0.03*	-0.01	-0.17	0.04*	-0.04
Total liabilities (5)	11,632,718	71,659,308.59	0.04*	0.38	0.78	0.91	1.00	0.84	-0.04	0.13	-0.08	-0.14	0.06	0.06
Total debt (6)	90,837,479	34,152,014.06	0.02*	0.33	0.57	0.70	0.84	1.00	-0.02	0.16	-0.11	-0.13	0.05	0.10
Bitcoin returns (7)	137,809,403	0.045	0.06	-0.01	-0.06	-0.05	-0.04	-0.02	1.00	-0.01	0.02*	-0.04	0.00	-0.02
FOG Index (8)	70,650,003	4.71	0.07	-0.03	-0.01	0.03*	0.13	0.16	-0.01	1.00	-0.09	0.09	0.01*	0.12
Topic relevance (9)	32,679,803	2.81	-0.01	-0.10	0.03*	-0.01	-0.08	-0.11	0.02*	-0.09	1.00	-0.40	0.07	-0.19
Topic (10)	0.002	0.11	0.02*	0.09	-0.17	-0.17	-0.14	-0.13	-0.04	0.09	-0.40	1.00	-0.10	0.27
Word count(11)	9.3	305.62	0.15	0.03*	-0.04	0.01	0.10	0.13	-0.02	0.07	-0.13	0.02*	-0.02	0.17
Sentiment (12)	5.18	0.021	0.04*	-0.05	0.03*	0.04*	0.06	0.05	0.005**	0.01*	0.07	-0.10	1.00	-0.55

Note: ** p<0.01; * p<0.05

It was found that initially, when the BTC closing prices were slowly rising (nearly stagnant change), the number of announcements was scant. However, nearing June 2018, as the BTC price touched 7,000 US dollars, the number of announcements also rose sharply to over 15. As the Bitcoin market rise petered off subsequently in the later part of 2018, the announcements also dropped. A similar high was noticed in October 2020, wherein the BTC market price touched 67,000 US dollars. The announcements again increased to 120 gradually, with the BTC market being in a bull market mode. This validates hypothesis H1 that technological companies are indeed timing their blockchain-based announcements with Bitcoin market movements. This provides us with a cue to conduct a further detailed investigation using the event study approach to prove the second hypothesis H2, i.e., whether Blockchain-based announcements have significant abnormal returns. Table 3 illustrates the abnormal returns for different event windows and is consistent in the FF5 model.

Table 3 – Abnormal Returns and Its Significances for Multiple Event Windows

Event Window	[-1,1]	[-1]	[0]	[1]
Mean abnormal return (non-standardized) (%)	-0.29 %	0.90%	-0.14%	-0.16%
T-test	-6.48***	1.32***	-5.79***	-6.85***
Median AR (%)	-61.37%	-16.30%	-22.74%	-22.69%
Wilcoxon rank sum test	-13.24***	-9.15***	-15.71***	-12.64***
Percentage negative	63.38%	60.38%	64.96%	63.00%
Binomial sign test(p-values)	-13.65***	-10.59***	-15.26***	-13.26***

Note: *** p<0.01; ** p<0.05, * p<0.1. All statistical tests are one-tailed tests; Mean and median returns are averaged over all the events and the event window.

Except for day [-1], all other event windows illustrate the mean abnormal returns to be of negative sign and are found to be statistically significant. The results of the FF5 model analysis for the event window [-1,1] depict an average drop in the market value to the tune of 0.3% per day per firm. This is equivalent to approximately a 0.9% market value drop in the adjoining three-day period (for the event window [-1,1], the one day before and after are also considered for the impact to recede). The results are consistent for the day of the announcement as well, with a market value loss of 0.14% per firm. The abnormal event in the window [-1, 1] is considered the dependent variable for further regression analysis. Initially, the baseline OLS model was formulated as follows:

$$AR[-1,1]_f = \beta_{1f} Topic\ probabilities_f + \beta_{2f} Topic\ relevance_f + \beta_{3f} Sentiment\ related\ variables_f + \beta_{4f} Word\ count_f + \beta_{5f} FOG\ index_f + \beta_{6f} Bitcoin\ returns_f + \beta_{7f} Control\ variables_f \quad (2);$$

The WLS estimates for the coefficients are shown in equation 3, where we represent the predictor matrix, “wt" represents the computed weights, and the abnormal returns AR represents the dependent variable.

$$\hat{\beta}_{wls} = (I^T wtI)^{-1} I^T wtAR \quad (3)$$

Table 4 – OLS and WLS Regression Results for Dependent Variable AR [-1,1]

Variables	M0	M1	M2	M3
Intercept	-0.09(0.14)	25.998(0.02)	0.26(0.23)	18.15(0.09)
Length of words	0.06(0.01)	0.061(0.42)	-0.01(0.08)	0.1(0.12)
Revenue	-0.02*(0.02)	-0.02 (0.12)	-0.03**(0.01)	-0.02*(0.16)
Income	-0.02(0.03)	-0.012(0.5)	-0.04(0.04)	-0.06(0.7)
Capitalization	0.03(0)	-0.03(0.59)	0.04**(0.02)	0.08*(0.14)
Total assets	0.02(0.02)	-0.041(0.94)	0.02(0.13)	-0.08(0.08)
Total liabilities	-0.01(0.05)	0.023(0.51)	-0.12(0.04)	0.05*(0.15)
Total debt	-0.02(0.06)	0(0.87)	0.06(0)	0.09(0.71)
Bitcoin returns	**Not included**	-2.09*** (0.04)	**Not included**	-2.74*** (0)
Complexity	**Not included**	-0.003(0.74)	**Not included**	0.01(0.52)
Topic relevance	**Not included**	-0.015(0.6)	**Not included**	0.01(0.8)
Topic one	**Not included**	-26.15*** (0.02)	**Not included**	-19.72*** (0.06)
Topic two	**Not included**	-25.45*** (0.02)	**Not included**	-18.52*** (0.08)
Topic three	**Not included**	-25.619*** (0.02)	**Not included**	-18.14*** (0.09)
Topic four	**Not included**	-25.661*** (0.02)	**Not included**	-18.4*** (0.08)
Topic five	**Not included**	-26.094*** (0.02)	**Not included**	-18.93*** (0.07)
Topic six	**Not included**	-24.616*** (0.02)	**Not included**	-17.57*** (0.1)
Topic seven	**Not included**	-25.181*** (0.02)	**Not included**	-18.38*** (0.08)
Topic eight	**Not included**	-25.11*** (0.02)	**Not included**	-17.95*** (0.09)

Table 4 – OLS and WLS Regression Results for Dependent Variable AR [-1,1]				
Variables	**M0**	**M1**	**M2**	**M3**
Topic nine	**Not included**	-25.894*** (0.02)	**Not included**	-18.93*** (0.07)
Topic ten	**Not included**	-25.49*** (0.02)	**Not included**	-18.34*** (0.08)
Word count	**Not included**	0(0.73)	**Not included**	-25.59** (0.01)
Sentiment	**Not included**	-64.024(0.48)	**Not included**	-218.86** (0.01)
R-Squared	0.014	0.02	0.011	0.0282
F-Statistic	1.416***	2.69***	1.45	2.826***
Max VIF	4.53	7.4	3.4	6.8
(p-value)	0.17	0.02	0.03	0.02

Note: ***p<0.01; ** p<0.05, * p<0.1. All statistical tests are one-tailed tests. Standard error in parentheses.

The OLS model and WLS model results are included in Models M0 – M3 in Table 4. Model M0 is the basic model representing all the financial control variables and word length. M1 demonstrates the inclusion of all control variables, textual variables including the FOG index, topic relevance, topic proportions, sentiment, and the critical hypothesis variable "Bitcoin returns." Models M2 and M3 represent the weighted OLS (WLS) model estimates, wherein M2 is a baseline model, and M3 incorporates all variables. The variables are expressed in terms of coefficient and standard error in parentheses. A point to note is that the R-squared values, though they seem low, are appropriate for studies on financial variables (Srinivasan et al., 2022) as they explain a stationary variable, i.e., the stock market reaction.

The second model, M1, is the most explanatory model with an adjusted R-squared of 0.017 (1.7%). The topic coverage variables are found to be negative and significant, validating H5. On further investigation, it is found that out of the ten variables, topics five to ten are particularly causing a dip in abnormal returns, as illustrated above in Table 4. These topics particularly link blockchain, cryptocurrencies, and trading and are not factored in with immediate optimism by investors due to their inherent perception of cryptocurrencies as risky investments.

The critical hypothesis variable, Bitcoin returns, was found to be significant and negative. This implies that Bitcoin returns are being confounded with the company's blockchain announcements to boost the financial indicators, validating hypothesis H2. However, the market is demonstrating a conservative and pessimistic initial reaction to the Bitcoin returns, i.e., if the Bitcoin prices are impacted by one basis point, the market is taking a cynical, pessimistic response to the tune of two basis points. Investors are cautious when making decisions about trading in company stocks that are co-moving with Bitcoin market returns. The complexity of the announcement text, which was anticipated to be significant, was in reality, not found significant. Thus, hypothesis H4 was not validated.

The third model, M2 (weighted OLS regression), depicts that Revenue and Capitalization also demonstrate the significance of firm size (measured by market capitalization) on abnormal returns. However, the effect is found to negatively impact market performance, as hypothesized by Meligkotsidou et al. (2019). Similarly, the weighted OLS consolidated regression model M3 demonstrates the significance of topic coverage, revenue, word count, and sentiment variables (significantly validating H3), again negatively impacting the abnormal returns and showing a similar cautious, pessimistic reaction to financial control variables. Overall, the WLS model outperforms the OLS model in terms of explainability while validating the variable significance to a large extent.

Robustness Checks

An additional robustness check is performed to validate the above WLS estimates by winsorizing the outcome variable. Winsorization (Cheng et al., 2022) is a technique wherein the data entries corresponding to the top ten percentile and bottom ten percentile values of the dependent variable [abnormal returns] are imputed, and the regression results are re-run on the winsorized dataset. Table 5 illustrates the winsorized OLS regression results:

Table 5 – Winsorized Regression Results				
Variables	**M0**	**M1**	**M2**	**M3**
(Intercept)	-0.3(0.084)	20.28(6.565)	-0.06(0.14)	23.34(6.547)
Length of words	0.05(0.005)	0(0)	0.03(0.05)	0(0)
Revenue	-0.08**(0.05)	-0.05(0)	-0.02**(0)	-0.01*(0)
Income	-0.02**(0.001)	-0.02(0)	-0.03(0.05)	0(0)
Capitalization	0.07*(0.003)	0.07(0)	0.09(0.06)	0(0)
Total assets	-0.09**(0.003)	-0.08(0)	0*(0.002)	-0.05*(0)

Table 5 – Winsorized Regression Results				
Variables	**M0**	**M1**	**M2**	**M3**
Total liabilities	0.07***(0.002)	0.05(0)	0.05***(0.002)	0.04*(0)
Total debt	0.03(0.002)	0.02(0)	-0.08(0.002)	-0.01(0)
Bitcoin returns	**Not included**	-1.25*** (0.024)	**Not included**	-0.95*** (0.006)
FOG Index	**Not included**	0.01(0.006)	**Not included**	0(0.64)
Topic relevance	**Not included**	0(0.017)	**Not included**	0.02(0.016)
Topic 1	**Not included**	-21.18*** (6.577)	**Not included**	-24.04*** (6.564)
Topic 2	**Not included**	-20.65*** (6.574)	**Not included**	-23.43*** (6.559)
Topic 3	**Not included**	-20.78*** (6.578)	**Not included**	-24.02*** (6.569)
Topic 4	**Not included**	-20.84*** (6.574)	**Not included**	-23.74***(6.558)
Topic 5	**Not included**	-20.74*** (6.579)	**Not included**	-23.53*** (6.565)
Topic 6	**Not included**	-20.43*** (6.571)	**Not included**	-23.43*** (6.557)
Topic 7	**Not included**	-20.55*** (6.563)	**Not included**	-23.55*** (6.545)
Topic 8	**Not included**	-20.23*** (6.579)	**Not included**	-23.31***(6.556)
Topic 9	**Not included**	-20.7*** (6.584)	**Not included**	-23.59*** (6.57)
Topic 10	**Not included**	-20.58*** (6.582)	**Not included**	-23.34*** (6.557)
Word count	**Not included**	0(0)	**Not included**	0(0)
Sentiment	**Not included**	-1.79**(0.024)	**Not included**	-2.01**(1.071)
R-Squared	0.013	0.026	0.015	0.030
F-Statistic	1.54***	2.11***	1.67	2.34***
Max VIF	3.84	8.4	5.4	9.8

Note: ***p<0.01; ** p<0.05, * p<0.1. All statistical tests are one-tailed tests. Standard error in parentheses

The topic proportion variables are again consistently and significantly validating H5, and the hypothesis variable "Bitcoin returns" continues to hold importance; additionally, for the winsorized baseline OLS model, financial control variables other than Revenue, i.e., Income, Capitalization, Total assets, and Total liabilities are found significant. For the winsorized WLS models, the sentiment computed by the “qdap” package is also significantly validating H3. The complexity of the announcement text is not significant; thus, H4 is not validated. Since, predominantly, there is no variation in results and primarily, the control variables and the hypothesis variable “Bitcoin returns” hold good, corroborating the hypotheses H1 and H2, thus, providing confidence that our initial analysis is indeed robust.

Discussion and Implications

Theoretical Implications

The study investigates whether technological firms leverage the confounding meaning of the terms “blockchain” and “Bitcoin” and boost their financial performance to mislead investors into correlating companies’ blockchain-based announcements and the Bitcoin market movement. Hypothesis H1 is tested by performing an event study on the announcements of the top 30 NASDAQ-listed companies, tracing their events and simultaneously the variation in Bitcoin market returns and other control financial indicator variables to observe instances of abnormal returns. The results evidence a substantial and significant impact of Bitcoin market returns on abnormal return instances, thus being in line with Cheng et al. (2019). Prior investigations have found cases of confounding both the terms blockchain and Bitcoin (Cahill et al., 2020; Treiblmaier, 2021). However, few are investigating the consequences of this interchangeable use of terms.

Our study contributes to the existing literature by examining how companies may exploit this phenomenon as false market signals to strategically time their blockchain-related announcements with bullish movements in the Bitcoin market. This strategic timing aims to prompt stakeholders to associate blockchain news with Bitcoin returns.

Also, some studies examined how Bitcoin trading volume influences the blockchain firm’s financial performance (Kozlowski et al., 2021), which impacts the firm's returns (Ante et al., 2021). This is validated in our study findings. Regression results also reveal that the variables corresponding to topic coverage proportions are statistically significant in elucidating the abnormal fluctuations in returns, thereby validating H4. However, the coefficients of the variables are found to be negative. This implies that whenever keywords about topics related to blockchain and Bitcoin are framed in the announcements, the events demonstrate a conservative, pessimistic reaction to the topics. Abnormal returns take time to adjust to the arrival of information about any of the keywords

related to blockchain and Bitcoin. The reaction does not factor in the topic-related news with immediate optimism. The inclusion of the primary hypothesis variable "Bitcoin returns" and the stage-wise incorporation of other financial indicator control variables do not alter the nature of reaction to these topics. This validates the findings of Falchetti et al. (2022).

Our study also highlights the importance of sentiment extracted from blockchain announcements in influencing abnormal returns. As computed by the GI dictionary, sentiment is found to impact abnormal stock returns (p ~0.01, illustrated in Table 4 M3). This is another crucial contribution to the literature.

Practical Implications

The study contributes practically by alerting stakeholders and investors not to confuse firms' positive blockchain news/announcements with bullish Bitcoin market outcomes. They need not necessarily attribute the bullish Bitcoin market to positive blockchain news/announcements from technological firms and get overly optimistic in investment decisions. Similarly, investors are advised not to be discouraged by the negative Bitcoin market movements and refrain from investing in technological firms making blockchain-related announcements. Instead, investors are encouraged to adopt a rational approach that does not overly prioritize the Bitcoin market movement for evaluating firm performance, particularly in countries like Japan and South Korea which are leaders in blockchain technology adoption. Additionally, the study underscores the importance of investor sentiment and confidence in announcements as potential indicators of company performance.

Cryptocurrency, a digital form of currency operating on decentralized networks based on blockchain technology, was first introduced in the Asia-Pacific region with the advent of Bitcoin in 2009 (Ganbold, 2024). Since then, the cryptocurrency landscape in the Asia-Pacific region has evolved rapidly with a rapid rise in number of startups in the blockchain space a number of startups in the blockchain space, with 26.8% of startups emerging from Asia (Ariela, 2024). Further, the market has experienced significant volatility, with a notable boom in 2021 followed by a downturn in 2022, marked by the bankruptcy of numerous crypto companies. Currently, the market is gradually recovering and is projected to grow in revenue in the coming years. The Asia-Pacific region is emerging as a leader in the cryptocurrency field, driven by higher institutional acceptance and growing consumer interest.

The regression results highlight the significant impact of variables related to topic coverage proportions on return fluctuations, although the direction of this impact is negative. This suggests that companies strategically incorporating certain keywords/topics in their reports may influence or reassure users/stakeholders (Dao & Abraham, 2021; Feuerriegel & Gordon, 2018). In the context of the paper, whenever keywords about topics related to “blockchain” and “Bitcoin” are used in proximity, a negative response emerges. This implies that investors take time to absorb information about Bitcoin market developments before deciding. Other specific market-related news is not factored in by users after processing this information about the Bitcoin market. Investors are showing prudence concerning Bitcoin market developments (Güler, 2023) and not making hasty investment/trading decisions solely based on Bitcoin market highs when investing in the company.

The importance of the investor sentiment variable in explaining abnormal returns is critical from an efficient market hypothesis perspective because investors and stakeholders are influenced by the sentiment extracted from annual reports, disclosures, and product announcements to estimate the firm's financial performance (stock price, revenue, and income). The inherent sentiment from corporate discourses indeed drives the direction of firm performance by providing a future roadmap of which areas are profitable/worth treading by the company (positive sentiment) and which areas/strategies are no longer viable for the company (negative sentiment). Sentiment is, therefore, a key leading indicator for future performance. In Singapore, a hub for fintech innovation, investor sentiment can significantly influence market dynamics, for instance. Positive sentiment towards blockchain initiatives can drive investment and market confidence (Arner et al., 2016).

Further, the complexity of the announcement text was not found to be a successful metric in determining firm performance. This implies that the degree of complexity of the language used in discourses cannot alone provide a direction for future courses of action to firms. The frequency of certain topics mentioned in disclosures coupled with the language complexity can change the future outlook of firms and influence their performance, and in that scenario, complexity can hurt firm performance (Cecchini et al., 2010). This finding particularly holds importance in emerging markets of the Asia Pacific where a positive tone of disclosures can help boost investor confidence, which in turn, has a positive impact on firm performance.

Limitations

This study is not without its share of limitations. First, this study analyzes the impact of blockchain-based news announcements on market value changes in a short time window. However, there is scope to study the long-term consequences of the confoundment between the terms "blockchain" and "Bitcoin" to ascertain the impact on stakeholders and investors. Second, the study is limited to only a few NASDAQ-listed companies with high market capitalization. There is a need to expand the study sample of firms to analyze the differential strategies adopted by high market capitalization firms and smaller firms in leveraging the Bitcoin market developments to boost strong financial indicators and present a different picture to investors and stakeholders. Another limitation of the study is its temporal scope, as it is confined to December 2021, a period preceded by the occurrence of black swan events such as Tesla's Bitcoin holdings liquidation, the FTX exchange crash, and the downturn in the Terra ecosystem. These events led to extraordinary and atypical fluctuations in Bitcoin prices. Nevertheless, this limitation opens up an avenue for future research that could explore the spillover effects of the Bitcoin market on firm shares during such impactful black swan events.

The above findings have prompted investors interested in companies to adopt a conservative reaction strategy to Bitcoin market announcements. Instead, investors and stakeholders are encouraged to focus on market indicators like news sentiment, which provide insights into the performance of the technological firms. Our study sheds light on this critical research area that remains underexplored. Further, our findings also indicate that the announcements need to be strategically framed without mentioning particular keywords about the confounding of blockchain and Bitcoin, which reveals a conservative pessimistic reaction to the financial key performance indicators. The interest of the investors can instead be captured by incidentally mentioning the Bitcoin market without explicitly influencing their psychology through “confounding” vocabulary to blockchain terms. They must be provided with the scope to process information and be allowed to form their perceptions based on cognitive understanding rather than imposing the mentions of confusing topics and clouding their decision-making ability.

Despite anticipating a positive market impact stemming from the sentiment of blockchain-based announcements by technological firms, our findings reveal a counterintuitive outcome. The empirical evidence shows a statistically significant correlation wherein higher positive announcement sentiment is associated with a subsequent loss in market value. This intriguing observation prompts further investigation into elucidating the precise mathematical relationship (linear, parabolic, exponential, etc.) between the two variables: the sentiment of the announcement and the market value of the firms.

Conclusion

The findings of this study underscore the importance of topic coverage, Bitcoin returns, investor sentiment, and the extent of stakeholder interest as critical signals driving firm performance. Firms are advised to highlight specific positively connoted topics and themes, ensuring that the proportion of relevant information is conveyed in a positive tone. This approach can reassure investors and users about the firm's value and market performance. Additionally, the findings suggest that firms should emphasize incorporating Bitcoin as a part of their digital business strategy rather than merely attributing blockchain technology to Bitcoin. By focusing on the positive connotations of specific themes, firms should underscore the weightage of blockchain features such as security, privacy, and decentralization in their announcements. This can enhance the transparency of technology integration and gain investor trust. By adopting these strategies, firms can ensure a win-win situation, boosting their performance while enabling investors to make judicious decisions for the growth of their portfolios.

Acknowledgement

The authors acknowledge the support of Science Foundation Ireland research Centre ADAPT through Grant 13/RC/2106_P2. The third author also acknowledges support from Faculty of Arts, Humanities and Social Sciences Benefactions Fund, Trinity College Dublin to support this project.

References

Agi, M. A., & Jha, A. K. (2022). Blockchain technology in the supply chain: An integrated theoretical perspective of organizational adoption. *International Journal of Production Economics*, *247*, 108458.

Ajina, A., Laouiti, M., & Msolli, B. (2016). Guiding through the fog: Does annual report readability reveal earnings management?. *Research in International Business and Finance*, *38*, 509-516.

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

Ali, I., & Kannan, D. (2022). Mapping research on healthcare operations and supply chain management: A topic modelling-based literature review. *Annals of Operations Research, 315*(1), 29-55.

Ali, O., Ally, M., & Dwivedi, Y. (2020). The state of play of blockchain technology in the financial services sector: A systematic literature review. *International Journal of Information Management*, *54*, 102199.

Alvarez, F. E., Argente, D., & Van Patten, D. (2022). Are cryptocurrencies currencies? Bitcoin as legal tender in El salvador. *Science, 382*(6677), eadd2844.

Ante, L., Fiedler, I., & Strehle, E. (2021). The impact of transparent money flows: Effects of stablecoin transfers on the returns and trading volume of Bitcoin. *Technological Forecasting and Social Change*, *170*, 120851.

Ariela R. (2024). *Crypto: Startups in Asia and Africa are surpassing the USA in terms of market share!* Cointribune. Retrieved 18 July, 2024, from https://www.cointribune.com/en/crypto-startups-in-asia-and-africa-are-surpassing-the-usa-in-terms-of-market-share/#:~:text=In%202024%2C%20crypto%20startups%20in,of%20cryptocurrencies%20in%20emerging%20markets

Arner, D. W., Barberis, J., & Buckey, R. P. (2016). FinTech, RegTech, and the reconceptualization of financial regulation. *Northwestern Journal of International Law & Business, 37*(3), 371-413.

Autore, D. M., Clarke, N., & Jiang, D. (2021). Blockchain speculation or value creation? Evidence from corporate investments. *Financial Management*, *50*(3), 727-746.

Bhattacharya, S., & Rana, K. (2021). A case study on cryptocurrency driven euphoria in 2020-21. *International Journal of Research in Engineering, Science and Management*, *4*(3), 9-11.

Bose, I., & Leung, A. C. M. (2019). Adoption of identity theft countermeasures and its short-and long-term impact on firm value. *Mis Quarterly*, *43*(1), 313-327.

Bose, I., & Pal, R. (2012). Do green supply chain management initiatives impact stock prices of firms?. *Decision Support Systems*, *52*(3), 624-634.

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

Carlini, F., Del Gaudio, B. L., Porzio, C., & Previtali, D. (2022). Banks, FinTech and stock returns. *Finance Research Letters*, *45*, 102252.

Cecchini, M., Aytug, H., Koehler, G. J., & Pathak, P. (2010). Making words work: Using financial text as a predictor of financial events. *Decision Support Systems*, *50*(1), 164-175.

Chan, C. M., Hackney, R., Pan, S. L., & Chou, T. C. (2011). Managing e-Government system implementation: A resource enactment perspective. *European Journal of Information Systems*, *20*(5), 529-541.

Chen, Y., Lu, Y., Bulysheva, L., & Kataev, M. Y. (2022). Applications of blockchain in industry 4.0: A review. *Information Systems Frontiers*, 1-15.

Chen, Y., & Zahedi, F. M. (2016). Individuals' internet security perceptions and behaviors. *MIS Quarterly*, *40*(1), 205-222.

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

Cheng, W. G., de Oliveira Leite, R., & Caldieraro, F. (2022). Financial contagion in internet lending platforms: Who pays the price?. *Finance Research Letters*, *45*, 102187.

Choudhury, P., Wang, D., Carlson, N. A., & Khanna, T. (2019). Machine learning approaches to facial and text analysis: Discovering CEO oral communication styles. *Strategic Management Journal*, *40*(11), 1705-1732.

Coën, A., & Desfleurs, A. (2022). The relative performance of green REITs: Evidence from financial analysts' forecasts and abnormal returns. *Finance Research Letters*, *45*, 102163.

Coinmarketcap. (2021). *Historical data of daily closing price of bitcoin.* Coinmarketcap. Retrieved 4 February, 2023, from https://coinmarketcap.com/currencies/bitcoin/

Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2011). Signaling theory: A review and assessment. *Journal of management*, *37*(1), 39-67.

Council of Supply Chain Management Professionals. (2018). *CSCMP Supply Chain Management Definitions and Glossary.* Council of Supply Chain Management Professionals. Retrieved 4 February, 2023, https://cscmp.org/CSCMP/CSCMP/Educate/SCM_Definitions_and_Glossary_of_Terms.aspx#:~:text=CSCMP's%20Definition%20of%20Supply%20Chain,and%20all%20logistics%20management%20activities.

Dao, V. T., & Abraham, T. (2021). An empirical examination of the use of IS-enabled sustainability initiatives across the integrated sustainability framework. *Pacific Asia Journal of the Association for Information Systems*, *13*(3), 57-85.

Darvish, M., & Bick, M. (2024). The role of digital technologies in the music industry—A qualitative trend analysis. *Information Systems Management*, *41*(2), 181-200.

Du, W. D., Pan, S. L., Leidner, D. E., & Ying, W. (2019). Affordances, experimentation and actualization of FinTech: A blockchain implementation study. *The Journal of Strategic Information Systems*, *28*(1), 50-65.

Du, Y., Liu, D., & Duan, H. (2022). A textual data-driven method to identify and prioritise user preferences based on regret/rejoicing perception for smart and connected products. *International Journal of Production Research, 60*(13), 4176-4196.

Eachempati, P., Srivastava, P. R., Kumar, A., Tan, K. H., & Gupta, S. (2021). Validating the impact of accounting disclosures on stock market: A deep neural network approach. *Technological Forecasting and Social Change*, *170*, 120903.

Erol, I., Ar, I. M., Ozdemir, A. I., Peker, I., Asgary, A., Medeni, I. T., & Medeni, T. (2020). Assessing the feasibility of blockchain technology in industries: Evidence from Turkey. *Journal of Enterprise Information Management, 34*(3), 746-769.

Euromoney. (2022). *What's the difference between blockchain and Bitcoin?*. Euromoney. Retrieved 10 February, 2023, from https://www.euromoney.com/learning/blockchain-explained/the-difference-between-blockchain-and-bitcoin

Falchetti, D., Cattani, G., & Ferriani, S. (2022). Start with "Why," but only if you have to: The strategic framing of novel ideas across different audiences. *Strategic Management Journal*, *43*(1), 130-159.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, *25*(2), 383-417.

Fernández-Méndez, C., & Pathan, S. (2022). Environmental stocks, CEO health risk and COVID-19. *Research in International Business and Finance*, *59*, 101509.

Feuerriegel, S., & Gordon, J. (2018). Long-term stock index forecasting based on text mining of regulatory disclosures. *Decision Support Systems*, *112*, 88-97.

Foye, J. (2018). A comprehensive test of the Fama-French five-factor model in emerging markets. *Emerging Markets Review*, *37*, 199-222.

Ganbold, S. (2024). *Cryptocurrency in the Asia-Pacific region - statistics & facts.* Statista. https://www.statista.com/topics/11122/cryptocurrency-in-the-asia-pacific-region/

Gao, Z., & Bao, Y. (2022). Do acquirers of mega mergers prefer to improve debt level? An investigation on mega deals and leverage change. *Finance Research Letters, 47*, 102780.

Güler, D. (2023). The Impact of investor sentiment on bitcoin returns and conditional volatilities during the era of Covid-19. *Journal of Behavioral Finance, 24*(3), 276-289.

Huang, A. H., Lehavy, R., Zang, A. Y., & Zheng, R. (2018). Analyst information discovery and interpretation roles: A topic modeling approach. *Management Science*, *64*(6), 2833-2855.

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

Jha, A. K., & Bose, I. (2013). A framework for addressing data privacy issues in e-governance projects. *Journal of Information Privacy and Security*, *9*(3), 18-33.

Jha, A. K., & Shah, S. (2021). Disconfirmation effect on online review credibility: An experimental analysis. *Decision Support Systems*, *145*, 113519.

Kamal, M. M. (2020). The triple-edged sword of COVID-19: Understanding the use of digital technologies and the impact of productive, disruptive, and destructive nature of the pandemic. *Information Systems Management*, *37*(4), 310-317.

Kashanipoor, M., Aghaee, M. A., & Mohseni Namaghi, D. (2020). Information disclosure tone and future performance. *Accounting and Auditing Review*, *26*(4), 570-594.

Kibekbaev, A., & Duman, E. (2016). Benchmarking regression algorithms for income prediction modeling. *Information Systems*, *61*, 40-52.

Kim, E. H., & Youm, Y. N. (2017). How do social media affect analyst stock recommendations? Evidence from S&P 500 electric power companies' Twitter accounts. *Strategic Management Journal*, *38*(13), 2599-2622.

Kim, J., Lim, J. H., & Yoon, K. (2022). How do the content, format, and tone of Twitter-based corporate disclosure vary depending on earnings performance?. *International Journal of Accounting Information Systems*, *47*, 100574.

Kozlowski, S. E., Puleo, M. R., & Zhou, J. (2021). Cryptocurrency return reversals. *Applied Economics Letters*, *28*(11), 887-893.

Kraus, M., & Feuerriegel, S. (2017). Decision support from financial disclosures with deep neural networks and transfer learning. *Decision Support Systems*, *104*, 38-48.

Le, T. L., Abakah, E. J. A., & Tiwari, A. K. (2021). Time and frequency domain connectedness and spill-over among fintech, green bonds and cryptocurrencies in the age of the fourth industrial revolution. *Technological Forecasting and Social Change*, *162*, 120382.

Lee, C. K. H. (2022). How guest-host interactions affect consumer experiences in the sharing economy: New evidence from a configurational analysis based on consumer reviews. *Decision Support Systems*, *152*, 113634.

Leewis, S., Smit, K., & van Meerten, J. (2021). An explorative dive into decision rights and governance of blockchain: A literature review and empirical study. *Pacific Asia Journal of the Association for Information Systems*, *13*(3), 25-56.

Li, X., Zhang, J., Du, Y., Zhu, J., Fan, Y., & Chen, X. (2022). A novel deep learning-based sentiment analysis method enhanced with emojis in microblog social networks. *Enterprise Information Systems, 17*(5), 2037160.

Li, Y., Nolte, I., Vasios, M., Voev, V., & Xu, Q. (2022). Weighted least squares realized covariation estimation. *Journal of Banking & Finance, 137*, 106420.

Liang, T. P., Kohli, R., Huang, H. C., & Li, Z. L. (2021). What drives the adoption of the blockchain technology? A fit-viability perspective. *Journal of Management Information Systems*, *38*(2), 314-337.

Liu, C., Liu, Y., Zhang, D., & Xie, C. (2022). The capital market responses to new energy vehicle (NEV) subsidies: An event study on China. *Energy Economics*, *105*, 105677.

Martin, R. D., & Xia, D. Z. (2022). Efficient bias robust regression for time series factor models. *Journal of Asset Management*, *23*(3), 215-234.

Masrom, M., & Rahimly, A. (2015). Overview of data security issues in hospital information systems. *Pacific Asia Journal of the Association for Information Systems*, *7*(4), 51-66.

Mattke, J., Maier, C., Reis, L., & Weitzel, T. (2021). Bitcoin investment: A mixed methods study of investment motivations. *European Journal of Information Systems*, *30*(3), 261-285.

Meligkotsidou, L., Panopoulou, E., Vrontos, I. D., & Vrontos, S. D. (2019). Quantile forecast combinations in realised volatility prediction. *Journal of the Operational Research Society*, *70*(10), 1720-1733.

Mitchell, M. L., & Mulherin, J. H. (1994). The impact of public information on the stock market. *The Journal of Finance*, *49*(3), 923-950.

Nakamoto, S. (2008). *Bitcoin: A Peer-to-Peer Electronic Cash System.* https://bitcoin.org/bitcoin.pdf

Ng, E., Tan, B., Sun, Y., & Meng, T. (2023). The strategic options of fintech platforms: An overview and research agenda. *Information Systems Journal*, *33*(2), 192-231.

Palmon, O., & Wald, J. K. (2002). Are two heads better than one? The impact of changes in management structure on performance by firm size. *Journal of Corporate Finance*, *8*(3), 213-226.

Panagiotidis, T., Stengos, T., & Vravosinos, O. (2019). The effects of markets, uncertainty and search intensity on bitcoin returns. *International Review of Financial Analysis*, *63*, 220-242.

Prokofieva, M., & Miah, S. J. (2019). Blockchain in healthcare. *Australasian Journal of Information Systems*, *23*.

Racicot, F. E., & Rentz, W. F. (2017). A panel data robust instrumental variable approach: A test of the new Fama-French five-factor model. *Applied Economics Letters*, *24*(6), 410-416.

Roeder, J., Palmer, M., & Muntermann, J. (2022). Data-driven decision-making in credit risk management: The information value of analyst reports. *Decision Support Systems*, *158*, 113770.

Rossi, M., Mueller-Bloch, C., Thatcher, J. B., & Beck, R. (2019). Blockchain research in information systems: Current trends and an inclusive future research agenda. *Journal of the Association for Information Systems*, *20*(9), 1390-1405.

Shao, Z., Zhang, L., Brown, S. A., & Zhao, T. (2022). Understanding users' trust transfer mechanism in a blockchain-enabled platform: A mixed methods study. *Decision Support Systems*, *155*, 113716.

Skare, M., de Obesso, M. D. L. M., & Ribeiro-Navarrete, S. (2023). Digital transformation and European small and medium enterprises (SMEs): A comparative study using digital economy and society index data. *International Journal of Information Management*, *68*, 102594.

Srinivasan, R., Jha, A. K., & Verma, N. K. (2022). To talk or not?: An analysis of firm-initiated social media communication's impact on firm value preservation during a massive disruption across multiple firms and industries. *Decision Sciences, 54*(4), 410-431.

Stankevičienė, J., & Akelaitis, S. (2014). Impact of public announcements on stock prices: Relation between values of stock prices and the price changes in Lithuanian stock market. *Procedia-Social and Behavioral Sciences*, *156*, 538-542.

Statista. (2022). *Blockchain use in banking and financial services market size worldwide*. Statista. Retrieved August 17, 2022, from https://www.statista.com/statistics/1229290/blockchain-in-banking-and-financial-services-market-size/

Stevens, J. A. (2022). Do changes in industry classification systems matter? Evidence from REITs. *Journal of Real Estate Research, 44*(3), 377-398.

Treiblmaier, H. (2021). The token economy as a key driver for tourism: Entering the next phase of blockchain research. *Annals of Tourism Research*, *91*, 103177.

Upadhyay, A., Mukhuty, S., Kumar, V., & Kazancoglu, Y. (2021). Blockchain technology and the circular economy: Implications for sustainability and social responsibility. *Journal of Cleaner Production*, *293*, 126130.

van de Wetering, R. (2021). Understanding the impact of enterprise architecture driven dynamic capabilities on agility: A variance and fsQCA study. *Pacific Asia Journal of the Association for Information Systems*, *13*(4), 32-68.

Völter, F., Urbach, N., & Padget, J. (2023). Trusting the trust machine: Evaluating trust signals of blockchain applications. *International Journal of Information Management*, *68*, 102429.

Wang, M., Wu, Y., Chen, B., & Evans, M. (2020). Blockchain and supply chain management: A new paradigm for supply chain integration and collaboration. *Operations and Supply Chain Management: An International Journal*, *14*(1), 111-122.

Weitkamp, E., & Eidsvaag, T. (2014). Agenda building in media coverage of food research: Superfoods coverage in UK national newspapers. *Journalism Practice*, *8*(6), 871-886.

Yi, S., Xu, Z., & Wang, G. J. (2018). Volatility connectedness in the cryptocurrency market: Is Bitcoin a dominant cryptocurrency?. *International Review of Financial Analysis*, *60*, 98-114.

Zhang, Y., Zhang, C., & Xu, Y. (2021). Effect of data privacy and security investment on the value of big data firms. *Decision Support Systems*, *146*, 113543.

Zhong, X., Chen, W., & Ren, G. (2022). The impact of corporate social irresponsibility on emerging-economy firms' long-term performance: An explanation based on signal theory. *Journal of Business Research*, *144*, 345-357.

Zhou, M., Lu, B., Fan, W., & Wang, G. A. (2018). Project description and crowdfunding success: An exploratory study. *Information Systems Frontiers*, *20*, 259-274.

Appendix

The number of topics given data is inherent to the nature of data and finding the optimal number of topics is crucial in segregating the issues and themes accordingly. Coherence scores are plotted to find the optimal number of topics between 1 to 20. It is found that the coherence score is high for ten topics. After identifying the optimal number of topics, the LDA topic modelling algorithm is employed to find the probability of documents belonging to topics based on their contents. These are the top 15 terms in each topic extracted to observe the context of each topic. Further analysis has revealed five emergent themes among the ten topics. Table I below describes the themes and the topics under each theme. When mapped to the individual announcements, these themes collectively aid in identifying the specific domain of interests of each company.

Table A – Topics Identified and Mapping to Significant Themes

Theme	Topics	Description
Digital	1	Focuses primarily on digital elements, social media, applications, digital content
Blockchain and innovation	2,6,8	Broadly encompasses things that are related to blockchain and innovation
Media news	3	Broadly focuses on media news and information
Blockchain in general	4	Covers general aspects of blockchain
Blockchain, cryptocurrencies, and trading	5,7,9,10	The focus is global market trading, cryptocurrencies, blockchain, and Bitcoin.

About the Authors

Venu Bhaskar Puthineedi is a doctoral candidate at Trinity Business School in Business Analytics. His research areas include business analytics, social media analytics, and cryptocurrencies. He has presented at international conferences like EURAM, EDSI and IAM and has international peer-reviewed publications under review in leading journals. He is currently an adjunct lecturer at the Trinity Business School and National College of Ireland.

Prajwal Eachempati holds a doctorate in Management Information Systems from Indian Institute of Management Rohtak and worked as a Machine Learning Data Analyst at Amazon. He is certified in Business Analytics from the Indian School of Business and AI/ML and Blockchain Architecture from IIIT Hyderabad. He completed a challenging industry-academia collaborative research assignment at Trinity College Dublin and is now a Senior AI/ML Technology Consultant at Ernst and Young Ltd. for the UK and Ireland. His research interests include Business Analytics, Investment Management, Marketing, Operations, Blockchain, MLOps, Generative AI and Explainable AI. He has published in peer-reviewed journals, with an H index of 12 and I index of 12, and serves as a peer reviewer.

Ashish Kumar Jha is an Associate Professor in the field of Business Analytics at Trinity Business School. He is a co-director of Trinity Centre for Digital Business and Analytics. He is a distinguished member of Association of Information Systems. He is a funded Investigator at SFI Research Centre ADAPT. His papers have been published in many top journals of the field including Journal of MIS (listed in FT list), Information and Management, Decision Sciences, International Journal of Production Economics, Decision Support Systems among others. He has also presented his work at numerous top conferences of field including International Conference on Information Systems, European Conference on Information Systems, Decision Sciences Institute Annual Meeting, Informs Annual Meeting among others. Ashish serves as an Associate Editor for European Journal for Information Systems and Information & Management among others.

Praveen Ranjan Srivastava is an Associate Professor in the Area of Information Technology Systems at IIM Rohtak. He did his Ph.D. in Computer Science & Engineering from Birla Institute of Technology & Science, Pilani. His research areas are software testing management, Analytics and E commerce, Software Project Management, Quality assurance, Agile Modeling & Management etc. He has published research papers in various leading international journals and conferences in the area of Information System/Computer Science and Engineering. His H index is 32 and I index is 76. He has been actively involved in reviewing various research papers submitted in his field to different leading journals and various international and national level conferences. He conducts several MDPs also.